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POKROČILÉ PROGNOSTICKÉ MODELY V OBLASTI ODPADOVÉHO HOSPODÁŘSTVÍ

ADVANCED PROGNOSTIC MODELS IN WASTE MANAGEMENT

DIZERTAČNÍ PRÁCE

DOCTORAL THESIS

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ABSTRAKT

Vydaný balíček oběhového hospodářství definuje opatření pro přechod od lineárního modelu hospodářství k oběhovému. Konkrétní cíle jsou implementovány do legislativy členských států EU. Prognózy produkce odpadů představují stěžejní informaci pro modifikaci stávající infrastruktury odpadového hospodářství tak, aby byl možný plynulý přechod k oběhovému hospodářství. V této práci je představen univerzální přístup k prognózování produkce odpadů pomocí optimalizačních modelů zahrnující přípravu dat, vlastní výpočet a zpracování do vhodné podoby pro konečné uživatele. Prognóza klade důraz na přípravné fáze a očištění vstupních dat od anomálií. Přístup je založen na modelování trendu v historických datech s následnou korekcí pro obnovení vazeb územního členění a frakcí odpadů. Nejistota prognózy je popsána pásy spolehlivosti konstruovanými pomocí bootstrapového přístupu. Dopad konkrétních opatření na podobu odpadového hospodářství je možné modelovat pomocí projekce. Předkládaná metodika je zpracována obecně a je vhodným základem pro strategické plánování na lokální, národní i nadnárodní úrovni.

KLÍČOVÁ SLOVA

Produkce odpadu, TiramisO, prognóza, analýza trendu, vyrovnávání dat

ABSTRACT

The issued Circular economy package defines the measures for the transition from a linear economy to a circular economy. The specific targets are implemented in the legislation of the EU Member States. Waste production forecasts are key information for modifying existing infrastructure to allow a smooth transition to a circular economy. This work presents a universal approach to waste production forecasting using optimization models including data preparation, calculation and processing into a suitable form for users. The forecast emphasizes the preparatory phases and the clean-up of input data from anomalies. The modeling principle is based on trend modeling in historical data with subsequent correction to restore the links between territorial divisions and waste fractions. Forecast uncertainty is described by confidence intervals constructed using a bootstrap approach. The impact of specific measures on the form of waste management can be modeled using projection. The presented methodology is developed in general and is a suitable basis for strategic planning at the local, national and supranational levels.

KEYWORDS

Waste generation, TiramisO, forecast, trend analysis, data reconciliation

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OBSAH

SEZNAM PŘÍLOH

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SEZNAM ZKRATEK

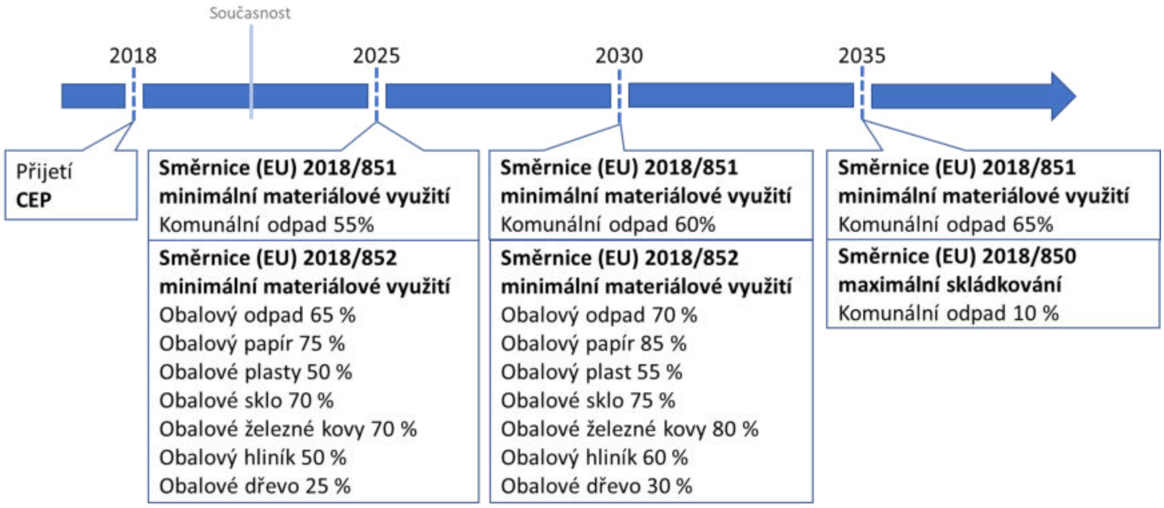
ARIMA	Autoregresní integrovaný klouzavý průměr (Autoregressive integrated moving average)
ARMA	Autoregresní klouzavý průměr (Autoregressive moving average)
BAU	Základní scénář (Business-as-usual scenario)
CEP	Balíček oběhového hospodářství (Circular economy package)
GIS	Geografický informační systém
ISOH	Informační systém odpadového hospodářství
Kat. č.	Katalogové číslo
KO	Komunální odpad
MS	Míra separace
MŽP	Ministerstvo životního prostředí
NO	Nebezpečný odpad
ObH	Oběhové hospodářství
OH	Odpadové hospodářství
ObjO	Objemný odpad
ORP	Obec s rozšířenou působností
PDISOH	Pracovní databáze ISOH
SARIMA	Sezonní autoregresní integrovaný klouzavý průměr (Seasonal autoregressive integrated moving average)
SEP	Separovaný odpad
SKO	Směsný komunální odpad
ÚPI	Ústav procesního inženýrství
ZEVO	Zařízení pro energetické využití odpadu

SEZNAM SYMBOLŮ

t	Nezávisle proměnná označující rok produkce odpadu
p_t	Závisle proměnná udávající modelované množství produkovaného odpadu
a, b, c	Regresní koeficienty
$\bar{x}$	Průměr historických dat produkce odpadu
c_i^{WASTE}	Investice do prevence před vznikem odpadu v lokalitě i
$\overline{w}_i$	Odhad produkce odpadu v závislosti na c_i^{WASTE}
w_{min}	Minimální možná produkce sledované frakce odpadu
w_{max}	Maximální možná produkce sledované frakce odpadu

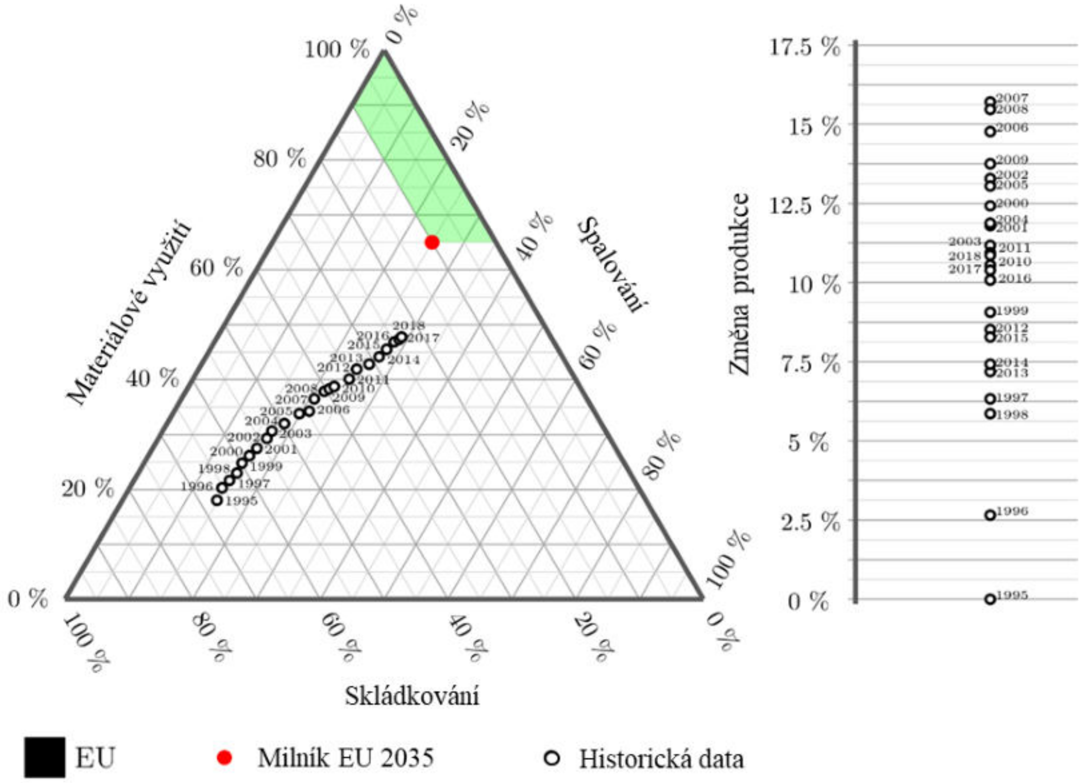
1 ÚVOD

Odpadové hospodářství (OH) EU v současné době přechází z lineární podoby na oběhové hospodářství (ObH) [C1]. Modifikace OH je motivována potřebou nakládat s velkým množstvím odpadu a šetřit životní prostředí. Vhodné zpracování odpadu by také mělo nahradit a ušetřit některé omezené primární zdroje [C2]. Hladký a udržitelný přechod na ObH a transformace OH jsou legislativně upraveny *Balíčkem oběhového hospodářství* (CEP – Circular economy package). Cílem CEP je udržet hodnotu výrobků, materiálů a zdrojů co nejdéle na základě *Hierarchie způsobů nakládání s odpady*, Směrnice 2008/98/ES [C3]. Pro komunální odpad (KO) jsou zásadní Směrnice (EU) 2018/850 [C4], Směrnice (EU) 2018 /851 [C5], Směrnice (EU) 2018/852 [C6]. Hlavními milníky zahrnutými v CEP jsou cíle materiálového využití KO v letech 2025, 2030 a 2035 a omezení jeho skládkování v roce 2035, viz obr. 1.



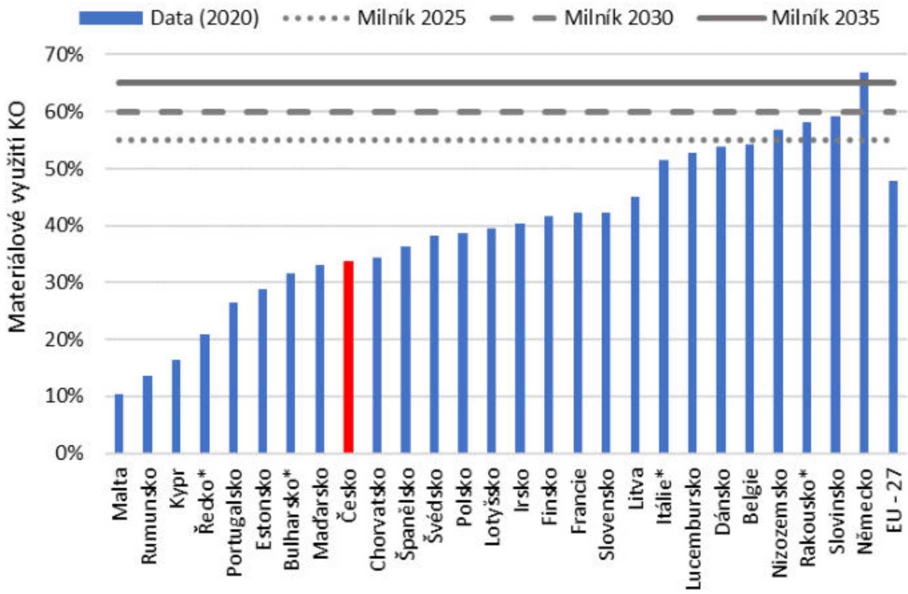
Obr. 1: Cíle Balíčku oběhového hospodářství [A1]

Na obr. 2 je znázorněn časový vývoj nakládání s KO na úrovni EU v období 1995–2018 pomocí ternárního diagramu. Orientace diagramu je zvolena podle Hierarchie způsobů nakládání s odpady [C3] tak, že preferované způsoby nakládání jsou umístěny nahoře. Je patrný zřejmý trend snižování skládkování a zvyšování materiálového využití KO. Současně dochází k mírnému nárůstu spalování odpadu. Spalování odpadu v zařízení pro energetické využití odpadu (ZEVO) představuje vhodnou metodu, jak naložit s nerecyklovatelnými složkami KO. Zeleně je v obr. 2 označena oblast, kde jsou splněny cíle v roce 2035 (poslední sledovaný rok dle CEP). Pravá část obr. 2 ukazuje procentuální změnu produkce odpadů vztaženou k počátečnímu roku 1995. Při plánování OH v EU je tedy nutné zohlednit také očekávanou produkci KO (viz obr. 2).



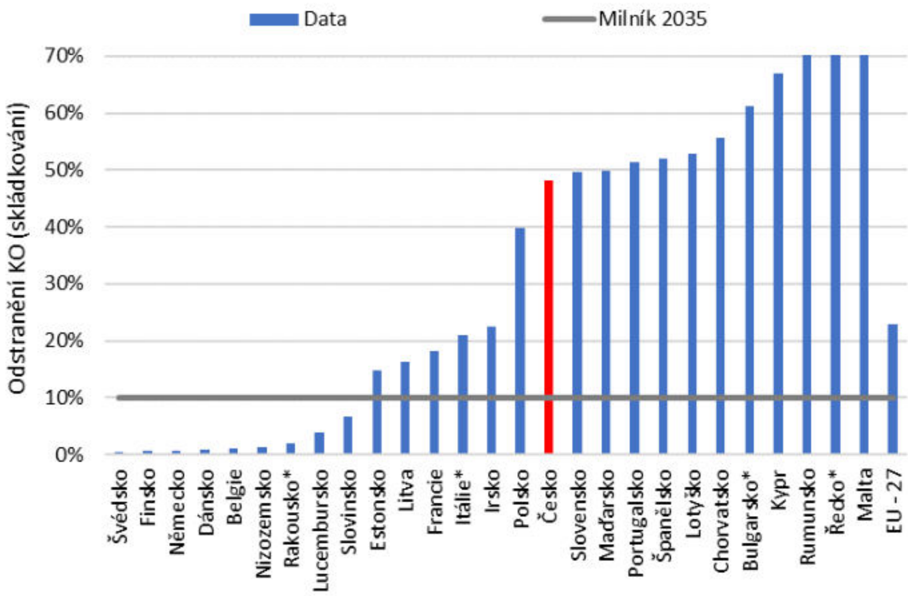
Obr. 2: Produkce a zpracování komunálního odpadu v EU, data 1995–2018, upraveno na základě [A1]

Hodnocení současné situace států EU ve vztahu k požadovaným recyklačním cílům je na obr. 3, jedná se o data za rok 2020 (nejnovější dostupná data o nakládání s KO databáze Eurostat [C7]). Jedinou zemí, která aktuálně plní nejpřísnější cíl stanovený pro rok 2035, je Německo. ČR, jako zástupce zemí v procesu přechodu z lineárního hospodářství na ObH, recykluje cca 34 % KO (červeně na obr. 3). Kromě recyklačních cílů musí členské státy reagovat také na omezení skládkování KO. Současný stav skládkování KO znázorňuje obr. 4. Limit pro skládkování stanovený pro rok 2035 již splňuje celkem 9 zemí EU, v ČR je v současnosti stále ukládáno na skládky asi 48 % KO. Celkem se v EU skládkuje asi 23 % KO. Bohužel většina zemí EU je v současnosti značně daleko od splnění recyklačních cílů a omezení skládkování. Je tedy nutný zásah do současné podoby OH, aby bylo možné tyto cíle splnit.



*Pozn: * z důvodu nedostupných dat za rok 2020 se jedná o hodnoty za rok 2019*

Obr. 3: Materiálové využití KO, členské státy EU, rok 2020, zdroj dat: Eurostat [C7]



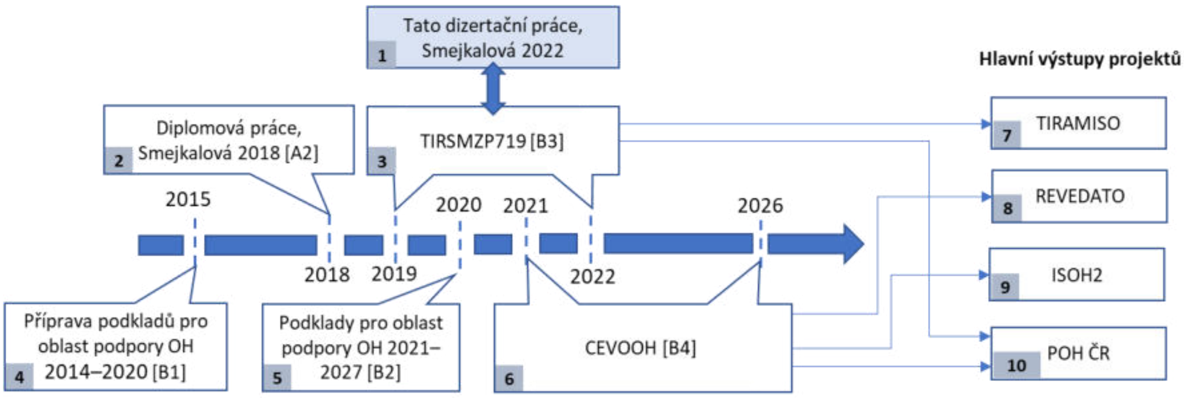
*Pozn: * z důvodu nedostupných dat za rok 2020 se jedná o hodnoty za rok 2019*

Obr. 4: Skládkování KO, členské státy EU, rok 2020, zdroj dat: Eurostat [C7]

Cíle EU jsou stanoveny na úrovni států, ale každá země EU má pro splnění CEP jinou výchozí pozici, protože mezi jednotlivými státy EU jsou významné rozdíly v produkci KO a ve způsobech nakládání. Většina států již vykazuje postupný růst materiálového využití KO a omezování skládkování [A1], otázkou je, zda tímto vývojem lze dosáhnout požadovaného cíle včas dle milníků EU (obr. 1). Očekávaný vývoj OH za neměnných podmínek je možné odhadnout pomocí prognózy produkce a nakládání s odpady. Prognóza za stávajících podmínek bude v tomto textu značena BAU (business-as-usual). Díky výsledkům BAU lze odhalit potřebu zasáhnout do systému OH tak, aby bylo podpořeno splnění cílů EU. Prognózou (BAU) se v tomto textu tedy rozumí nejpravděpodobnější scénář budoucího vývoje za stávajících podmínek. Vychází z historických dat a není do něj začleněn (až na nutné výjimky) expertní aspekt, tj. změna trendu vlivem očekávaných zásahů do OH. Prognóza nemá schopnost reagovat na legislativní a jiné zásahy do systému, ke kterým v budoucnu dojde. Projekce vzniká na základě definovaného scénáře budoucího vývoje a zohledňuje expertně nastavené okrajové podmínky, ovšem tak, aby co nejvíce odrážela historický průběh. Projekce by měla být co nejvíce v souladu s prognózou budoucího vývoje. Projekci lze tedy chápat jako expertní posouzení budoucího vývoje pomocí scénářů, které odráží situace, kdy je do systému zasahováno z vnějšku (legislativní vlivy, technologický pokrok atd.). Prostřednictvím projekcí je tedy možné modelovat scénáře dopadu konkrétních intervencí v OH. Prognóza a projekce produkce odpadů jsou důležitým podkladem pro strategické plánování OH na úrovni národní, krajské i obecní. Současně mohou být principy prognózy a projekce využity v komerční sféře.

1.1 Cíle dizertační práce a zasazení do kontextu činností na ÚPI

Problematika prognózování produkce odpadů je na Ústavu procesního inženýrství (ÚPI) řešena dlouhodobě a zapadá do koncepce činností pro podporu plánování OH. Schematicky jsou vazby vybraných aktivit řešených na ÚPI, které souvisejí s prognózami produkce odpadu, znázorněny na obr. 5. Tato dizertační práce sumarizuje činnost autorky po dobu studia, jedná se o vypracované studie v rámci projektů (obr. 5) a publikované články (Příloha 1 až Příloha 10).



Obr. 5: Znázornění vazeb činností na ÚPI

Prvním podnětem pro tvorbu prognóz produkce odpadu na ÚPI byl projekt řešený ve spolupráci se společností Ernst & Young (EY) v roce 2015 pro Ministerstvo životního prostředí (MŽP), [B1], v obr. 5 znázorněno číslem 4. Přístup k prognózování byl na ÚPI dále průběžně vyvíjen, např. formou diplomové práce [A2], která předcházela této dizertační práci a byla obhájena v roce 2018 (číslo 2 v obr. 5). Na dosavadní činnost navázal v roce 2019 projekt [B3], číslo 3 v obr. 5. a dále také jako „TIRMZP719“. Vypracování této dizertační práce bylo významnou měrou doprovázeno řešením projektu TIRSMZP719. V projektu TIRSMZP719 se autorka podílela na tvorbě Certifikované metodiky [B5] pro prognózování produkce odpadů, která slouží jako podklad pro nástroj *TiramisO* (číslo 7 v obr. 5) užívaného MŽP [B6]. Bližší popis činností projektu TIRSMZP719 je dále v této kapitole. Průběžné poznatky projektu TIRSMZP719 byly v roce 2020 využity v projektu řešeného opět s EY pro MŽP, číslo 5 v obr. 5) [B2]. Autorka se podílela na vytvoření prognóz produkce následujících frakcí odpadů: KO pro materiálové využití, odpady pro energetické využití, biologicky rozložitelné odpady, nebezpečné odpady a kaly z čištění komunálních odpadních vod.

Cílem aktuálně běžícího projektu CEVOOH [B4] (číslo 6 v obr. 5) je vybudování interdisciplinární výzkumné základny tvořené klíčovými výzkumnými organizacemi disponujícími expertízou a odbornou kapacitou pro provádění výzkumu v oblasti OH a ObH. Hlavní tematickou oblastí, řešenou na ÚPI, je rozvoj nových monitorovacích nástrojů v OH. Základním zdrojem dat o produkci a nakládání s odpady je Informační systém odpadového hospodářství (ISOH) [C8], do kterého se data získávají z každoročního hlášení o produkci a nakládání s odpady dle Zákona 541/2020 Sb. o odpadech [C9]. Na původní databázi (tzv. archivní) je proveden přepočet pro odstranění duplicit vzniklých zapojením firem do systému OH obce, dopočet podlimitních subjektů apod. Výsledkem těchto úprav specifikovaných v dokumentu [C10] je Pracovní databáze ISOH (PDISOH). V rámci projektu CEVOOH vzniknou podklady pro vytvoření nové databáze PDISOH (tzv. ISOH2, číslo 9 v obr. 5), na jejichž formulaci se bude autorka podílet. Prvním krokem je analyzovat současný stav nakládání s odpady, což představuje obtížný úkol. To dokládá skutečnost, že v ČR je znám pouze aktuální stav pro agregovaná data na státní úrovni. Důvodem je ztráta informace při předání a převzetí odpadu a chyby ve vykazování. Proto další členové řešitelského týmu pracují na nástroji REVEDATO (číslo 8 v obr. 5), který má být doplňkovým produktem pro systém ISOH2. Po získání kvalitního odhadu současného stavu nakládání s odpady i na regionálních úrovních je možné zjistit potenciál pro změnu a provádět věrohodné prognózy. V návaznosti na dosavadní činnost se předpokládá spoluúčast autorky této práce a dalších členů týmu ÚPI na sestavení Plánu odpadového hospodářství (POH) ČR pro následující období (číslo 10 v obr. 5).

Jak už bylo zmíněno, náplň této dizertační práce je motivována řešením projektu TIRSMZP719 (viz obr. 5). Aktivity zahrnuté v projektu TIRSMZP719 byly rozděleny do tří okruhů zahrnujících výsledky V1 až V13. Jedná se o výsledky typu výzkumné zprávy (Vsouhrn), certifikované metodiky (NmetC) a software (R) vykázané v RIV:

1) Složení odpadů (V1–V4, V13) – nastavení postupů pro analýzy složení odpadů a jejich realizace.
2) Prognózování produkce odpadů (V5–V9) – nastavení procesu prognózování produkce všech odpadů v ČR na základě historických dat.
3) Software (V10–V12) – implementace přístupu prognózování produkce ve výsledný software TiramisO [B6].

První ze zmíněných okruhů (Složení odpadů) nemá přímou souvislost s touto dizertační prací. Autorka této závěrečné práce se aktivně podílela na řešení pěti výsledků (V5 až V9) z celkových třinácti výsledků, které spadají do druhého okruhu (Prognózování produkce odpadů). Cílem bylo zvolit vhodný přístup k prognózování a sestavit metodiku pro provedení prognóz produkce odpadu. V první fázi byla zpracována rozsáhlá rešerše shrnující poznatky dostupné literatury na téma modelování produkce odpadu (V5, Vsouhrn, [B7]). Tato rešerše byla nad rámec výsledku V5 dále rozšířena a doplněna, viz kap. 2 a [A1]. Možné přístupy pro prognózování byly testovány ve výsledku V6 s ohledem na dostupná data, která jsou v ČR k dispozici v podobě velmi krátké časové řady v ročním detailu. Výstupem výsledku V6 (Vsouhrn) [B8] bylo doporučení prognózovat produkci odpadu pomocí analýzy trendu v historických datech s následným vyrovnáním pro zachování vazeb v systému. Výsledek V7 (Vsouhrn) [B9] popsal matematický model prognózy. Na výsledek V7 navázal

V8 (Vsouhrn) [B10], který specifikoval nastavení parametrů matematických přístupů a představil tvorbu projekcí produkce odpadu v podobě scénářů. Zásadní je výsledek V9 (NmetC), ve kterém vznikla Certifikovaná metodika pro provádění prognózy produkce odpadu [B5]. Metodika je rozdělena na čtyři fáze. Prvním krokem je příprava vstupních dat, následuje pre-processing zahrnující zejména odstranění anomálií v datech. V rámci processingu je proveden vlastní výpočet prognózy pomocí zvolené modelovací metody. Na závěr jsou v post-processingu výsledky zpracovány do vhodné podoby pro konečné uživatele. Přístup k prognóze popsaný v metodice V9 byl následně implementován do softwaru nazvaného TiramisO (obr. 6) [B6] v rámci výsledků V10 (R), V11 (Vsouhrn) a V12 (Vsouhrn). Hlavním uživatelem výsledků projektu TIRSMZP719 je MŽP. Požadavky na prognózu bylo tedy možné průběžně korigovat se zástupci MŽP s ohledem na budoucí využití certifikované metodiky a softwaru.

Obr. 6: Úvodní strana softwaru TiramisO [B6]

Navržený přístup pro prognózování produkce odpadu zohledňuje následující požadavky na prognózu [B10]:

1. Dostupná data o produkci odpadu
Přístup k prognóze je formulován obecně pro využití na různém detailu vstupních dat. Ve většině aplikací OH jsou však dostupné krátké časové řady historických dat. Základním zdrojem dat o produkci odpadu v ČR je databáze ISOH [C8], která vzniká z každoročního hlášení subjektů o produkci a nakládání s odpady. V současné době je v ISOH k dispozici 12 pozorování z minulých let počínaje rokem 2009, data jsou k dispozici v ročním detailu. U datové sady se očekává v budoucnosti nárůst dostupných dat a delší časová řada umožní podrobnější vhled do historického vývoje a tím i zpřesnění prognózy. Navržený přístup prognózování je tedy možné aplikovat na časové řady různých délek, avšak umožňuje využití na velmi krátké časové řady.

2. Období predikce
Délka predikčního horizontu je inspirována cíli EU. Požadavky Směrnice EU 2018/850 [C4] a Směrnice EU 2018/851 [C5] jsou dány do roku 2035 (viz obr. 1). Jako cílový rok prognózy byl zvolen rok 2040, aby bylo možné sledovat předpokládanou produkci odpadu také po klíčovém roku 2035. V současné době jsou dostupná data z období předchozích 12 let a prognóza je cílena na období následujících 20 let. Obecně nelze jasně stanovit hranici mezi krátkodobou a dlouhodobou prognózou, avšak úloha je komplikovaná tím, že se jedná o poměrně dlouhou prognózu na základě malého počtu historických dat.

3. Detail územního členění
Výpočet je cílen na více stupňů územního členění (stát, kraje, obce s rozšířenou působností – ORP, obce). Na základě konkrétní aplikace lze volit vhodný detail územního členění. Práce s daty na nižších úrovních má svá úskalí v podobě vysoké variability dat a vyššího výskytu odlehlých či chybějících hodnot. S ohledem na tento aspekt je tedy nutné věnovat značnou pozornost pre-processingu dat (kap. 3.2).

4. Členění frakcí odpadů
Model je sestaven tak, aby byl aplikovatelný na různé frakce odpadu, které jsou evidovány prostřednictvím katalogových čísel (kat. č.) [C11]. Kat. č. mohou být prognózována individuálně či v agregované formě (kap. 3.1).

5. Hierarchická struktura
Představený přístup využívá principů agregace dat, kdy díky agregaci dochází v některých případech k vyhlazení variability v datech. Agregace je uvažována jak z hlediska územního členění (obec, ORP, kraj, stát – viz bod 3. Detail územního členění), tak frakcí odpadů (papír, plast, sklo, separované složky, KO atd.– viz bod 4. Členění frakcí odpadu). Existence vazeb územního členění byla popsána v příspěvku [A3] jako „areal constraint“. Provázanost frakcí odpadu a územního členění bude nutné zachovat také v odhadech budoucí produkce, viz kap. 3.3.3.

6. Vyjádření nejistoty
Bodový odhad očekávané produkce odpadu je nutné doplnit o vyjádření nejistoty prognózy např. v podobě pásů spolehlivosti. Tato informace je nezbytná pro budoucí uživatele výsledků, kteří mohou zohlednit kvalitu prognózy a přizpůsobit se nejistotám. Součástí představeného přístupu k prognózování je konstrukce konfidenčních a predikčních pásů (kap. 3.3.4).

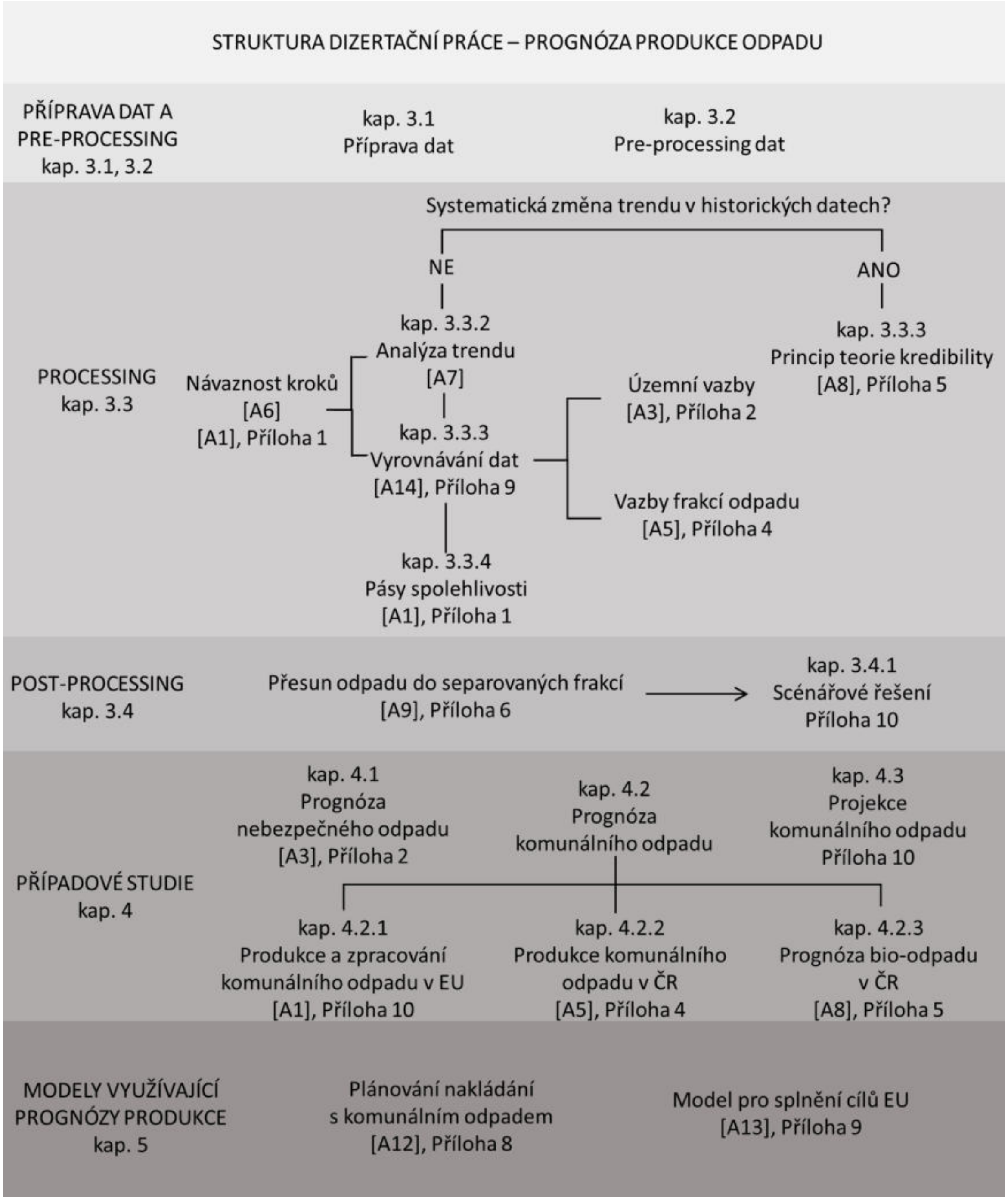
7. Scénářový přístup
Prognózu produkce odpadu lze přizpůsobit očekávaným scénářům produkce. Základní scénář BAU vychází z již nastavených podmínek historických dat a jejich trendů. Dále je možné modelovat budoucí produkci odpadu vzhledem např. k cílům EU v požadovaném roce. Stanovený scénář se poté stane ukazatelem nutných změn oproti stávajícímu systému, pokud má být dosaženo příslušných cílů.

Cílem dizertační práce je návrh přístupu pro prognózování produkce odpadu vzhledem k výše uvedeným podmínkám v bodech 1 až 7. Náplň této práce vznikala souběžně s řešením projektu TIRSMZP719 [B3], čímž je zaručena uplatnitelnost výsledků.

1.2 Koncepce dizertační práce

Dizertační práce je založena na tvorbě a využití matematických modelů pro prognózování produkce odpadu. Vhledem k rozsahu a složitosti těchto modelů není jejich detailní popis součástí vlastního textu dizertační práce, ale jsou uvedeny a vysvětleny v přílohách Příloha 1 až Příloha 10. Struktura dizertační práce, návaznost výstupů a jejich umístění v přílohách tohoto textu jsou shrnuty v obr. 7.

V následující části textu (kap. 2) je uveden souhrn rešeršní činnosti, která předcházela návrhu přístupu k prognózování. Navazuje kap. 3 popisující koncept přístupu k prognóze a nezbytné části modelu, které by měla každá prognóza zohlednit. Návrh modelu byl aplikován na případové studie v kap. 4. Kap. 5 představuje využití prognózy produkce odpadu v modelech pro plánování OH. Závěrečné shrnutí je v kap. 6 a jsou přiblíženy možnosti dalšího vývoje. Výsledky prognóz produkce odpadu jsou zásadním podkladem při strategickém plánování v oblasti OH na státní i lokální úrovni.



Obr. 7: Pokročilé prognostické modely představené v této práci

2 PROGNÓZA PRODUKCE ODPADU – LITERÁRNÍ REŠERŠE

V první fázi literární rešerše je věnována pozornost dříve publikovaným rešeršním pracím na téma modelování produkce odpadu (viz tab. 1). V tabulce je u každé studie uvedeno období vydání prostudovaných publikací, počet publikací a zaměření výzkumu či sledovaná kritéria.

Tab. 1: Přehled předchozích rešerší o modelování produkce odpadu [A4]

Reference	Období	Počet publikací	Zaměření výzkumu/sledovaná kritéria
(Beigl et al., 2008); [C12]	Do 2005	45	Kritéria: úroveň území, frakce odpadu, nezávisle proměnné, modelovací metoda.
(Cherian and Jacob, 2012); [C13]	Do 2011	9	Kritéria: úroveň území, frakce odpadu, nezávisle proměnné, modelovací metoda.
(Kolekar et al., 2016); [C14]	2006–2014	20	Kritéria: modelovací metoda, úroveň území, počet a detail časově závislých dat, nezávisle proměnné, frakce odpadu.
(Goel et al., 2017); [C15]	1972–2016	106	Rozdělení na klasické (vícenásobná lineární regrese, analýza časových řad, faktorová analýza) a nekonvenční (fuzzy metody, umělé neuronové sítě) přístupy.
(Abdallah et al., 2020); [C16]	2004–2019	85	Umělá inteligence v OH – popsáno šest aplikací; více modelů včetně hybridních.
(Guo et al., 2021); [C17]	2003–2020	40	Metody strojového učení v modelech produkce biologicky rozložitelném KO.
(Xu et al., 2021); [C18]	2010–2020	177	Modely umělých neuronových sítí; kritéria: makro (zaměřené především na produkci odpadů), mezo (vlastnosti odpadů a procesní parametry), mezo-mikro (účinnosti zpracování odpadů), mikro (reakční mechanismy nebo mikrostruktury).

Rešerše [C12] zahrnuje klasické metody modelování, oproti tomu uvedené novější rešerše [C16], [C17] a [C18] se zabývají výhradně umělou inteligencí a neuvažují jiné metody pro modelování. Články [C13] a [C14] studovaly klasické metody i metody strojového učení, cílová období jsou ale popsána pouze malým počtem publikovaných modelů (viz tab. 1). V článku [C15] byla představena poměrně rozsáhlá rešerše, avšak hlavní nevýhodou je nerozlišení odpadových frakcí, což může mít významný vliv na podobu modelu. Ve většině zmíněných rešerší nejsou přístupy rozlišovány na modelování současné a budoucí produkce odpadu, pouze v případě [C15] byly studovány modely pro odhad budoucí produkce (prognostické). Avšak není evidována informace o délce predikčního horizontu, což je zásadní informace pro volbu vhodného modelovacího přístupu. Dále v tomto textu je uvedeno shrnutí rešerše, která se věnovala výhradně modelům pro prognózy produkce odpadu, tedy s výhledem do budoucna. Tato rešerše vychází z výsledku V5 projektu TIRSMZP719 [B3] a došlo k jejímu rozšíření do roku 2021 v rámci publikace [A4] na celkový počet 308 článků. V rešerši [A4] byly studovány modely současné i budoucí produkce odpadu publikované od roku 2006 (v návaznosti na rešerši [C12]) do vzniku studie [A4] v roce 2021. Níže bude uvedeno shrnutí 108 publikací, které se věnovaly modelům prognostickým.

Cílem této rešerše je shromáždit podpůrný materiál pro vývoj komplexního modelu pro prognózování produkce odpadů. Před prostudováním dostupné literatury jsou formulovány otázky, které by měly být prostudováním dřívějších modelů zodpovězeny:
- Na jaké frakce odpadu jsou modely cíleny?
- Jaké jsou společné nedostatky dostupných dat a kolik datových bodů v časové řadě je dostatečné?
- Jaké metody byly použity pro prognózování?
- Lze formulovat obecná doporučení pro další parametry, jako je územní členění, frakce odpadu, délka období prognózy atd.?
- Jaká je adekvátní délka prognózy v porovnání s dostupnou časovou řadou?

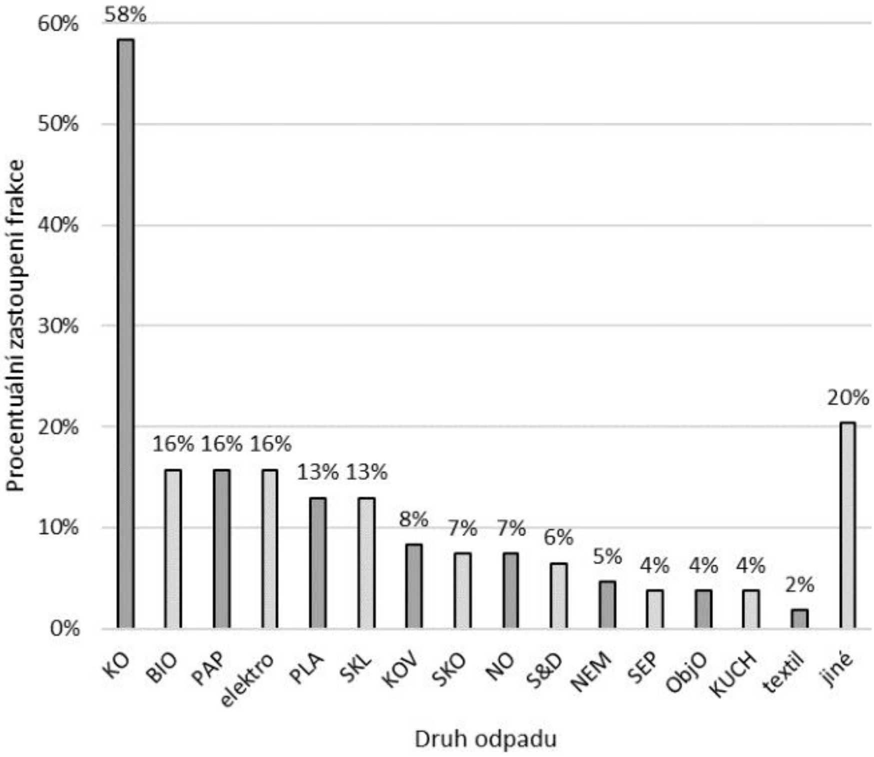
Příspěvky byly vyhledávány v databázích ScienceDirect a Scopus s klíčovými slovy: “msw prediction“, “msw forecast“, “waste prediction“, “waste forecast“, “waste generation“, “waste production“, “waste forecasting“, “municipal waste prediction“, “municipal waste forecast“. Níže jsou uvedeny výstupy rešerše, které se zabývaly prognózou produkce odpadu, tedy výhledem do budoucna. Celkem se jedná o 108 článků. Dále v této kapitole jsou shrnuty výsledky rešerše s ohledem na pre-processing dat (kap. 2.1), detail datové sady (kap. 2.2) a modelovací přístupy (kap. 2.3). Následně je krátce popsán přístup prognózování využívaný EU (kap. 2.4).

2.1 Pre-processing dat v modelech prognózy produkce odpadu

Pre-processing dat je zahrnut ve 26 příspěvcích ze 108, ale často se jedná o velmi stručnou zmínku o úpravě dat bez podrobného popisu skutečně použitých postupů. Asi 27 % z těchto 26 článků s pre-processingem dat využívalo týdenní nebo denní data [C19] a asi 71 % článků s pre-processingem využívalo roční data. Modely s ročními daty jsou však obvykle vytvářeny na mnoha územních jednotkách, kde bylo i přes krátké časové řady opět možné použít běžné metody jako z-skóre [C20], Grubbův test nebo Dixonův test [C21]. Je třeba zmínit, že pre-processing dat se nezabýval detekcí změn trendu nebo skoků v datech, i když mohou mít významný dopad na výsledek prognózy (kap. 3.2.3).

2.2 Detail datové sady

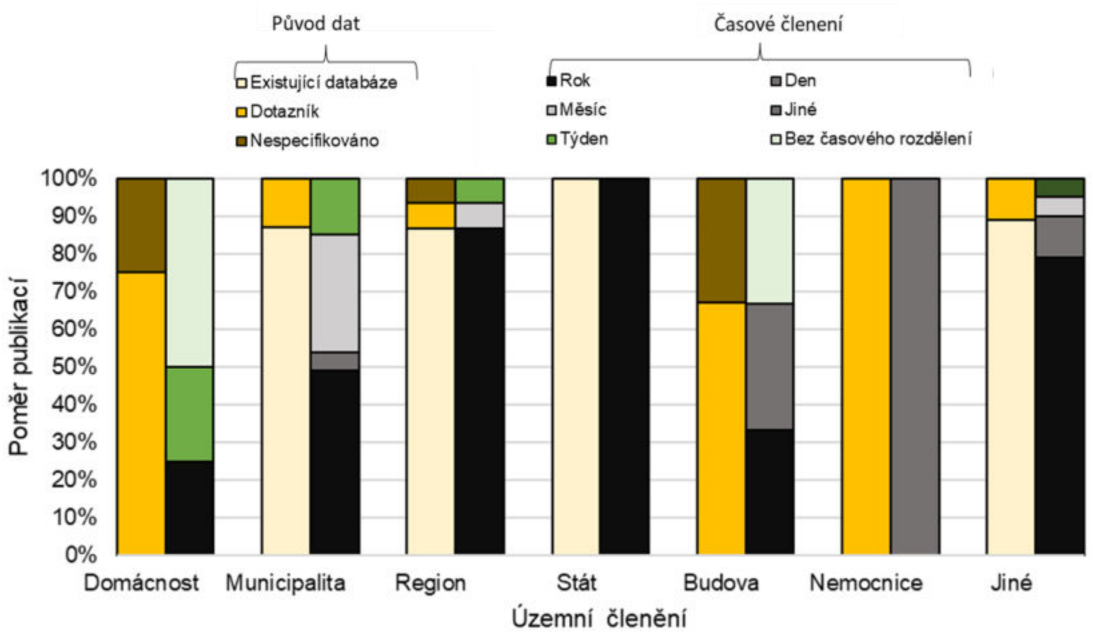
Vybrané publikace se věnovaly různým druhům odpadů, jak je znázorněno na obr. 8. Uvedená hodnota udává, v kolika procentech publikací byl model aplikován na příslušnou frakci odpadu, tzn. jednotlivé publikace se mohly věnovat více frakcím. Nejčastěji modelovanou složkou byl KO s 58% zastoupením. Následoval odděleně sbíraný odpad s vysokým potenciálem materiálového využití (bio-odpad, papír, plast, sklo a elektro-odpad) se zastoupením v 13 až 16 % publikací. Separovaný odpad byl také v některých případech modelován jako jeden proud, tj. odděleně sbírané složky KO jako celek. Za zmínku stojí, že relativně malé procento publikací (7 %) se zaměřilo na produkci směsného komunálního odpadu (SKO) (terminologie není jednotná, v některých publikacích nazývaná také zbytkový odpad). Důvodem může být to, že tento proud je poměrně obtížné modelovat kvůli vztahu mezi SKO a tříděnými složkami.



Poznámka: KO – komunální odpad, BIO – bio-odpad, PAP – papír, PLA – plast, SKL – sklo, KOV – kovy, SKO – směsný komunální odpad, NO – nebezpečný odpad, S&D – stavební a demoliční odpad, NEM – nemocniční odpad, SEP – separovaný odpad, ObjO – objemný odpad, KUCH – kuchyňský odpad

Obr. 8: Zastoupení frakcí odpadů ve studovaných publikacích

Územní členění dat bylo sledováno v následujících kategoriích: stát, kraj, obec, domácnost, budova, nemocnice a „jiné“ (které zahrnovaly všechny zbývající úrovně z důvodu jejich málo častému výskytu). Některá územní členění přímo souvisela s konkrétními druhy odpadu, např. budova (stavební a demoliční odpad), nemocnice, hotel nebo letadla. Na obr. 9 je znázorněn vztah územního detailu a způsobu získávání vstupních dat. Pokud se jedná o údaje na úrovni domácností (produkce odpadů a socioekonomické informace), byly obvykle získány prostřednictvím průzkumů a rozhovorů. U vyšších územních celků jsou data většinou součástí existujících databází, které vznikly agregací reportovaných údajů nižších celků. Jak již bylo zmíněno, míra detailu územního členění ovlivňuje také časový detail dat. Údaje o domácnostech jsou častěji dostupné ve větším časovém detailu, pocházely totiž z průzkumů, ve kterých byl vyprodukovaný odpad běžně sbírán ze vzorku domácností a vážen. Údaje na národní úrovni byly naopak k dispozici výhradně v ročním detailu.



Obr. 9: Vztah mezi původem dat a územním dělením (levý sloupec) a časovým a územním dělením (pravý sloupec)

2.3 Modelovací přístupy

Pro prognózování produkce odpadu byly využity přístupy běžně využívané v různých oblastech při zpracování dat. Jednotlivé využité přístupy nebudou v tomto textu detailně představeny, SWOT analýza je zpracovaná v příloze článku [A4]. Tab. 2 přiřazuje prostudované články k modelovacím přístupům. Procentuální hodnoty udávají zastoupení článků využívající jednotlivé metody. V některých studiích bylo využito více modelů, nejčastěji za účelem porovnání jejich úspěšnosti, případně pro vytvoření kombinované metody. Nejběžnější metodou (vyskytující se ve 25 % studií) je analýza časových řad, která tvoří odhad budoucí produkce na základě historického vývoje. Následuje lineární regrese, aplikovaná v 19 % publikací. V tomto případě byla produkce odpadu odhadnuta na základě vývoje dostupných sociologických, ekonomických, demografických a dalších údajů. Umělé neuronové sítě, které patří mezi metody strojového učení, jsou v posledních letech stále populárnější a byly využity v 17 %. Následovaly další přístupy specifikovány v tab. 2. Některé publikace také uváděly jiné metody než ty, které jsou výslovně uvedeny v tab. 2 (seskupeny pod sloupec „Jiné“). Jednalo se například o hmotnostní bilanci, teorii plánovaného chování nebo modely založené na geografických informačních systémech (GIS).

Tab. 2: Využití metod pro prognózování produkce odpadů

TSA	LR	ANN	GM	GR	SVM	SD	DES	CA	FL	DT	Jiné
25 %	19 %	17 %	14 %	11 %	11 %	8 %	6 %	5 %	2 %	1 %	36 %
[A3]	[C22]	[C29]	[C27]	[A3]	[C19]	[C86]	[C53]	[C40]	[C61]	[C105]	[A3]
[A5]	[C28]	[C37]	[C41]	[A5]	[C29]	[C92]	[C87]	[C45]	[C63]		[A5]
[A6]	[C32]	[C39]	[C54]	[A6]	[C37]	[C93]	[C100]	[C55]			[A6]
[A7]	[C36]	[C40]	[C63]	[A7]	[C42]	[C94]	[C101]	[C83]			[A7]
[A8]	[C44]	[C42]	[C73]	[C25]	[C46]	[C95]	[C102]	[C104]			[A8]
[C22]	[C45]	[C59]	[C74]	[C32]	[C61]	[C96]	[C103]				[C25]
[C23]	[C46]	[C61]	[C75]	[C46]	[C70]	[C97]					[C28]
[C24]	[C47]	[C62]	[C76]	[C59]	[C79]	[C98]					[C29]
[C25]	[C48]	[C63]	[C77]	[C84]	[C88]	[C99]					[C37]
[C26]	[C49]	[C64]	[C78]	[C85]	[C89]						[C38]
[C27]	[C50]	[C65]	[C79]	[C86]	[C90]						[C49]
[C28]	[C51]	[C66]	[C80]	[C87]	[C91]						[C52]
[C29]	[C52]	[C67]	[C81]								[C55]
[C30]	[C53]	[C68]	[C82]								[C61]
[C31]	[C54]	[C69]	[C83]								[C70]
[C32]	[C55]	[C70]									[C83]
[C33]	[C56]	[C71]									[C86]
[C34]	[C57]	[C72]									[C89]
[C35]	[C58]										[C93]
[C36]	[C59]										[C94]
[C37]	[C60]										[C97]
[C38]											[C104]
[C39]											[C106]
[C40]											[C107]
[C41]											[C108]
[C42]											[C109]
[C43]											[C110]
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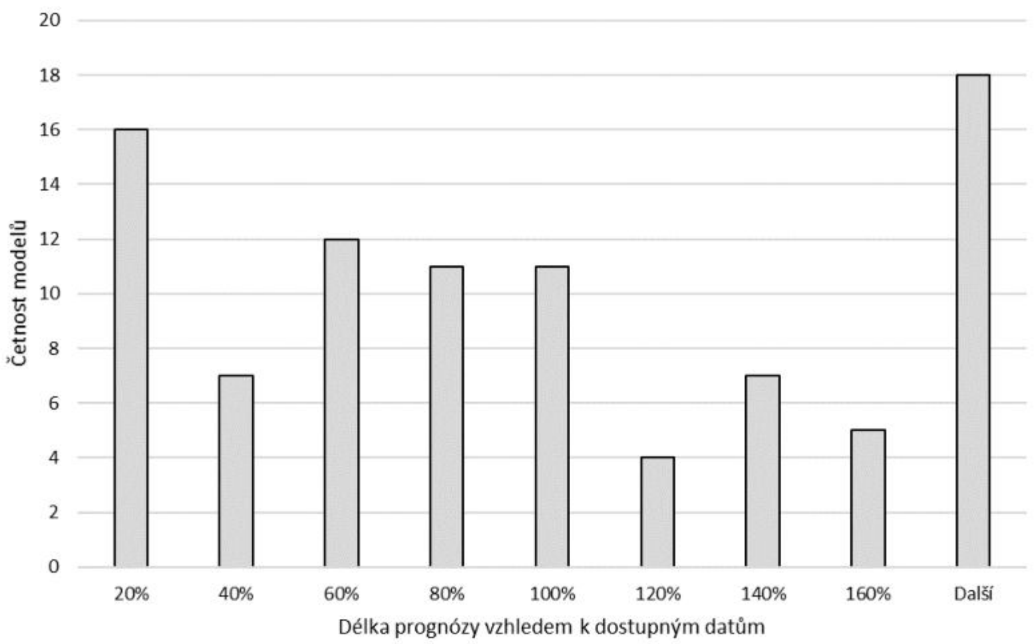
											[C117]
											[C118]
											[C119]
											[C120]
											[C121]
											[C122]

Poznámka: TSA (time-series analysis) – analýza časových řad, LR – lineární regrese, ANN (artificial neural network) – umělé neuronové sítě, GM – gray models, SVM (support vector machine) – metoda podpůrných vektorů, SD – system dynamics, DES (descriptive) – popisné, CA (correlation analysis) – korelační analýza, FL (fuzzy logic) – fuzzy logika, DT (decision trees) – rozhodovací stromy.

Různé modely pro časové řady byly porovnány v článku [C33]. Autoregresní klouzavý průměr (ARMA – autoregressive moving average model) poskytl nejpřesnější výsledky na testovaných datech. Obecně Box-Jenkinsonova metodika (ARMA, autoregresní integrovaný klouzavý průměr – ARIMA a jejich modifikace) dosahuje kvalitních výsledků na dlouhých časových řadách. Modely S-křivky byly v článku [C25] představeny jako nejvhodnější možnost pro analýzy trendů v historických datech. Možností jsou také hybridní modely, které kombinují výhody jednotlivých použitých metod. Výsledky prezentované v příspěvku

[C41] ukázaly, že kombinace sezónního ARIMA (SARIMA) a gray model byla dostatečně robustní, aby odpovídala sezónnímu a ročnímu dynamickému chování produkce odpadu. Zmíněné modely jsou ale použitelné na dlouhých časových řadách. Metodologie navržená ve studii [C65] kombinovala trend S-křivky a umělé neuronové sítě, kde u budoucích stavebních projektů byl trend S-křivky korigován charakteristikami projektu prostřednictvím umělé neuronové sítě. Kombinovaný přístup byl představen také ve studii [A3], kde analýza trendu byla doplněna o následnou korekci pro zachování hierarchických vazeb v systému. Konečný přístup vypracovaný v této dizertační práci je implementován do Certifikované metodiky [B5].

Prognózy produkce odpadu lze dohledat v různých délkách predikčního horizontu. Pohybují se od krátkodobých až po prognózy výrazně delší, než je řada historických dat. Délka prognózy v procentuálním vyjádření vzhledem k délce časové řady historických dat je zobrazena na obr. 10. Číslo na vodorovné ose větší než 100 % znamená, že predikovaný časový horizont byl delší, než interval dostupných dat.



Pozn.:
Příklad: Uvažujme 20 bodů ročních historických dat.
Pro prognózu na 4 roky, hodnota na ose x by odpovídala 20 %.
Pro prognózu na 20 let, hodnota na ose x by odpovídala 100 %.

Obr. 10: Délka prognózy s ohledem na vstupní data

Překvapivý může být počet dlouhodobých prognóz, které využívají výrazně kratší datovou sadu, než je samotná doba prognózované produkce odpadu. Důvodem je především častá evidence dat o produkci odpadu v ročním detailu. Výstupy prognózy se potom stávají diskutabilními navíc s ohledem na to, že obvykle odhadovaná produkce není doplněna o vyjádření nejistoty predikovaných hodnot např. v podobě pásů spolehlivosti.

Výběr vhodných metod prognózování závisí především na charakteru vstupních dat, predikčním horizontu a následném využití prognózy. Hodnocení kvality modelu prezentovaného v různých studiích je problematické z důvodu rozdílné kvality vstupních dat, ověřování souladu s předpoklady metody apod. Obecně však platí, že kvalitnější modely lze získat na vyšších úrovních územního členění z důvodu nižší variability dat.

2.4 European Reference Model on Waste

Kromě publikací z vědeckých databází je pozornost také věnována metodikám zaměřeným na OH užívaných EU. V rámci *Impact Assessment* při Evropské komisi byl představen model tzv. *European Reference Model on Municipal Waste Management* [C123]. Jedná se o přístup modelování vztahů v OH, který je aplikovatelný pro všech 27 členských států EU. Tento model byl využit především pro modelování scénářů, které vysvětlí rozdíly mezi pravděpodobným vývojem OH členských států a stanovenými cíli pro recyklaci apod. Současně s pomocí modelu lze vyčíslit dopad různých scénářů na životní prostředí, počet pracovních míst, nákladů aj. Představeným způsobem lze analyzovat dopady evropské odpadové politiky do roku 2030. Specifické informace pro jednotlivé státy byly shromážděny pomocí dotazníků a případného doplňujícího rozhovoru [C124].

V dokumentu [C124] byly formulovány celkem tři scénáře:

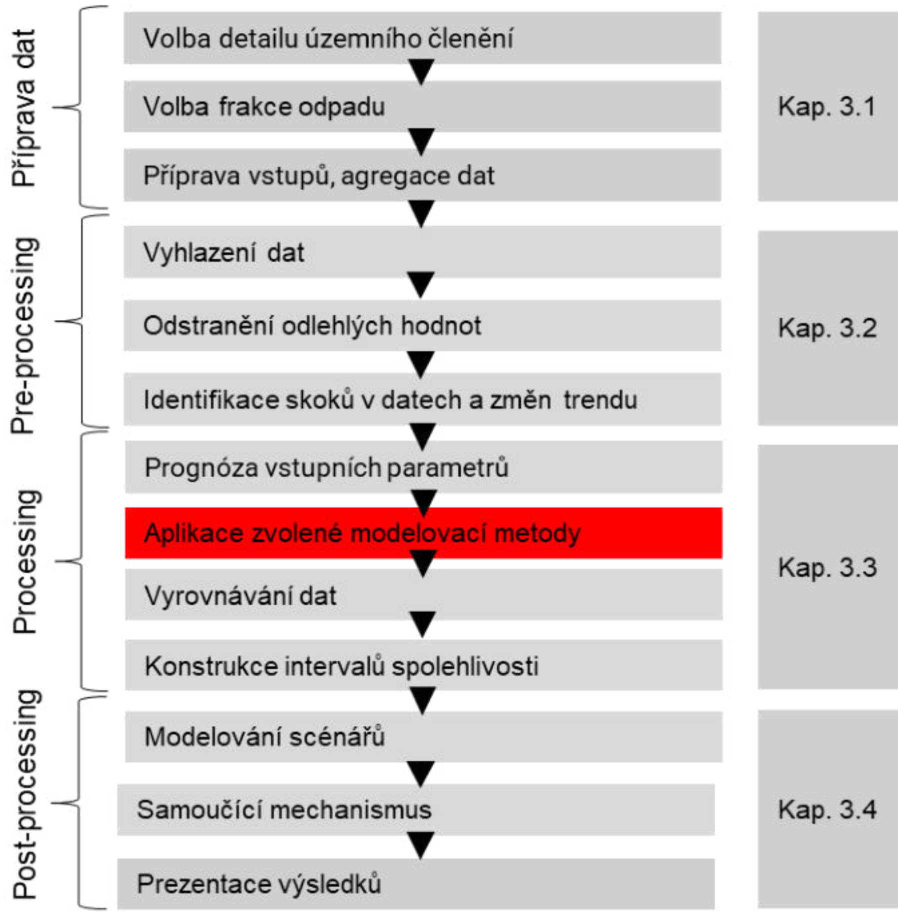
1) BAU: Scénář předpokládá neměnnou úroveň recyklace a podíl způsobů pro zpracování odpadů od posledního sledovaného roku. Pomocí tohoto základního případu lze porovnat dynamičtější budoucí vývoj (další scénáře).
2) Baseline 1: Scénář zohledňuje pravděpodobný vývoj na základě dostupných informací.
3) Baseline 2: Scénář reaguje na plány a záměry členských států EU.

Model se skládá ze šesti částí, z nichž hlavní princip přístupu je obsažen v části *Mass Flow Module*, který zohledňuje materiálové toky. Dále jsou uvažovány části: *Waste Prevention Module*, *Collections Module*, *Financial Costs Module*, *Environmental Impacts Module* a *Employment Module*. Z pohledu prognózy je zajímavá zejména část *Mass Flow Module*, která zahrnuje také část o produkci odpadu *Waste Generation and Projection.* Důležitou informací, která byla zmíněna v dokumentech [C123] a [C124] je, že do celkové koncepce modelu byly pro evropské státy zahrnuty prognózy produkce odpadu, které si jednotlivé státy tvoří samy. Tam, kde nebyly prognózy k dispozici, nebo kde byly prognózy členských států považovány za nereálné nebo neaktuální (např. pokud byly vypracovány před finančním poklesem, který začal v roce 2008), pak byla tvořena nová prognóza produkce nebo se přistoupilo k mírné změně předpokládané míry růstu stávajících prognóz. Pokud nebyly k dispozici žádné informace, byl učiněn výpočet pro vytvoření projekce pro příslušnou zemi na základě řady parametrů. Tato obecná prognóza vychází z metodologie představené v dokumentu [C125]. Tentýž model byl představen v příspěvku [C84], který byl zahrnutý mezi vybrané publikace k prostudování v rámci rešerše (viz kap. 2). Rovnice pro odhad produkce odpadu je, podle navrženého přístupu, závislá na následujících proměnných: ekonomické charakteristiky, velikost populace nebo počet domácností a čas.

Shrnutí: V průběhu let byly navrženy různé modely pro prognózování produkce odpadu, jejich využití závisí na konkrétní aplikaci v OH. Pro volbu modelovacího přístupu jsou rozhodující zejména dostupná data, jejich územní a časový detail a také horizont prognózy. Pokud jsou pro modelování použity vlivné faktory a jejich vazby na produkci odpadu (např. lineární regrese), je třeba nejdříve prognózovat tyto faktory (viz kap. 3.3.1). Použití analýzy časových řad je často omezeno požadavky na délku časových řad (viz kap. 3.3.2). Existujících přístupů nelze často využít, protože ve většině případů nejsou splněny požadavky na data (délka a detail časové řady, dostupnost socio-ekonomických dat). Navíc dosavadní přístupy nezohledňují vazby hierarchické struktury v datech. Proto byl vyvinut přístup „na míru“ pro prognózování produkce odpadu v ČR. Z provedené rešerše je patrné, že je často podceňována kvalita vstupních dat a měl by být významně větší důraz kladen na přípravu a pre-processing dat. Zároveň by měla být uživateli výsledků poskytnuta informace o nejistotě prognózy.

3 PROGNÓZA PRODUKCE ODPADU – POPIS PŘÍSTUPU

Na základě provedené rešerše (kap. 2) a testovacích výpočtů provedených v projektu TIRSMZP719 (Výsledky V6–V8) byl navržen obecný přístup k prognóze (viz obr. 11). Prognóza produkce odpadu by měla zahrnovat 13 na sebe navazujících kroků, které lze rozdělit do čtyř částí: příprava dat, pre-processing, processing, post-processing. Aplikace zvolené metody (na obr. 11 zvýrazněno červeně) je pouze jedním z uvedených kroků. Přestože je výběr vhodné metody nezbytný pro získání kvalitního modelu, zásadní jsou i zbývající kroky, které jsou bohužel většinou opomíjeny [A4]. Dále v textu budou formulovány hlavní doporučení k jednotlivým částem prognózy. Detailní popis lze nalézt v rešerši [A4] a Certifikované metodice [B5].



Obr. 11: Schematické znázornění postupu prognózování produkce odpadu

3.1 Příprava dat

3.1.1 Volba detailu územního členění

V prvním kroku je třeba shromáždit dostupná data. Historická data je nutné upravit na požadovanou územní jednotku. Dostupné datové sady nezávislých proměnných se mohou lišit pro různý detail územního členění. Obecně platí, že u většího detailu územního členění (např. úroveň obcí) dochází k větší variabilitě dat (kap. 7.1 Certifikované metodiky [B5]).

3.1.2 Volba frakce odpadu

Prognózované frakce odpadu jsou voleny s ohledem na cíle prognózy (kap. 7.2 Certifikované metodiky [B5]). Data o produkci odpadů mohou zahrnovat frakce, které ovlivňují produkci dalších složek. Vzájemně závislé frakce odpadu by měly být modelovány společně a tato vazba by měla být zohledněna. Například lze očekávat závislost mezi produkcí SKO a separovaného odpadu (SEP) [A9]. V některých aplikacích může být vhodné prognózovat produkci těchto závislých frakcí odpadu v absolutním množství jako celek (např. SKO + SEP) a současně množství jednotlivých frakcí jako poměrnou část z celku (např. SKO/(SKO+SEP)). Tímto způsobem prognózování dojde k vyhlazení historických dat.

3.1.3 Příprava vstupů, agregace dat

Charakter dostupných dat ovlivňuje výběr modelovací metody (kap. 8.1 Certifikované metodiky [B5]). Údaje nižších celků lze agregovat pro získání chybějících hodnot za vyšší územní celky. Agregace také snižuje variabilitu dat, která je výraznější na nižších úrovních. Dostupný soubor dat lze navíc rozšířit pomocí prediktivních modelů [C126], kdy je produkce odpadu modelována na základě vlivných faktorů. Data musí být často normována na vhodnou jednotku, aby bylo možné hledat vazby s vybranými proměnnými. Normování nebo standardizace se vztahuje jak na data o produkci odpadu, tak na socioekonomická data. Nejběžnější je normování na obyvatele nebo plochu. Rozsah dat lze také přizpůsobit pro lepší interpretovatelnost (např. počet obchodů na 1000 obyvatel). Pokud údaje nejsou normovány na obyvatele, doporučuje se v modelech neuvažovat extrémní hodnoty. Obvykle se může jednat o hlavní města, která kvůli své velikosti mohou mít značný vliv na podobu výsledného modelu. Pro některé proměnné je přínosné transformovat data pomocí vhodné funkce, aby bylo dosaženo rovnoměrnějšího rozložení hodnot. Správná transformace dat je výhodná vzhledem k častému výskytu heteroskedasticity, nejčastěji se používá logaritmická transformace. S případnými nulovými hodnotami je třeba zacházet opatrně. Pro nulové hodnoty není logaritmická transformace definována vůbec, hodnoty blízké nule budou mít po logaritmické transformaci neúměrně velký vliv na výsledky prognózy.

3.2 Pre-processing dat

Při práci s daty je nutné zabývat se vlastnostmi, které by mohly negativně ovlivnit výsledný model. Fáze pre-processingu byla zahrnuta pouze u 26 studovaných článků z celkového počtu 108. Problém s identifikací různých datových anomálií (odlehlé hodnoty, skoky v datech a změny trendu) nastává zejména v koncových bodech časových řad. Označit koncový bod jako anomálii je riskantní, protože není známý následný vývoj dat a koncový bod má významný vliv na podobu trendu v datech. Jediný způsob, jak zhodnotit výsledky a vyhodnotit kvalitu pre-processingu, je vizuální posouzení historických dat.

3.2.1 Vyhlazení dat

Před modelováním produkce odpadu je vhodné zvážit úpravu historických dat, pokud existuje významná vazba na některé regresory. Příkladem mohou být ekonomické cykly nebo jednorázové situace, jako je pandemie covid-19 (kap 8.2 Certifikované metodiky [B5]). Historická data je možné očistit o jejich vliv v průběhu času a následně modelovat očekávaný vývoj bez vlivu těchto faktorů.

3.2.2 Odstranění odlehlých hodnot

Zásadní je sledovat výskyt odlehlých hodnot v datech, které mohou výrazně zkreslit výslednou prognózu [C127]. Využití běžných metod pro krátké časové řady je problematické [C128]. Je tedy nutné použít nějakou kombinaci přístupů, které s daty nakládají opatrně a doplňují je o expertní názor. Tímto způsobem lze eliminovat riziko chybné identifikace odlehlých hodnot. Na základě zkušeností s OH lze doporučit kombinaci Holtovy metody pro odstranění trendu a Grubbsova testu pro identifikaci odlehlých hodnot z reziduí (kap. 8.2.1 Certifikované metodiky [B10]). V souvislosti s daty z databáze ISOH se doporučuje pro další analýzy zcela vyloučit první rok dostupných dat, 2009. Tento rok vykazuje významně vyšší výskyt odlehlých hodnot, z důvodu přechodu na novou metodiku vykazování produkce odpadu.

3.2.3 Identifikace skoků v datech a změn trendu

Pro identifikaci skoků v datech a změn trendu byly testovány běžně užívané přístupy, avšak nebylo dosaženo přijatelných výsledků pro krátké časové řady [B9]. Byla tedy sestavena metoda, která je schopna identifikovat skoky v datech a změny trendu na krátké časové řadě [B5]. Doporučuje se dodržet následující body, viz Příloha 3 Certifikované metodiky [B11]:

- Využít vizualizace dat, pokud to množství časových řad umožňuje.
- Neidentifikovat více skoků nebo změn trendu v jedné časové řadě, pokud časová řada nemá více než 15 hodnot.
- Pokud je tvořen obecný postup, pak data znormovat, což umožní nastavit stejnou hodnotu kritické meze pro všechny časové řady.
- Zaměřit se na úhly mezi dílčími subsekvencemi dat a úhly spojnic historických dat s osou x, na které je průběh v čase.
- Stanovit minimální počet dat, který má být po pre-processingu zachován pro další kroky přístupu prognózování.

Pro další kroky prognózy jsou uvažovány body časové řady za identifikovanou změnou. Detailní popis navrženého přístupu je k dispozici v (Příloha 3 Certifikované metodiky [B11]).

3.3 Processing

3.3.1 Prognózy vlivných faktorů

Pokud mají být pro prognózu produkce odpadu využity vlivné faktory z oblasti ekonomie, sociologie aj., je nutné nalézt kvalitní model, který popisuje produkci odpadu pomocí těchto vlivných faktorů. Kvalitu modelů je možné zlepšit s využitím shlukové analýzy a následným sestavením modelů pro jednotlivé shluky [C129]. Pro provedení prognózy produkce odpadu pomocí vlivných faktorů je nutné disponovat prognózami všech těchto faktorů [C130]. Na státní úrovni jsou k dispozici prognózy mnoha vlivných faktorů (zejména ekonomických), požadované hodnoty však nejsou dostupné pro větší detail území. Často jsou tvořeny jen krátkodobé prognózy nepokrývající celý predikční horizont [A1], proto je dostupnost těchto prognóz velmi limitující požadavek. Navíc platí, že mnoho prognóz vlivných faktorů není doplněno vyjádřením nejistoty. Pokud jsou k dispozici intervaly spolehlivosti, je zřejmé, že prognózy vlivných faktorů mají značnou míru nejistoty [C131]. Do modelování produkce odpadu by zahrnutím těchto faktorů vstoupila významná chybovost. Není tedy žádoucí zahrnout tyto chyby, které jsou součástí prognózy vlivných faktorů, do prognózy produkce odpadů.

Prognózy demografických faktorů se ale liší od socioekonomických charakteristik diskutovaných výše. Demografické projekce jsou obvykle prováděny z dlouhodobého hlediska s uspokojivou přesností [C132], ale bohužel obecně nejsou dostupné pro menší regiony. Je třeba poznamenat, že demografické modely jsou projekce, protože jsou vytvářeny ve formě scénářů. Pro prognózu produkce KO se doporučuje využít informaci o demografické projekci na úrovni státu a krajů, jako zdroj dat lze využít projekce obyvatelstva do roku 2070 vyhotovené Českým statistickým úřadem (ČSÚ) [C133].

Vzhledem k tomu, že nejsou dostupné prognózy všech vlivných faktorů v potřebném detailu a kvalitě, doporučuje se využít pro prognózování v OH přístupy založené na analýze časových řad se zohledněním demografie.

3.3.2 Aplikace zvolené metody

Konkrétní metoda pro analýzu časových řad musí být zvolena s ohledem na detail historických dat a zejména délku časové řady. Úlohy lze rozdělit do dvou základních typů:

1) Data jsou k dispozici v detailu let: V datech je možné zkoumat pouze trendovou složku, kterou lze modelovat vhodným funkčním předpisem. Do této kategorie spadá většina dat dostupných ke strategickému plánování OH.
2) Data jsou k dispozici v detailu dnů, týdnů, maximálně měsíců: Je možné navíc sledovat cyklickou a sezónní složku. Obvykle se jedná o krátkodobé prognózy [A4].

Navržený přístup k prognóze je založen na modelování trendu v historických datech umožňující využití na datech v detailu let (viz bod 1 výše). Jedná se však o univerzální přístup aplikovatelný na data v různém časovém detailu, ale modelován je výhradně trend v datech bez zohlednění cyklické a sezónní složky. Podle charakteru dat se doporučuje využít pro model trendu mocninnou funkci (1), nebo S-křivku v podobě logistické funkce (2). Model S-křivky (2) by měl být aplikován, pokud data vykazují exponenciální nárůst/pokles produkce, protože umožní omezení nereálného nárůstu/poklesu trendu. Případně je možné využít jiné funkční předpisy splňující předpoklad monotonie, které kvalitně popisují chování dat.

$$p_t = a + bt^c, \tag{1}$$

$$p_t = \frac{1}{1 + e^{-(a+bt)}}, \tag{2}$$

$$p_t \geq 0. \tag{3}$$

Ve výše uvedených rovnicích p_t zastupuje závisle proměnnou, tedy množství produkovaného odpadu, a t představuje čas. Hledané regresní koeficienty jsou a, b, c. Předpokládá se nezápornost produkce odpadu v podmínce (3). Závisle proměnná p_t je uvažována v absolutním množství vyprodukovaného odpadu, nebo vztažená na jednoho obyvatele v závislosti na tom, zda se pro modelovanou řadu zohledňuje demografická projekce (viz 3.3.1). Detaily pro volbu funkčního předpisu jsou popsány v dokumentech [B5] a [A1]. Z důvodu nelinearity je pro dosažení kvalitního proložení dat zásadní nastavení počátečních hodnot koeficientů a, b, c (resp. a, b pro logistickou funkci). V případě mocninné funkce (1) se doporučuje využít linearizaci bez absolutního členu a, poté pro nastavení počátečního odhadu b, c využít zlogaritmovanou rovnici:

$$\ln p_t = \ln b + c \ln t. \tag{4}$$

Tato rovnice vede na řešení úlohy lineární regrese. Logistickou funkci lze linearizovat na tvar:

$$\ln \frac{p_t}{1 - p_t} = a - bt. \tag{5}$$

Hodnoty koeficientů a, b linearizované podoby (5) jsou počátečními odhady logistické funkce (2).

K proložení dat jednoduchým modelem s konstantní hodnotou se doporučuje přistoupit v následujících případech:

1. Vyloučením dat po pre-processingu zůstává pro modelování trendu příliš krátká časová řada. Jako minimální množství dat pro modelování trendu křivkami v projektu TIRSMZP719 [B3] jsou požadovány aspoň 4 body historických dat v posledních 6 letech a současně minimálně 5 bodů historických dat celkově. Počet minimálního počtu dat lze přizpůsobit konkrétní délce časové řady.
2. Model trendu v datech s využitím výše popsaných funkcí je málo kvalitní. Jako kritérium se doporučuje využít R^2. V kritickou mez R^2 je možné přizpůsobit. V aplikaci softwaru TiramisO [B6] je extrapolace provedena průměrem v datech, pokud pro model trendu v datech platí, že $R^2 < 0{,}1$.
3. Jednoduchý model s konstantním průběhem vede ke srovnatelným výsledkům jako složitější model. Je přistoupeno k modelování trendu průměrem, aby se zabránilo využití komplikované podoby modelu, pokud změna oproti jednoduchému modelu (průměru v datech) je velmi malá. Kritérium pro model pomocí průměru se doporučuje následující:

$$\frac{|p_{2040} - \bar{x}|}{\bar{x}} < 0{,}05, \tag{6}$$

kde index p_{2040} značí hodnotu trendu v datech v roce 2040, tedy posledním roce sledovaného období. Dále $\bar{x}$ je průměr historických dat pro sledovanou časovou řadu. I v tomto případě je možné kritickou mez 0,05 v podmínce (6) uzpůsobit konkrétním datům a požadavkům na prognózu.

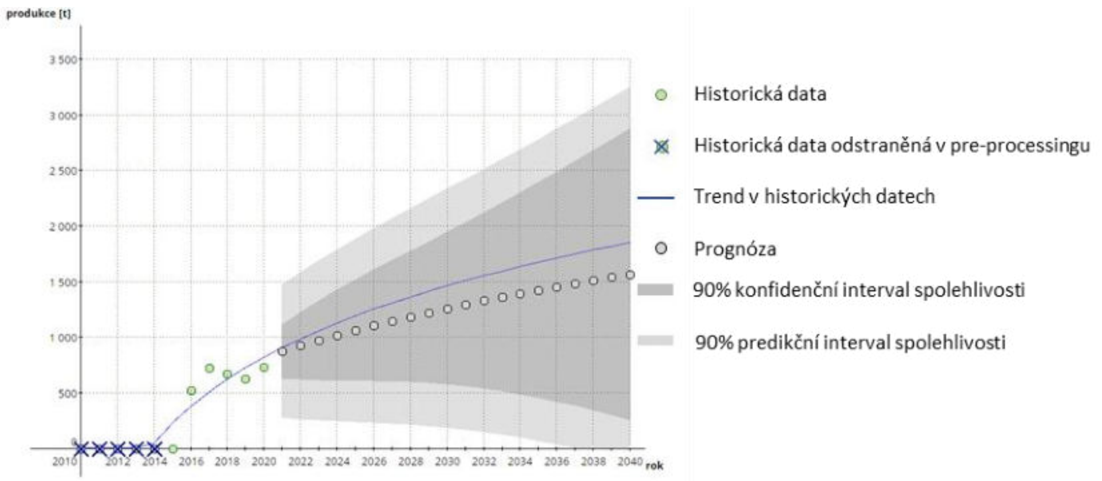
Specifický přístup se doporučuje uvažovat pro časové řady, které v posledních letech evidovaly nulovou produkci modelovaného odpadu. V takových časových řadách se nepředpokládá opětovné zahájení produkce tohoto odpadu a doporučuje se extrapolovat jako nulovou hodnotu (podrobnosti viz Příloha 4 Certifikované metodiky [B11]).

Při výběru vhodné metody modelování je třeba věnovat pozornost speciálním případům nebo vazbám v odpadových tocích. Příkladem může být vliv vnějšího zásahu do systému např. v podobě legislativní změny, která způsobí změnu trendu. V některých případech legislativních zásahů mohou být zavedeny i zcela nové toky odpadů. Tyto anomálie by měly být odhaleny v rámci pre-processingu (kap. 3.2). Problém je v tom, že historická data ovlivněná vnějším zásahem nelze použít pro prognózování obvyklým způsobem. Jednou z možností je při prognóze se změnou trendu zohlednit vývoj v ostatních regionech s využitím principů teorie kredibility. Tedy regiony, které již zareagovaly na vnější zásah změnou trendu, mohou naznačovat budoucí směřování těch regionů, které na zásah reagují se zpožděním. Obdobu lze pozorovat na státní úrovni, kde se postupně instalují zpracovatelské kapacity pro materiálové a energetické využití i v zemích s méně rozvinutým OH. Tato úvaha byla využita pro prognózu bio-odpadu v ČR (kap. 4.2.3 a [A11]). Povinnost umožnit separovaný sběr bio-odpadu je v ČR platná od roku 2014 a producenti se této změně přizpůsobovali postupně.

Přístup k prognózování se doporučuje přizpůsobit také v případech frakcí odpadu, jejichž množství přímo reaguje na vývoj některých vnějších faktorů. Typickým příkladem je kovový odpad, který je vázán na výkupní cenu suroviny. Výkupní cenu je obtížné předvídat kvůli jejímu cyklickému chování, což značně komplikuje prognózu kovového odpadu.

3.3.3 Vyrovnávání dat

Historická data o produkci odpadů mohou obsahovat vnitřní vazby zejména z důvodu agregace dat, které tvoří hierarchickou strukturu [A3]. Vlivem agregace dat je možné specifikovat dva základní typy vazeb – pro územní členění a odpadové frakce. Předpokládá se, že množství odpadu vyprodukovaného na území vyššího územního celku se rovná součtu množství odpadů na územích, která mu náleží (např. obce nacházející se v určitém kraji). Vazba platí také pro agregace odpadových frakcí. Navíc se mohou vyskytovat vazby mezi frakcemi odpadu (např. SKO a SEP) [A5], kdy vyšší produkce separovaného odpadu snižuje produkci SKO. Tyto vazby by měly být zachovány také v modelech prognózy (kap. 8.3.3 Certifikované metodiky [B5]). Většina modelovacích přístupů nezajišťuje konzistenci na různých úrovních hierarchie, rozdílnost modelů v důsledku jiného pořadí agregace byla popsána v článku [A3], viz kap. 4.1. Pro obnovení základních pravidel agregace by měly být vyrovnány výsledky aplikovaného modelu z kap. 3.3.2. Doporučuje se upravit výsledky modelů pomocí vyrovnávání dat (data reconciliation [A3]). Kvalita vstupních modelů z předchozího kroku (kap. 3.3.2) by pro vyrovnání dat měla být zohledněna ve formě nastavení vah [A1]. Vyrovnávání dat v rámci prognózy má navíc schopnost případně zkorigovat model trendu v historických datech, který nemá zřejmý vývoj např. důsledkem nejednoznačného pre-processingu dat. Příklad na obr. 12 ukazuje historická data, kde byla identifikována změna trendu v roce 2015 a pro model jsou tedy uvažována data od roku 2015. Podle vizuálního posouzení této časové řady by další možností bylo shledat v datech skok v roce 2016 a uvažovat data až od tohoto roku, což by vedlo k trendu v datech s pomalejším růstem. Rozhodnutí o typu anomálie v těchto datech není jednoznačné. Výsledná prognóza po vybilancování dat očekává nižší produkci odpadu, než je modelovaný trend v datech (viz obr. 12). Došlo tak ke zkorigování trendu díky vyrovnání dat odpovídající územní hierarchii. Výsledkem tohoto kroku je základní scénář prognózy (BAU).



Obr. 12: Ukázka odklonu prognózy od trendu v datech, TiramisO [B6]

3.3.4 Konstrukce intervalů spolehlivosti

Pro uživatele výsledků prognózy je zásadní informace o nejistotě modelu. Každá prognóza by měla mít k dispozici konfidenční intervaly (intervalový odhad trendu) a ideálně i predikční intervaly (intervalový odhad pro individuální pozorování). Pokud byl u dat využit model pro vyrovnávání dat (předchozí krok), není možné použít běžné přístupy pro konstrukci těchto intervalů využívající normální rozdělení pravděpodobnosti kolem modelu. Doporučuje se tedy simulovat konfidenční i predikční intervaly s využitím principu bootstrapu. Historická data vystupují jako jeden konkrétní scénář (kap. 8.3.4 Certifikované metodiky [B5] a [A1]) a rozptyl historických dat se využívá pro generování nových datových sad. Pro tato vygenerovaná data se vytvoří prognóza, čímž vznikají různé realizace prognózy. Na základě vlastností prognóz pro jednotlivé realizace jsou sestaveny intervaly spolehlivosti [A1]. Rozptyl jednotlivých prognóz různých datových sad se využije pro nadefinování konfidenčního intervalu kolem základního scénáře pomocí kvantilu Studentova rozdělení. Predikční interval je doplněn o rozptyl skutečných historických dat kolem trendu.

Bohužel časové řady jsou pro dlouhodobé posouzení úspěšnosti prognózy včetně intervalů spolehlivosti příliš krátké, takže přístup byl hodnocen pouze pro prognózu s ročním výhledem. Prognóza byla provedena na historických datech z období 2010–2019 a data z roku 2020 byla zachována pro vyhodnocení. Celkový datový soubor pro testování obsahoval 206 ORP a 17 frakcí odpadů, což odpovídá 3 502 časovým řadám. 90% predikční interval pro prognózu v roce 2020 pokrýval 85 % reálných dat z roku 2020. Tato hodnota byla získána mediánem z výsledků jednotlivých druhů odpadů. Mediánový přístup je méně citlivý na odlehlé frakce odpadu, které se mohou objevit v případech neočekávaných legislativních zásahů nebo chyb v historických datech. Podobně podhodnocené výsledky byly získány pro intervaly s různou hladinou významnosti. 70% predikční intervaly pokrývají 62 % datových bodů a 50% predikční intervaly pokrývají 49 %. Predikční intervaly by dle výsledků měly být širší. Na druhou stranu lze výsledky považovat za vyhovující, protože odchylka není velká s ohledem na vývoj v oblasti OH. Testování tohoto přístupu potvrzuje výhodu vyrovnávání dat (kap. 3.3.3), protože reálná data jsou ve většině případů blíže vyrovnaným datům než trendům.

3.4 Post-processing

3.4.1 Modelování scénářů

Klasické přístupy pro modelování obvykle neposkytují projekce, přestože se jedná o velice přínosné informace z pohledu plánování OH. Vytvořené projekce se odklánějí od BAU tak, že splňují požadavky scénáře a předem definované okrajové podmínky [C93]. OH je obor, ve kterém často dochází k úpravám legislativy a je užitečné odhadnout potenciál pro případné změny. V souvislosti s cíli EU (kap. 1) je zásadní plánovat zejména materiálové využití KO, jehož nutným předpokladem je dostatečná separace odpadu. Legislativní zásahy probíhají na úrovni státu nebo jiných samosprávních celků, splnění cílů na státní úrovni je však výsledkem činnosti nižších územních celků. Součástí přístupu k modelování projekcí je rozpuštění jednotlivých scénářů až na úroveň obcí podle jejich potenciálu pro změnu (kap. 4.3 Certifikované metodiky [B5]). Při použití projekcí se doporučuje zohlednit vazby mezi frakcemi odpadu [A9], které mají značný vliv na potenciál pro navýšení separace odpadu.

Projekce produkce KO vycházejí z informace o složení odpadu, zejména SKO. Separovatelné frakce odpadu (papír, plast, sklo atd.) vyskytující se v SKO specifikují potenciál pro zvýšení míry separace KO. Složení SKO se obvykle určuje pomocí manuálních rozborů, ale lze provést pouze omezený počet takových analýz. Pro odhad výsledného složení SKO je rozhodující výběr vzorků pro provedení rozborů založený na stratifikaci území. V příspěvku [A10] byly popsány metody územní stratifikace a byl představen model pro výběr reprezentantů. Představený přístup byl aplikován na socioekonomická a demografická data za ČR na úrovni ORP. Model rozděluje území do shluků a vybírá vhodné reprezentanty tak, aby byla pokryta co největší variabilita území. Současně je zohledněn počet obyvatel a počet ORP v každém shluku pro počet vybraných reprezentantů v jednotlivých shlucích.

3.4.2 Samoučící mechanismus

Při změně nebo doplnění sady vstupních dat je vyžadována aktualizace výsledků. Databáze ISOH [C8] je každoročně doplněna o data za uplynulý rok z hlášení o produkci a nakládání s odpady. Hlášení podávají do 28. února subjekty, které produkují více než 600 kg nebezpečných odpadů nebo 100 tun ostatních odpadů, nebo s odpadem nakládají [C9]. V případě dynamických dat je nutné rychle reagovat a vyvinout adekvátní metodiku [C134]. Příkladem může být prognóza při použití chytrých technologií, např. nádoby vybavené čipy a senzory sledující naplněnost.

3.4.3 Prezentace výsledků

Důležitou součástí prognózy je vhodná interpretace a prezentace výsledků. Výsledky musí být předány tak, aby je uživatelé prognóz mohli snadno interpretovat. Je možné použít grafy, tabulky nebo mapové výstupy, reprezentativní vizualizaci výsledků lze nalézt např. v článku [C47].

4 PŘÍPADOVÉ STUDIE PRO VYBRANÉ FRAKCE ODPADU

V následujícím textu jsou představeny případové studie, kdy byl aplikován přístup k prognózování představený v kap. 3 dle Certifikované metodiky [B5]. V jednotlivých studiích bude upřesněn zdroj historických dat vstupujících do výpočtu. Většinou jsou využita data z databáze ISOH [C8], která byla ÚPI poskytnuta pro řešení projektu TIRSMZP719. Jedná se o neveřejná data, proto nebudou historická data u některých případových studií konkretizována a v grafických výstupech budou nahrazena trendem. Zobrazena budou pouze volně dostupná data, která jsou součástí Veřejné databáze ISOH (VISOH) [C135]. Případové studie v této kapitole jsou dále zařazeny do prognózy nebezpečného odpadu (NO) v kap. 4.1, prognózy KO v kap. 4.2 a projekcí KO v kap. 4.3.

4.1 Prognóza produkce nebezpečného odpadu

NO je odpad, který vykazuje alespoň jednu z nebezpečných vlastností dle Zákona o odpadech [C133], nebo se zařazuje do druhu odpadu, kterému je v *Katalogu odpadů* [C11] přiřazena kategorie NO. Opakem je tzv. „ostatní odpad“, jedná se o odpad, který není řazen k NO. U NO tedy je nutné rozlišovat dvě různé kategorie, podle kterých může být odpad klasifikován jako NO:

1. Kategorie odpadu dle Katalogu odpadu: NO je určen seznamem konkrétních kat. č. specifikovaných v Katalogu odpadů (např. kat. č. 20 01 13 – rozpouštědla). Katalog odpadů [C11] zahrnuje celkem 331 kat. č. řazených k NO z celkového počtu 842 kat. č.
2. Kategorie odpadu ohlášená: při evidenci produkce a nakládání s odpady má zadavatel povinnost do systému označit odpad za nebezpečný, pokud vykazuje nebezpečné vlastnosti, bez ohledu na nebezpečnost podle 1. Kategorie (výše). Podle tohoto kritéria se jako NO mohou vyskytovat i odpady označené podle Katalogu odpadu jako ostatní.

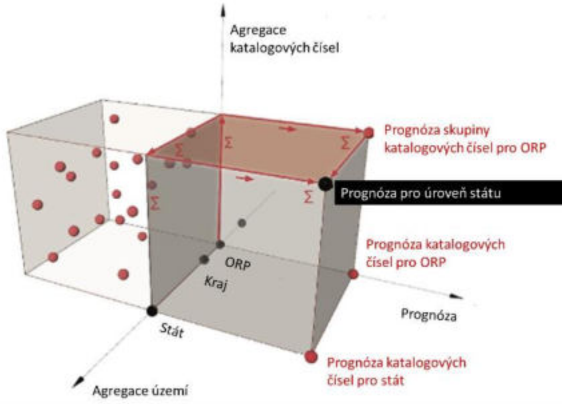
Ve většině případů však obě kategorie pro hodnocení nebezpečných vlastností odpadů korespondují. V dalších výpočtech bude jako NO uvažován odpad podle 2. Kategorie. V databázi ISOH je tato informace označena jako „Kategorie odpadu ohlášená“.

Je možné rozlišovat mnoho druhů NO podle fyzikálních vlastností, složení, výhřevnosti, nebezpečných vlastností (toxicita) atd. Podle Zákona o odpadech [C9] jsou stanovena pravidla pro nakládání s NO. Pro případovou studii v ČR [A3] byl NO rozdělen podle preferovaného způsobu zpracování do následujících proudů:

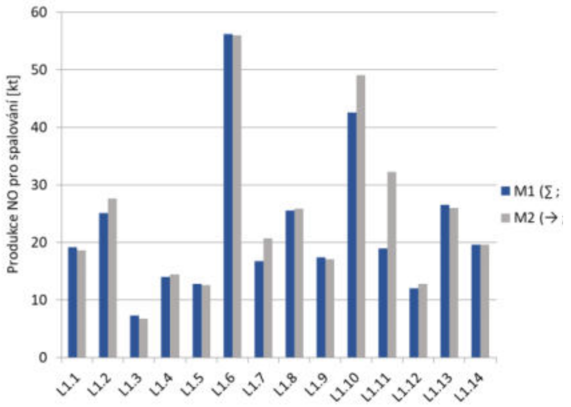
- NO pro spalování,
- NO pro stabilizaci,
- NO pro biodegradaci,
- NO pro deemulgaci/neutralizační linku,
- NO pro spalování nebo stabilizaci,
- NO pro deemulgaci/neutralizaci nebo stabilizaci.

Agregací kat. č. NO do kategorií výše dle nakládání došlo k významnému snížení výpočetní náročnosti úlohy a byla zachována informace očekávané produkce NO s určitým způsobem nakládání. Současně byla zohledněna hierarchie územního členění pro ORP, kraje a ČR. Pro případovou studii [A3] byla dostupná historická data z období 2009–2015, prognóza byla provedena do roku 2020.

Na historických datech byla provedena extrapolace dat s využitím mocninné funkce (viz kap. 3.3.2) na všech úrovních územního členění a pro všechny kategorie NO dle nakládání. Extrapolované hodnoty byly následně bilancovány pro zachování hierarchické struktury územního členění (viz kap. 3.3.3). Ve studii [A3] je detailně popsán přístup k bilancování extrapolovaných dat. Na obr. 13 je vyobrazen různý přístup k prognóze, který je závislý na různém pořadí agregace dat (Σ) a provedením prognózy (→). Pořadí úkonů (Σ; →) resp. (→;Σ) před bilancí je v obr. 14 označeno jako model M1, resp. M2 pro kraje ČR (LAU 1 ozn. L1) specifikované jako L1.1–L1.14. U některých krajů L1 je patrný významný rozdíl M1 a M2 modelů, lze zmínit zejména kraj L1.11 (Ústecký kraj). Cílem bilance je vyrovnat tyto rozdíly.



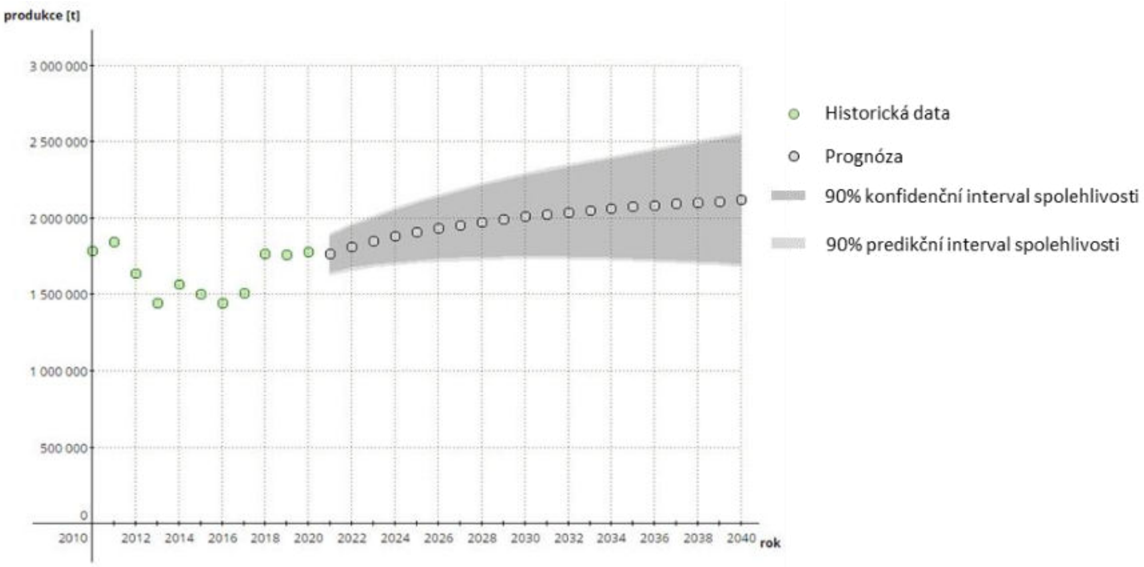
Obr. 13: Znázornění různých přístupu k prognózování s různým pořadím agregace (Σ) *a prognózy (→), upraveno na základě [A3]*



Obr. 14: Rozdíl mezi modely s různým pořadím agregace a prognózy, NO pro spalování, kraje ČR, upraveno na základě [A3]

Prognóza produkce NO byla oproti studii [A3] aktualizována v rámci softwaru TiramisO s dostupnými daty 2010–2020. Dále budou prezentovány aktualizované výsledky. V rámci softwaru byla prognózována všechna kat. č. bez zařazení do kategorií podle zpracování, jako tomu bylo ve studii [A3]. Prognóza pro všechna kat. č. byla možná díky efektivnější implementaci výpočtů.

NO bylo v ČR v posledním roce 2020 vyprodukováno 1 781 kt [C135]. Většina z tohoto množství je odpad produkovaný firmami, obce produkovaly v roce 2020 pouze asi 2 % NO z jeho celkové produkce. Na obr. 15 je znázorněna prognóza NO daná agregací kat. č. NO. Do roku 2040 se očekává nárůst produkce NO asi o 19 % na 2 118 kt, pokud bude zachován dosavadní trend. Tento fakt by měl být zohledněn při plánování zpracovatelských kapacit.



Obr. 15: Prognóza produkce NO, úroveň ČR, výpočet: TiramisO [B6], zdroj dat: [C135]

4.2 Prognóza pro oblast komunálního odpadu

Prognóza KO je pro plánování OH zásadní zejména s ohledem na cíle přijaté v CEP (kap. 1). Pomocí prognózy KO je možné odhalit nutnost zásahu do stávajícího systému OH tak, aby bylo možné dosáhnout cílů EU. KO je dle Zákona o odpadech [C9] směsný a tříděný odpad z domácností a z jiných zdrojů, pokud je do povahy a složení podobný odpadu z domácností. KO nezahrnuje odpad z výroby. V ISOH je KO evidován kat. č. poskupiny 15 01 a skupiny 20 (bez 20 03 04 a pro data za rok 2020 a roky následující i bez 20 03 06 a 20 02 02). Od roku 2021 došlo ke změně legislativy ČR [C9] a podskupina 15 01 již není uvažována jako KO. Odpad doposud evidovaný kat. č. 15 01 je od roku 2021 evidován ekvivalentními kat. č. skupiny 20. Např. odpad kat. č. 15 01 01 (papírové obaly) je evidován jako kat. č. 20 01 01 (papír a lepenka).

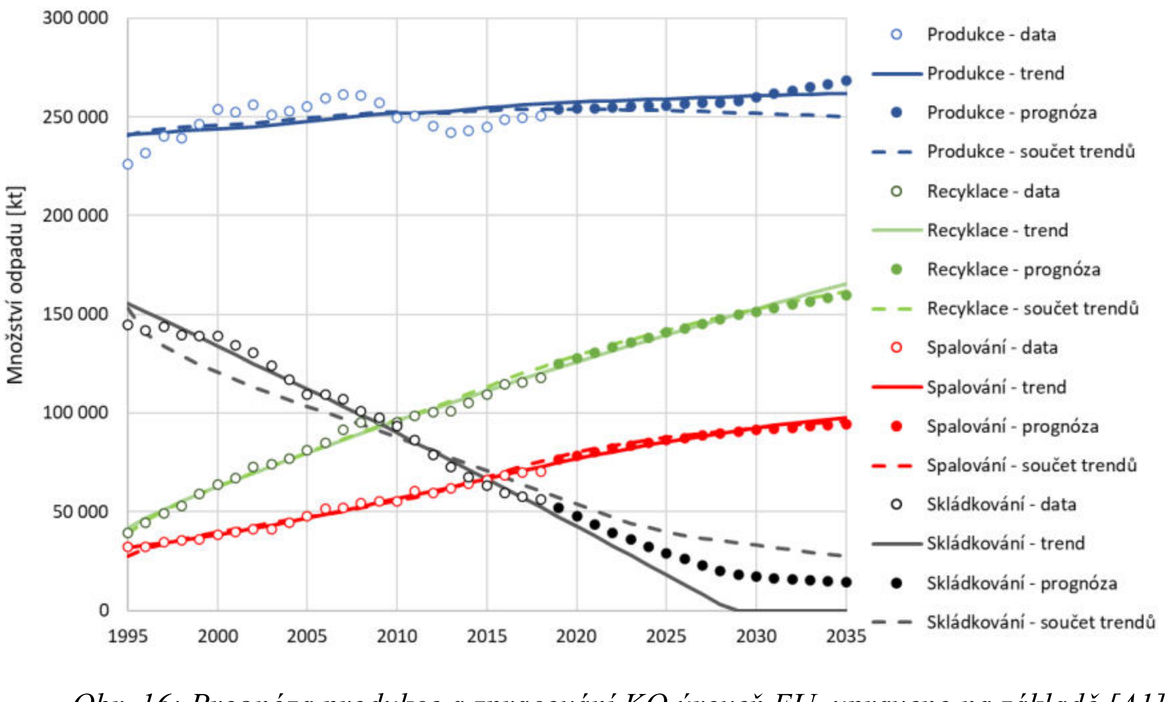
4.2.1 Prognóza produkce a zpracování komunálního odpadu ve státech EU

Úroveň nakládání s odpady se v jednotlivých státech EU výrazně liší, proto mají odlišnou výchozí pozici při dosahování stanovených cílů EU (obr. 1). Některé státy EU jsou již na cestě ke splnění cílů obsažených v CEP se svou současnou formou OH. V ostatních případech bude nutné zavést změny v OH, aby byly cíle CEP splněny včas. Klíčové informace o nutnosti změny poskytne prognóza produkce a nakládání s KO.

Příspěvek [A1] představil přístup pro prognózu produkce a nakládání s KO ve státech EU. Byl aplikován přístup (viz kap. 3) dle Certifikované metodiky [B5] se zachováním vazeb územního členění (státy, EU). Navíc byl model doplněn o podmínku zachování vazby mezi produkcí a nakládáním s odpady. Důvodem je předpoklad, že se všemi vyprodukovanými odpady je třeba nějakým způsobem nakládat. Rozlišeny byly tři způsoby nakládání: materiálové využití, spalování a skládkování. V posledních letech je asi 98 % spalovaného KO v EU energeticky využito. Díky prognóze nakládání s KO lze přímo posoudit plnění cílů EU. Vyrovnávání dat je založeno na metodě představené v kap. 3.3.3.

Pro provedení studie byla využita veřejně dostupná data Eurostat [C136] z období 1995–2018, predikční horizont byl uvažován do roku 2035, což je poslední rok zahrnutý v cílech CEP. Trend v historických datech o produkci odpadu byl modelován v kg na obyvatele a po provedení extrapolace byla data přepočtena na absolutní množství s využitím demografické projekce. V případě dat o nakládání s odpady byl trend modelován v absolutních hodnotách, protože tento vývoj není přímo ovlivněn počtem obyvatel ale spíše infrastrukturou a zpracovatelskou kapacitou. Výsledek prognózy ukázal očekávaný vývoj podle BAU, viz obr. 16 pro celou EU. Data o produkci oscilují kolem průměrné hodnoty, takže hodnota koeficientu determinace pro mocninnou funkci je velmi nízká, trend byl z tohoto důvodu modelován průměrem v datech přepočteným na obyvatele. Následně byla zohledněna demografická projekce pro přepočet na absolutní množství produkovaného odpadu. Údaje o spalování KO vykazují mírně exponenciální charakter. Z důvodu omezení růstu trendu nad všechny meze byl trend modelován logistickou funkcí. Detailní popis volby funkčního předpisu je k dispozici v článku [A1].

Na obr. 16 je znázorněno absolutní množství odpadu prognózovaného na úrovni EU. Trend v absolutním množství (plná čára) vstupuje do modelu vyrovnávání dat. Obr. 16 je zobrazen na úrovni EU, takže vyrovnání dat je ovlivněno i trendy nižších územních celků – států. Součet trendů na národní úrovni je znázorněn přerušovanou čarou. Výsledná prognóza po vyrovnání dat je zobrazena plnými tečkami. Je zřejmé, že výsledky vyrovnávání dat pro recyklaci a spalování KO jsou soustředěny kolem dvou trendů: na základě dat EU (trend) a na základě součtu trendů za státy EU (suma trendů). Omezení poklesu skládkování v důsledku nezápornosti musí způsobit změny v jiných časových řadách. Podle aktuálního přístupu byla v důsledku změny trendu skládkování zrychlena produkce KO. Zpomalení skládkování by mělo mít vliv spíše na jiné typy zpracování KO než na produkci. V dalším výzkumu by bylo vhodné model upravit na postupné vyrovnávání dat nebo implementovat korelace mezi časovými řadami. Výsledky prognózy pro jednotlivé státy EU jsou v publikaci [A1].



Obr. 16: Prognóza produkce a zpracování KO úroveň EU, upraveno na základě [A1]

Podle prognózy mnoho států EU čelí situaci, kdy jejich současný stav OH nevede ke splnění milníků, zejména v souvislosti s materiálovým využitím [A1]. Lze však pozorovat relativní odklon od skládkování, které je nahrazováno většinou spalováním. Pokud nebudou cíle stanovené v CEP splněny, budou státy EU vystaveny sankcím, protože povinností státu je zajistit vhodné podmínky pro žádoucí nakládání s odpady, zejména vybudovat potřebná zpracovatelská zařízení. Jak uvádí příspěvek [A11], produkci a zpracování KO ovlivňují některé ekonomické, sociologické a demografické proměnné. Zaměření se na tyto ovlivňující faktory může přispět k transformaci OH. Důrazně se doporučuje výsledky prognózy každý rok aktualizovat a pružně reagovat na aktuální vývoj.

4.2.2 Prognóza produkce komunálního odpadu v České republice

V České republice bylo v roce 2020 vyprodukováno 5 730 kt KO [C135]. Přestože míra materiálového využití KO v ČR roste [A1], vzhledem k cílům EU je nutné zabývat se otázkou budoucího vývoje. Množství očekávané produkce jednotlivých frakcí odpadu v následujících letech je zásadní z pohledu nastavení vhodné infrastruktury tak, aby bylo možné splnit cíle stanovené EU.

Výpočet prognózy produkce KO byl proveden na úrovni ČR, krajů a ORP s vyrovnáním trendů pro zajištění vazeb hierarchie (viz kap. 3.3.3). KO je specifický tím, že mezi jednotlivými frakcemi existují významné vazby, které by se měly v prognóze projevit. Jedná se zejména o vazbu mezi SEP a SKO. Tato vlastnost byla zohledněna ve studii [A5], kdy bylo současně prognózováno více frakcí KO. Výpočet byl proveden pro běžně separované frakce odpadu (papír, plast, sklo a bio-odpad) s vazbou na SKO. S rostoucí produkcí separovaného odpadu bylo snižováno množství dané frakce v SKO. Pro tento přístup je zásadní odhad složení SKO, čímž je určen potenciál pro možné navyšování separace. Pro případ chybějících dat byl v článku [A5] navržen odhad složení SKO pomocí regresního modelu podle typu zástavby v dané lokalitě, protože v době vzniku zmíněného článku ještě nebyly k dispozici rozbory SKO zpracované v rámci projektu TIRSMZP719 (viz kap. 1.1). Statistická analýza dat prokázala, významný vliv nového odpadového proudu množství produkovaného bio-odpadu, z tohoto důvodu nebyla vazba bio-odpadu a SKO v této studii zahrnuta. Dále bude problematika bio-odpadu řešena v kap. 4.2.3.

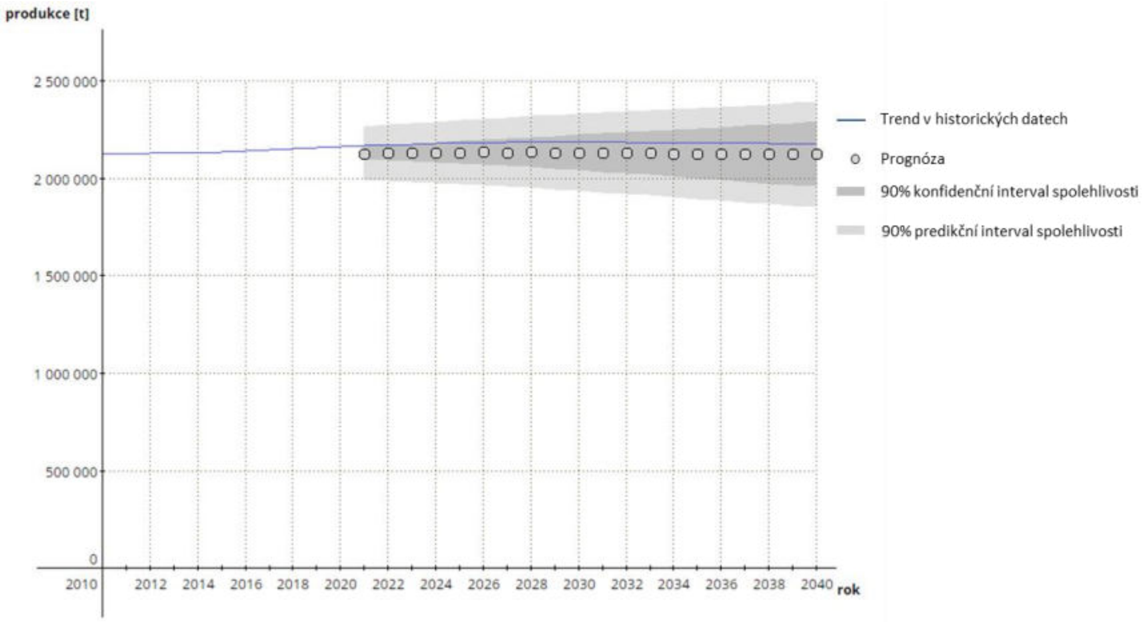
Případová studie v [A5] byla provedena na datové sadě z období 2009–2014 s výhledem na následujících 10 let. Dle této prognózy se očekává souhrnná separace papíru, plastu a skla 44,3 % v roce 2024 oproti 34,8 % v roce 2014. Výhodou této případové studie je současná prognóza složení SKO v roce 2024.

Kvalitnějších výsledků prognózy tohoto typu je možné dosáhnout pomocí přesnějších odhadů složení SKO. Touto otázkou se zabývá jedna z oblastí projektu TIRSMZP719 (kap. 1.1). Dále vlivem nových odpadových proudů lze předpokládat, že ne veškerý nově vyseparovaný odpad pochází z SKO. Nové odpadové proudy mohou být důsledkem využívání jiných materiálů, změn legislativy atd. Vliv těchto proudů na produkci byl modelován ve studii [A9]. Vazby mezi SEP a SKO byly odhadnuty pomocí modelu vyrovnávání dat, výsledkem je hodnota $\delta_{f,j}$, která udává odhad, jaké procento nově vyseparovaného odpadu frakce f pochází z SKO na území j. Výsledky $\delta_{f,j}$ jsou v tab. 3. Ze sledovaných frakcí separovaného odpadu (papír, plast, sklo, textil, bio-odpad a kovy) dochází podle výsledků k nejméně významnému přesunu mezi SKO a SEP v případě kovů. Nízká hodnota $\delta_{f,j}$ značí významný vliv nových odpadových proudů na produkci dané frakce. Vysoká hodnota $\delta_{f,j}$ znamená, že se zvyšuje separace odpadu, a to zejména přesunem odpadu z SKO do SEP. Na základě těchto výsledků lze odhadnout složení SKO v budoucnu, což je nutná vstupní informace pro projekce KO (kap. 4.3).

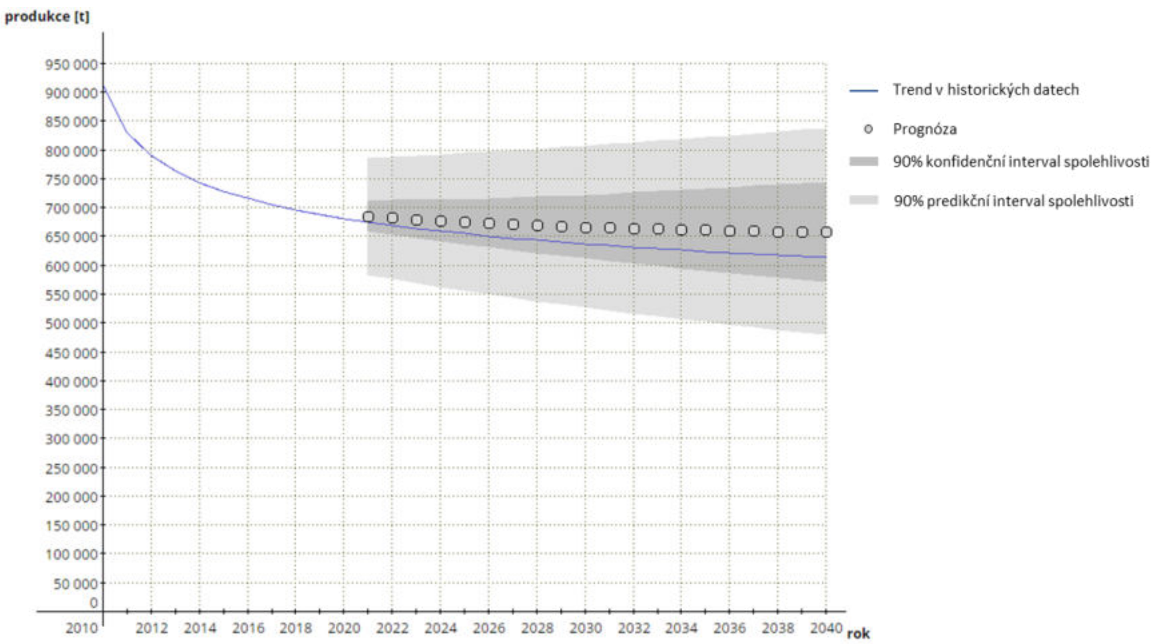
Tab. 3: Odhad přesunu odpadu mezi SEP a SKO, [A9]

	Papír	Plast	Sklo	Textil	Bio-odpad	Kovy
ČR	0.75	0.82	0.69	0.98	0.26	0.11
Kraje						
Vážený průměr	0.74	0.82	0.69	0.98	0.26	0.11
Vážená směrodatná odchylka	0.14	0.15	0.13	0.02	0.06	0.01
ORP						
Vážený průměr	0.61	0.82	0.67	0.98	0.28	0.11
Vážená směrodatná odchylka	0.26	0.20	0.26	0.04	0.20	0.07

Výpočet prognózy produkce KO je zpřesňován při každém doplnění datové sady za další kalendářní rok. V současné době jsou pro prognózu využita data z období 2010–2020, viz kap. 3.2.2. Aktuální prognózy KO jsou součástí softwaru TiramisO [B6]. Pro prognózu KO byl identifikován a zahrnut vlivný faktor demografického vývoje na úrovni ČR a krajů, pro nižší územní celky nejsou demografické projekce k dispozici. Jako zdroj dat očekávaného demografického vývoje byly využity projekce obyvatelstva do roku 2070 vyhotovené ČSÚ v roce 2020 [C133]. V případě dostupných projekcí obyvatelstva i pro nižší územní celky se doporučuje tento demografický vývoj do prognózy také zahrnout. Z důvodu výpočetní náročnosti bylo prognózováno každé kat. č. zvlášť bez definované vazby mezi kat. č. Zachována byla vazba územního členění. Níže na obr. 17 je ukázka výstupů prognózy KO, konkrétně SKO od obcí a od firem na úrovni ČR včetně intervalů spolehlivosti. Z důvodu omezeného zveřejňování dat ISOH, jsou historická data nahrazena trendem.



a) Producent – obec



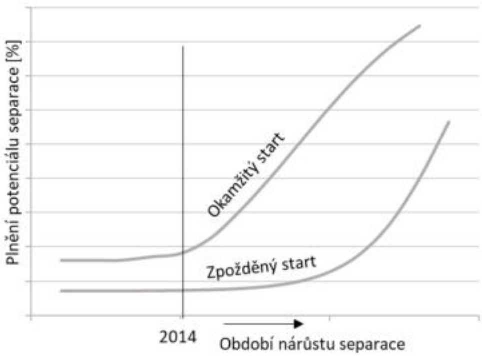
b) Producent – firma

Obr. 17: Prognóza produkce SKO, úroveň ČR, zdroj: TiramisO [B6]

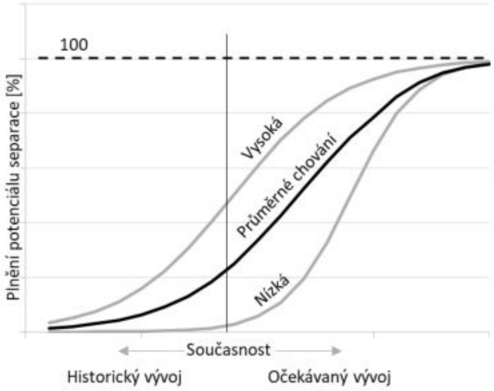
4.2.3 Prognóza produkce bio-odpadu v České republice

Bio-odpad s kat. č. 20 02 01 je z pohledu produkce specifický tím, že v minulosti došlo k legislativní změně. Od roku 2014 jsou obce dle Vyhlášky č. 321/2014 Sb. [C137] v ČR povinné umožnit občanům bio-odpad separovat, což způsobilo náhlou změnu v produkci této frakce odpadu. V případě bio-odpadu, či jiných frakcí odpadu se systematickou změnou trendu, je obtížné odhadnout budoucí produkci odpadu na základě historických dat [A8]. Klasické metody nejsou schopny taková data modelovat, pokud u všech producentů ještě neproběhla reakce na vnější zásah do systému. Přístup prezentovaný ve studii [A8] odhaduje očekávanou produkci bio-odpad na konkrétním území s využitím tzv. kolektivní informace.

Lze očekávat, že jednotlivá území reagují na změnu systému s různou efektivitou, obr. 18 a). Tohoto faktu využívá navržený přístup způsobem, že území reagující na danou situaci se zpožděním mohou přebírat informaci od těch, která již změnou prošla. Na svislé ose obr. 18a) a obr. 18b) je vyznačeno plnění potenciálu separace bio-odpadu. Hodnota potenciálu separace vzniká jako odhad množství odpadu, které je možné na daném území separovat a tento odhad je nutným vstupem pro model. Obr. 18b) znázorňuje předpokládaný vývoj produkce odpadu se skokovou změnou trendu ve dvou scénářích možného vývoje, a to s vysokou a nízkou současnou separací. Předpokládá se, že následující vývoj se bude v obou případech přibližovat průměrnému území.



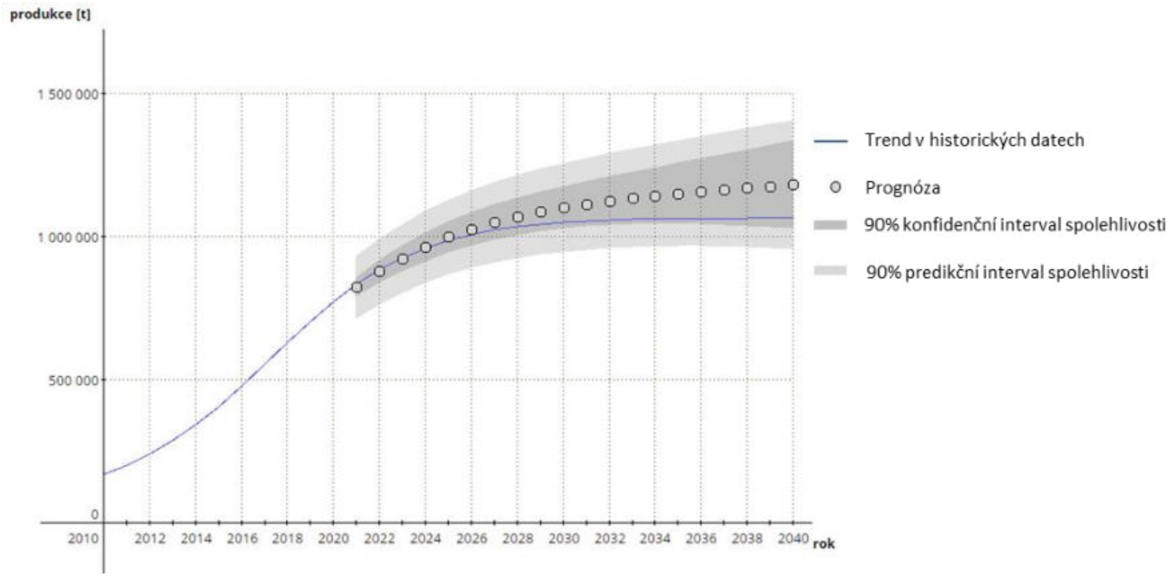
a) Reakce na vnější zásah do produkce bio-odpadu odpadu v roce 2014, upraveno na základě [A8]



b) Možnosti vývoje produkce bio-odpadu u různých producentů, upraveno na základě [A8]

Obr. 18: Schematické znázornění očekávaného vývoje produkce bio-odpadu [A8]

Výpočet ve studii [A8] byl proveden na datové sadě z období 2009–2017 (v době vydání zmíněné studie ještě nebyla odstraněna data v roce 2009 z důvodu krátké časové řady). Potenciál separace bio-odpadu byl dle literární rešerše stanoven na 60 kg/os. a rok pro městskou zástavbu a 200 kg/os. a rok pro venkovskou zástavbu. Na základě těchto vstupních dat se očekávalo, že většina ORP v ČR do roku 2030 dosáhne svého potenciálu separace, pro celou ČR se jedná asi o 1 390 kt/rok. Výpočet byl následně aktualizován s novou datovou sadou 2010–2020 a doplněn o vyrovnávání dat pro zachování hierarchie územního členění. Na úrovni ČR a krajů se v historických datech trend již projevil a je tedy možné jej modelovat stejným způsobem jako ostatní frakce odpadu (viz kap. 4.2.2), navíc trend na úrovni ČR od roku 2017 zpomalil svůj růst. Na úrovni ORP byl trend modelován zmíněným speciálním přístupem pro data se změnou trendu [A8]. V rámci vyrovnávání dat došlo ke korekci různých přístupů pro jednotlivé úrovně území. Výsledkem je prognóza zobrazená na obr. 19 pro ČR včetně pásů spolehlivosti.



Obr. 19: Prognóza produkce bio-odpadu, úroveň ČR, zdroj: TiramisO [B6]

Hlavním nedostatkem metody je nutnost stanovit potenciál separace, tj. množství odpadu, které je možné vyseparovat. Samotná analýza trendu není schopna vůbec reagovat u některých ORP na nastalou změnu, pokud se zatím neprojevila v historických datech. Avšak představený přístup předpokládá postupný nárůst produkce i u producentů, kteří na změnu systému doposud nereagovaly. Tato změna je inspirována vývojem ostatních producentů. Představený přístup je aplikován pouze na úrovni ORP. U vyšších úrovní (kraje a ČR) jsou trendy v datech již patrné a byly modelovány mocninnou nebo logistickou funkcí stejně jako jiné frakce odpadu (kap. 3.3.2). Díky následnému vyrovnání dat (kap. 3.3.3) se nedostatky přístupu pro ORP potlačí.

4.3 Projekce produkce komunálního odpadu

Pro splnění cílů EU je nutné zefektivnit materiálové využití KO, viz kap. 1, předpokladem materiálového využití je separace odpadů. Pokud do systému OH zasahují vnější vlivy (legislativní, technologický pokrok atd.) lze očekávat změnu historického trendu produkce odpadu. Proto se často přistupuje k modelování projekcí, tedy scénářů budoucího vývoje, ve vztahu ke konkrétním podmínkám zvolených autorem. Modelované scénáře jsou porovnávány s BAU za účelem simulace a hodnocení dopadu různých zásahů do systému. Dosažení cíle definovaného scénářem na úrovni státu je však výsledkem činnosti nižších územních celků, např. pro požadovanou separaci odpadů v ČR je nutné dosáhnout adekvátní separace odpadů již v domácnostech a firmách. Dopady intervencí budou tedy v rámci scénáře promítnuty na nižší územní celky až na úroveň obcí. V následujícím textu bude popsán přístup k modelování scénářů separace KO.

Množství separovaného odpadu je ve scénáři zvýšeno odkloněním separovatelných frakcí (PAP, PLA, SKL aj.) ze zbytkového odpadu (SKO, objemný odpad – ObjO) nebo produkcí nového odpadového proudu. Dále je možné do scénáře promítnout snížení produkce KO z důvodu předcházení vzniku odpadů. Východiskem pro sestavení scénáře je BAU [A1]. Scénáře separace KO jsou ovlivněny vazbou mezi produkcí separovaného a zbytkového odpadu, tyto vazby jsou analyzovány přístupem prezentovaným v článku [A9]. Začlenění těchto vazeb do konstrukce scénářů umožní lépe odhadnout potenciál pro zvýšení separace.

Výsledkem modelu [A9] je odhad hodnoty, která udává, jaké procento nově separovaného množství vybrané frakce pochází z jednotlivých zbytkových frakcí (SKO, ObjO). Přístup k projekci produkce KO je v současné době zpracován a připraven k publikování, text uveden v příloze (Příloha 10).

Jedinečnost prezentovaného přístupu je především ve využití vlastností hierarchické datové struktury, protože je potřeba zajistit provázanost procesu na státní i lokální úrovni. Modelované scénáře odrážejí názor expertů a jsou obvykle vytvořeny pro několik variant od pesimistické přes neutrální až po optimistickou. Navržený přístup k projekci separace KO se skládá ze dvou hlavních kroků. V první fázi je na státní úrovni nastaven scénář tak, aby bylo dosaženo požadovaného cíle. V navazující fázi jsou národní cíle rozděleny na regionální (obecní) úroveň. Detailní popis přístupu je k dispozici také v Certifikované metodice [B5]. Vstupní hodnoty pro výpočet na státní úrovni jsou výsledky BAU a následující parametry zadávané uživatelem:

- Prevence před vznikem KO [%].
- Míra separace (MS) sledované frakce KO ze zbytkového odpadu (SKO, ObjO) [%].
- Celková produkce nového odpadového proudu (tzn. separovaného i zůstatek ve zbytkovém odpadu) [t].

Výstupem scénáře pro státní úroveň jsou hodnoty uvedené níže, detailní popis přístupu je k dispozici v příloze (Příloha 10):

- Separovaná frakce odpadu, která má původ v konkrétním zbytkovém odpadu [t].
- Celková produkce separovaného odpadu [t].
- Vyseparovaný odpad nového odpadového proudu [t].
- Separovatelná frakce ve zbytkovém odpadu [t].
- Produkce zbytkového odpadu [t].
- Množství nové frakce v zbytkového odpadu [t].

Následně jsou rozděleny státní cíle (změny od BAU) na nižší územní celky s ohledem na současný stav separace KO každého území (potenciál pro změnu). Prezentovaný přístup zohledňuje následující logické podmínky pro rozdělení scénáře na úroveň obce:

- Všechny obce přispívají k státnímu cíli, pokud mají potenciál pro změnu.
- Je zachována monotónnost z hlediska plnění potenciálu (obce se při přechodu z BAU na scénář nepředbíhají). Přístup reflektuje rozdíly v produkci a složení odpadu v obcích a podporuje tak racionalitu scénáře.
- Zohledňuje se prevence před vznikem odpadů. Tento aspekt má vliv na celkovou produkci odpadů a jejich složení, čímž ovlivní potenciál pro změnu.
- Připouští se možnost nových odpadových toků.
- Zahrnuje se produkce odpadů od obecních a firemních producentů.
- Všechny aspekty jsou propojeny do jednoho analytického modelu. Přístup je sestaven obecně pro libovolný počet separovaných frakcí odpadu a detail územního členění.

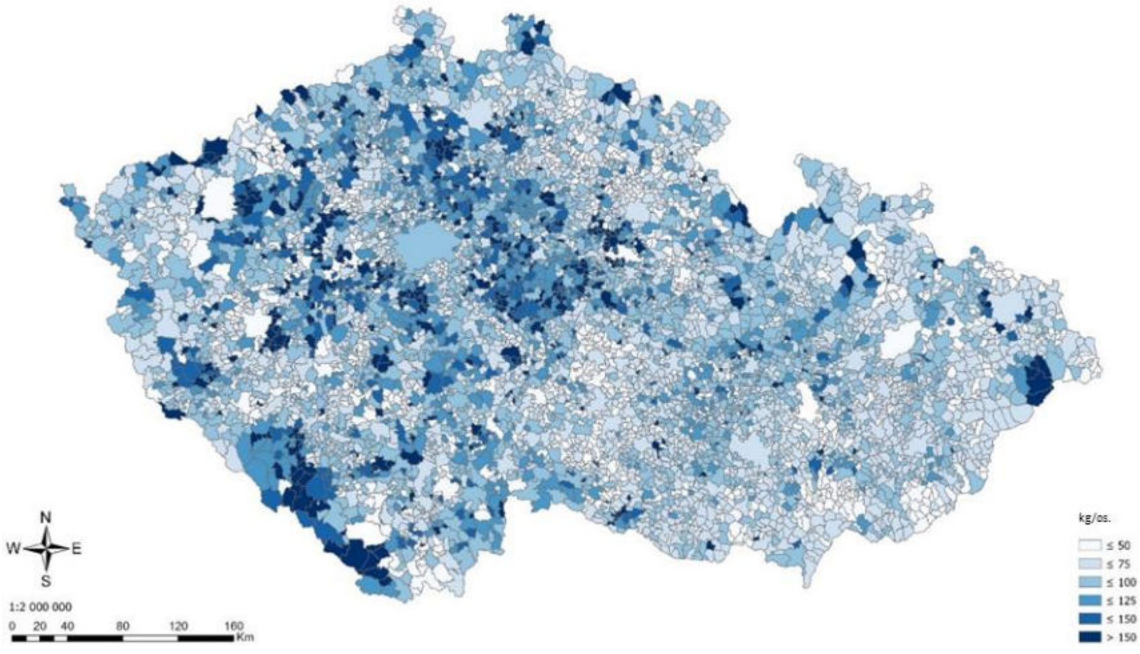
Byla provedena případová studie projekcí produkce KO v ČR pro rok 2035 (Příloha 10). BAU produkce KO byl vytvořen na základě historických dat z období 2010–2018 (viz kap. 3.2.2). Scénáře byly modelovány pro 6258 obcí ČR a pro vybrané druhy KO, které vykazují potenciál materiálového využití. Výsledky identifikovaly konkrétní obce, kde je vhodné zaměřit podporu na zvýšení separace KO. MS KO se dle BAU v roce 2035 odhaduje na 44 % za ČR s prognózou produkce KO 6 823 kt. V rámci scénářů je MS navyšována.

Legislativa ČR podporuje separaci odpadů následovně (Zákon 541/2020 Sb. o odpadech, [C9]):

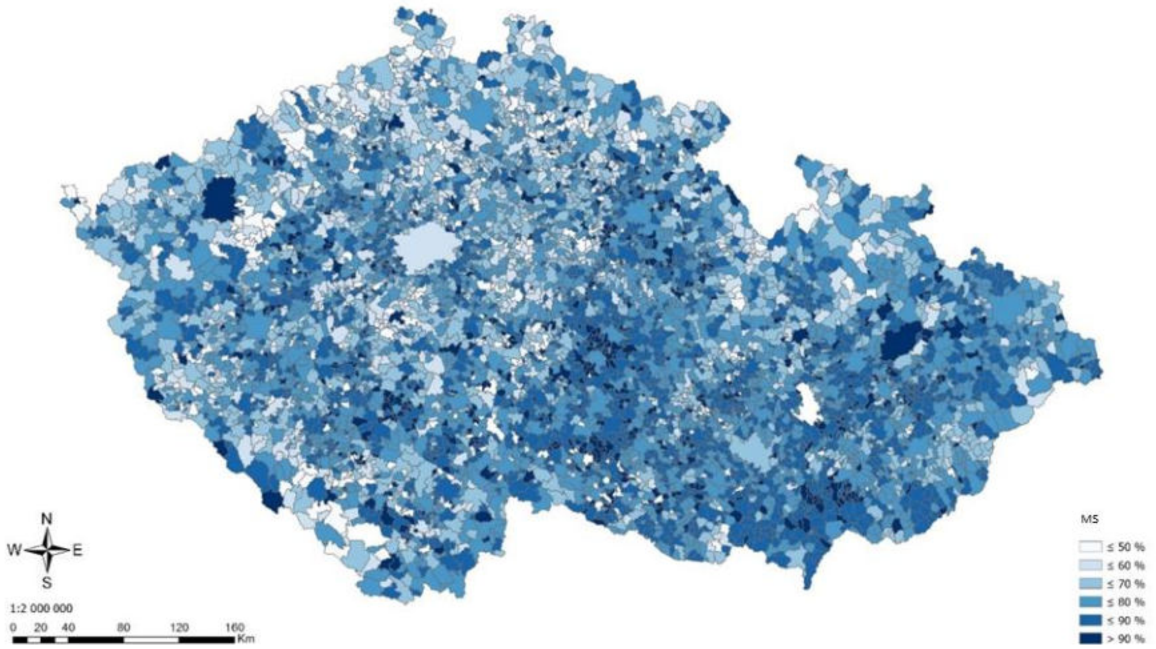
- Separace nových frakcí odpadu: textil od roku 2025.
- Zvýšení poplatku za skládkování: každoroční nárůst do roku 2029.
- Povinnost obcí dosáhnout minimální separace: 60 % v roce 2025 a dalších 5 % každých pět let až do roku 2035.
- Třídění ObjO: od roku 2023 minimálně kovy, plasty a dřevo.
- Povinnost separovat KO ve firmách: papír, plasty, sklo, kov, bioodpad od roku 2021.
- Omezení skládkování pro některé frakce odpadu: odpady z elektrozařízení, baterií, pneumatik a KO s výhřevností vyšší než 6,5 MJ / kg v sušině.
- Zákaz skládkování využitelných odpadů: od roku 2030.
- A další.

Tyto legislativní zásahy nad rámec BAU pravděpodobně povedou k vyšší separaci odpadu. V separovaných odpadech lze však očekávat větší znečištění odpadů nebo jinak nevhodných odpadů pro materiálové využití kvůli cílenému navyšování separace. Je tedy nutné počítat s tím, že ne všechen separovaný KO je materiálově využitelný. Po vytřídění odpadu na dotřiďovacích linkách je nevyužitelný zbytek ve formě zpětných toků určen k energetickému využití nebo v nejhorším případě ke skládkování. Od roku 2030 nebude možné na skládku ukládat odpady s výhřevností v sušině vyšší než 6,5 MJ/kg [C9].

Konkrétní vstupní hodnoty složení SKO a ObjO, které určují potenciál pro navýšení separace KO jsou k dispozici v příloze (Příloha 10). Hlavními kritérii pro posouzení potenciálu navýšení separace KO je současné složení zbytkového odpadu a současná MS. Množství separovatelného odpadu v SKO je znázorněno na mapě obcí ČR (obr. 20). Mapový výstup poskytuje zajímavý výsledek, kdy obce v Čechách vykazují větší množství separovatelného odpadu v SKO než obce na Moravě. Vyhodnocení MS ve scénáři BAU na úrovni obcí je znázorněno na mapě (obr. 21) pro SKO produkovaný obcemi. Nízká hodnota MS znamená velký potenciál pro zlepšení a je často spojena s vysokým množstvím SEP v SKO. Tyto obce jsou schopny více přispět k národnímu cíli.



Obr. 20: Množství separovatelného odpadu v SKO, úroveň ČR, úroveň obcí, BAU rok 2035



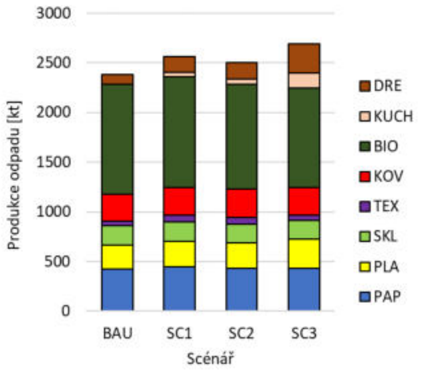
Obr. 21: Míra separace odpadu z SKO vyprodukovaného obcemi, úroveň ČR, úroveň obcí, BAU rok 2035

Na základě konzultace s odborníky na OH při řešení projektu TIRSMZP719, kteří se podílejí na tvorbě české legislativy [C9], byly formulovány tři scénáře separace KO: realistický (SC1), pozitivní (SC2), optimistický (SC3), viz tab. 4.

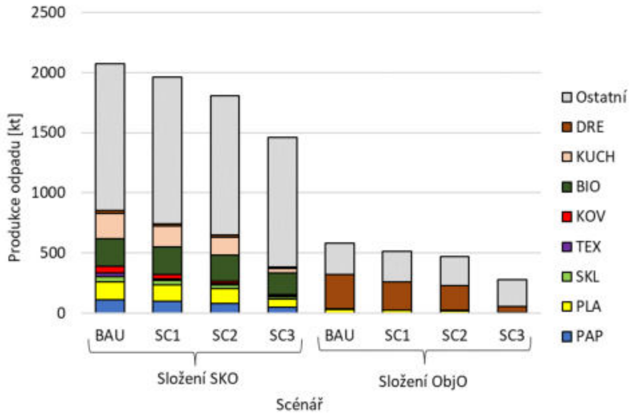
Tab. 4: Nastavení modelovaných scénářů separace KO, úroveň ČR, rok 2035

Producent		Obce				Firmy			
Scénář		BAU	SC1	SC2	SC3	BAU	SC1	SC2	SC3
Prevence [%]		0%	0%	5%	12%	0%	0%	5%	12%
MS z SKO [%]	PAP	78%	82%	84%	90%	89%	91%	91%	95%
	PLA	62%	65%	67%	80%	13%	20%	25%	80%
	SKL	79%	84%	86%	90%	43%	46%	48%	90%
	TEX	65%	75%	80%	90%	50%	50%	52%	55%
	KOV	82%	88%	93%	95%	41%	43%	50%	85%
	BIO	84%	83%	83%	85%	74%	74%	74%	85%
	KUCH	2%	20%	27%	80%	53%	60%	65%	80%
	DRE	83%	85%	86%	87%	82%	84%	86%	87%
MS z ObjO [%]	PLA	0%	20%	25%	80%	0%	20%	25%	80%
	KOV	0%	20%	25%	80%	0%	20%	25%	80%
	DRE	0%	20%	25%	80%	0%	20%	25%	80%

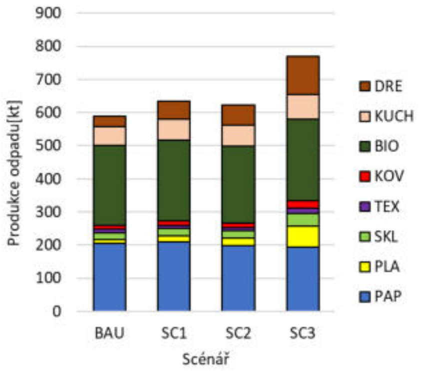
Se vstupními hodnotami uvedenými v tab. 4 a informací o složení odpadu [B12] byly scénáře modelovány nejprve na úrovni státu a poté pro obce v ČR. Graficky je složení separovaného odpadu a zbytkového odpadu znázorněno na obr. 22. První sloupec na obr. 22 vždy znázorňuje BAU a následují modelované scénáře. Ve scénářích je vyšší produkce separovaných frakcí, ačkoli je celková produkce v SC2 a SC3 korigována prevencí před vznikem KO. Podle BAU je v SKO již více než polovina neseparovatelného odpadu („Ostatní“), tento odpad nelze omezit separací z SKO. Scénáře ukazují, že některé frakce mají větší potenciál pro navýšení separace než jiné. Lze zmínit bio-odpad z kuchyní v SKO, který v případě odpadu z obcí zaujímá významnou část SKO.



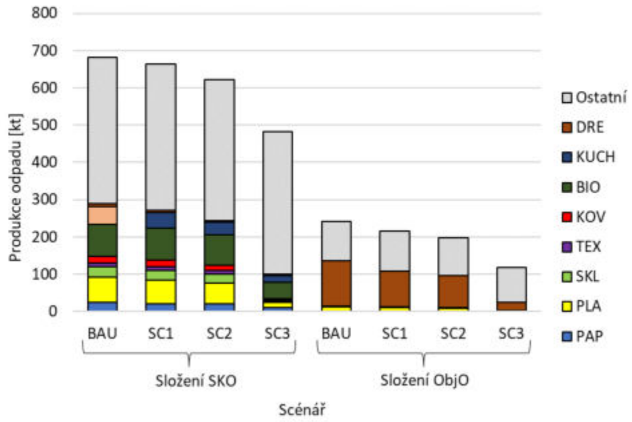
a) Separovaný odpad z obcí



b) Zbytkový odpad z obcí



c) Separovaný odpad z firem



d) Zbytkový odpad z firem

Obr. 22: Výsledky modelování scénáře, úroveň ČR, rok 2035

Hodnocení BAU pomůže vybrat konkrétní obce, kam je vhodné zaměřit podporu na zvýšení separace KO (obr. 20 a obr. 21). Nutné podotknout, že výpočet vychází z odhadu složení SKO [A10]. Namodelované scénáře umožňují zacílit konkrétní zásahy do OH za účelem dosažení stanoveného cíle na národní úrovni. Rozhodující je MS v dané obci a zároveň velikost producenta, protože větší producent může cílením OH efektivněji přispět k naplnění národních cílů. Studie je podkladem pro rozhodování v plánování OH. Prognóza podle BAU totiž ukazuje, že současná legislativa nemusí být dostatečná pro naplnění cílů CEP. Prezentovaný přístup umožňuje opakované modelování budoucího vývoje a slouží jako sofistikovaná podpora plánování ve OH.

Kvalitu scénáře výrazně ovlivňuje odhad potenciálu v obcích. Je proto nezbytné mít odpovídající odhad složení zbytkového odpadu a odhad přesunu odpadu mezi frakcemi. Obecně jsou tyto parametry závislé na lokálních podmínkách, a proto je vhodné je vyhodnocovat individuálně pro každou obec. V případové studii (Příloha 10) došlo ke zjednodušení, s ohledem na nedostatek dat bylo u každé obce uvažováno stejné složení zbytkového odpadu a přesun odpadu mezi frakcemi. Navazující vývoj by měl být zaměřen především na zlepšení kvality vstupních dat.

5 MODELY VYUŽÍVAJÍCÍ PROGNÓZY PRODUKCE ODPADU

Stávající systémy OH v zemích EU jsou upravovány tak, aby odpovídaly příslušným milníkům (kap. 1). Cílem je vytvořit systém OH, který je udržitelný z ekonomického i ekologického hlediska. OH je velmi komplexní obor, ve kterém se lze při plánování setkat s mnoha úkoly a problémy. Každá úloha řešená v OH je svou povahou jedinečná a vyžaduje specifická vstupní data lišící se především časovým nebo územním detailem. Strategické plány modernizace a výstavby infrastruktury sběru a zpracování odpadů vyžadují jako primární zdroj dat informace o produkci a složení odpadů, včetně jejich předpokládaného vývoje. Pro plánování v oblasti OH jsou na ÚPI dlouhodobě vyvíjeny podpůrné modely a nástroje. Autorka této dizertační práce se podílela na konkrétních studiích, kde se využívaly výsledky prognóz a projekcí. V této kapitole jsou představeny vybrané publikace.

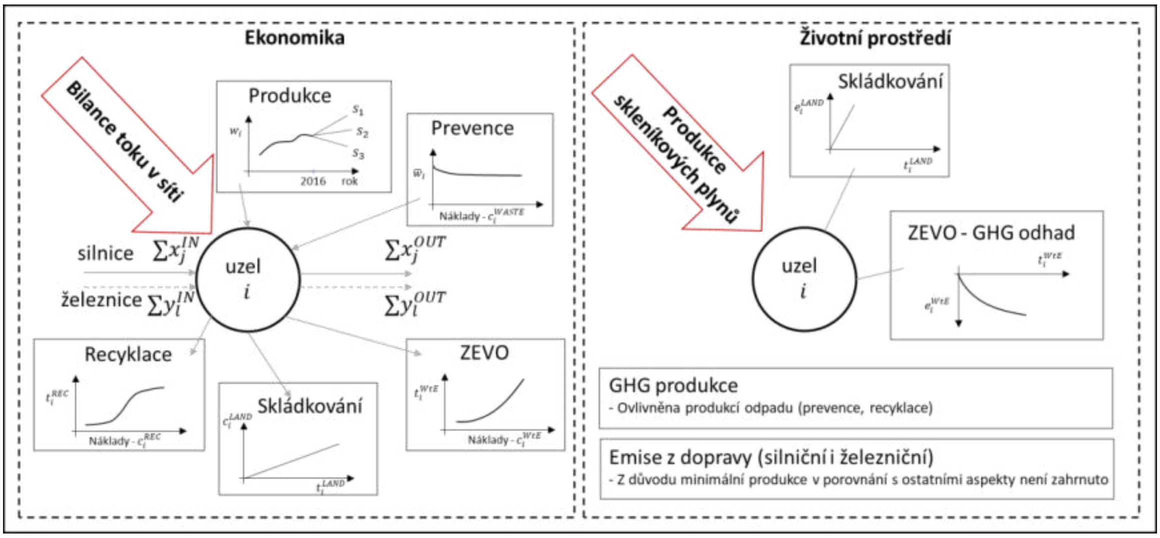
Článek [A12] představil model pro optimalizaci nakládání s KO. Cílem je snížit produkci KO, co nejvyšší možnou měrou KO recyklovat a zbytkový KO energeticky využít. Systém nakládání s KO byl modelován pomocí smíšeného celočíselného lineárního programování zohledněním dvou kritérií – hodnocení skleníkových plynů (GHG – greengouse gas) a minimalizace nákladů (viz obr. 23). Ekonomická udržitelnost nových projektů je zásadním aspektem pro skutečně realizované projekty. Motivace založená pouze na ekonomické ziskovosti má ale omezené možnosti pro efektivnější nakládání s KO. Vzhledem k tomu, že existuje vazba na životní prostředí a kvalitu života, je potřeba podporovat státní intervence na podporu materiálového a energetického využití.

Funkční závislosti z obr. 23 byly odhadnuty na základě reálných dat. Navrhované nelineární funkce nákladů jsou nahrazeny po částech lineární aproximací, aby se snížila výpočetní náročnost. Jednou ze zásadních vstupních informací je produkce KO (obr. 23), matematický model navíc uvažuje náhodnost v produkci odpadu. Produkce KO může být dle principů modelu redukována prevencí před vznikem odpadu. Navržený postup předpokládá možnost ovlivnění produkce odpadů investicí do osvěty. Reálná data o produkci odpadu byla modelována nelineární regresí s využitím S-křivky v podobě logistické funkce:

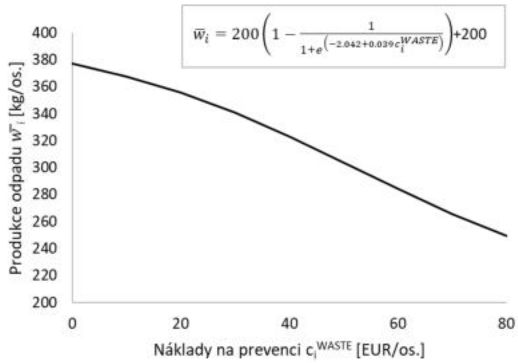
$$\overline{w}_i\left(c_i^{WASTE}\right) = \left(w_{max} - w_{min}\right)\left(1 - \frac{1}{1 + e^{-\left(a + bc_i^{WASTE}\right)}}\right) + w_{min}. \tag{7}$$

kde $\overline{w}_i$ značí odhad produkce odpadu v závislosti na investici do prevence před vznikem odpadu c_i^{WASTE} v lokalitě i. Hledané regresní parametry jsou označeny a a b. Hodnoty w_{min} a w_{max} udávají minimální a maximální možnou produkci sledovaných frakcí KO, což je nutná informace pro využití modelu S-křivky.

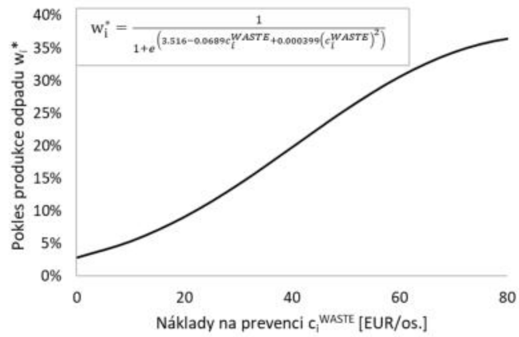
Případová studie vycházela z dat o produkci odpadu v roce 2015 v ČR, jednalo se o nejnovější dostupná data v době vydání článku [A12]. Závislost popisující produkci odpadu je popsána v obr. 24 včetně tvaru regresních funkcí, odhad w_{min} resp. w_{max} byl stanoven na 200 kg/os. resp. 400 kg/os., což odpovídá nejlepším a nejhorším regionům při uplatňování prevence před vznikem KO. Podobná situace byla pozorována také v Rakousku, viz [C138]. Dále byla zohledněna prognóza produkce vybraných frakcí KO v roce 2024. Závislosti pro odhad recyklace odpadu, skládkování a spalování v ZEVO byly modelovány také na základě dat z roku 2015 s využitím vhodných regresních funkcí, detaily jsou popsané v příspěvku [A12]. Výsledky případové studie mimo jiné poukázaly na potenciál v předcházení vzniku odpadu. Představený model [A12] je určený pro vytvoření podkladů při rozhodování o nakládání s KO.



Obr. 23: Schéma systému nakládání s odpadem skládajícího se z ekonomické a environmentální složky, upraveno na základě [A12]



a) Závislost produkce odpadu na investici do prevence

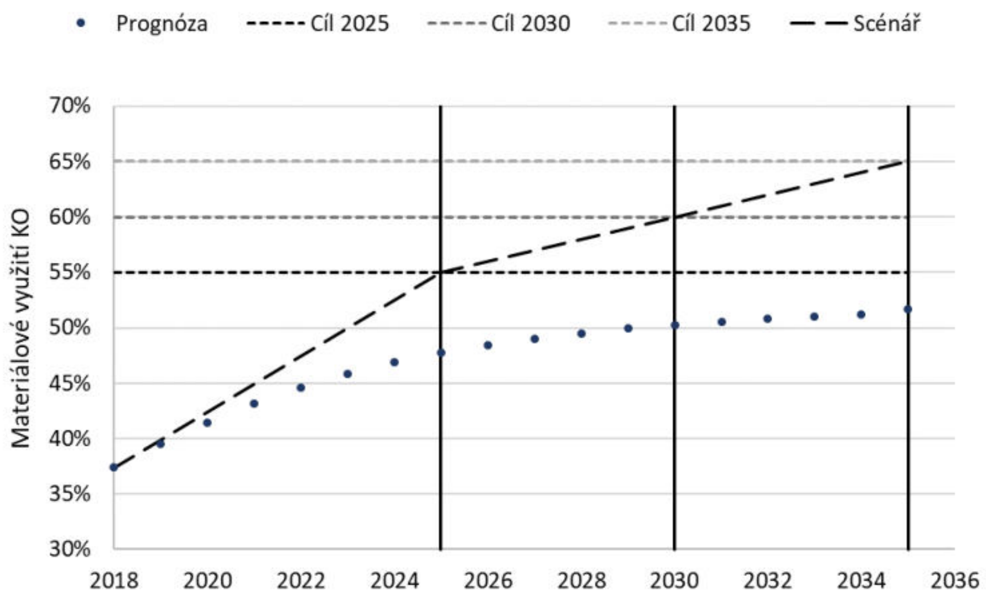


b) Závislost poklesu produkce odpadu na investici do prevence

Obr. 24: Vliv investice do prevence před vznikem odpadu na produkci, upraveno na základě [A12]

Dosažení ambiciózních cílů zahrnutých v CEP je náročným úkolem, zejména pro členské státy EU s méně rozvinutými systémy nakládání s odpady. Pro řešení takového problému byl navržen přístup využívající vícestupňové stochastické programování [A13]. Představený model zohledňuje aktuální míru materiálového využití, přičemž nejistá produkce odpadu je předpovídána možnými scénáři. Model umožňuje sekvenční rozhodování a posuzování různých strategií různých budoucích scénářů pro konkrétní roky, lokality, technologie a kapacity infrastruktury zpracování odpadů.

Využití modelu a jeho výpočetní náročnost jsou představeny v článku [A13] na případové studii ČR. Cílem úlohy je vybrat optimální umístění a velikosti zařízení na zpracování odpadů ve vybraných městech. Uvažují se dva typy zařízení: ZEVO, kde se odpad spaluje za účelem výroby tepla a elektřiny, a zařízení na mechanickou biologickou úpravu (MBÚ), kde se KO třídí a poté buď zpracovává anaerobní digescí, nebo se ukládá na skládku. Účelová funkce je čistě ekonomická a minimalizuje očekávané náklady celého systému nakládání s odpady v uvažovaném časovém období (náklady na přepravu, poplatky na bráně v ZEVO a zařízení MBÚ, penalizace za nevyužitou kapacitu a poplatky za skládkování). Model funguje na principu zachování hmoty, tedy odpad vyprodukovaný v konkrétním městě nebo přepravený do tohoto města je buď odvezen, nebo zde zpracován. Současně jsou zahrnuta omezení pro plnění cílů EU. Zásadní informací pro aplikaci modelu je materiálové využití KO, protože přímo ovlivňuje množství KO, které bude určeno ke zpracování v ZEVO a MBÚ. Na obr. 25 je znázorněna prognóza materiálového využití KO podle BAU a současně scénář, který vede ke splnění recyklačních cílů EU. Nejistota v podobě produkce odpadů s materiálovým využitím byla modelována pro tři scénáře (1. scénář – BAU; 2. scénář – splnění cílů EU s 5letým zpožděním; 3. scénář – včasné splnění cílů EU). Všechny scénáře byly dále rozvětveny, aby zachytily možný budoucí vývoj. Výsledkem modelu je návrh výstavby nových zařízení a jejich kapacit, aby bylo možné plnit cíle EU. Síla modelu spočívá v tom, že jej lze použít pro plánování tzv. rolling-horizon, což znamená, že jej lze po několika letech znovu přepočítat a aktualizovat nadcházející rozhodnutí o nově dostupná data.



Obr. 25: Prognóza materiálového využití KO v ČR a scénář pro splnění cílů EU, historická data 2010–2017, upraveno na základě [A13]

Shrnutí: Prognózy produkce odpadu mají zásadní význam při plánování OH. Jedná se o vstupní data pro různé aplikace vedoucí ke změnám legislativy, strategickému plánování infrastruktury, nebo operativnímu řízení systému (viz [A4]). Konkrétní podoba prognózy by měla zohledňovat následující využití výsledků z pohledu územního detailu, časového detailu, délky prognózy, frakce odpadu atd. Kvalita prognózy může významně ovlivnit navazující modely a plány v OH, proto by měly být zohledněny všechny kroky prognózy definované v kap. 3.

6 ZÁVĚR

Modely budoucí produkce různých frakcí odpadu jsou zásadní vstupní informací pro plánování v oblasti OH. Vybudování vhodné infrastruktury OH s dostatečnou kapacitou a splnění cílů EU je podmíněno kvalitními odhady produkce odpadu. Pro členské země EU byl představen tzv. European Reference Model on Municipal Waste Management, který preferoval co nejvíce zahrnout modely produkce odpadů, které byly vytvořeny samotnými členskými státy. Motivace pro vznik této práce vycházela ze skutečnosti, že nebyl k dispozici jednotný přístup pro prognózování produkce odpadu v ČR.

Pro prognózování produkce odpadu, se využívají různé modelovací přístupy z oblasti statistického zpracování dat, optimalizace, metod strojového učení atd. (viz kap. 2). Jejich volba závisí především na charakteru vstupních dat a požadovaném detailu prognózy. Jak ukázala rešerše v kap. 2, velmi častým nedostatkem představených modelů je minimální pozornost věnovaná přípravě a pre-processingu dat. Ve většině prostudovaných příspěvků jsou tyto fáze modelování zahrnuty pouze okrajově, nebo jsou zcela opomenuté. Dalším zásadním problémem dosavadních přístupů je chybějící informace o nejistotě prognózy např. v podobě pásů spolehlivosti. V návaznosti na výše uvedené poznatky byl navržen přístup k prognózování produkce odpadů, který se skládá celkem ze 13 kroků rozdělených na přípravu dat, pre-processing, processing a post-processing. Prognóza je poté výsledkem všech těchto na sebe navazujících kroků. Současně s touto prací byl řešen projekt TIRSMZP719 [B3], na jehož řešení se autorka významně podílela. V rámci řešení projektu TIRSMZP719 vznikla Certifikovaná metodika pro provádění dlouhodobé prognózy produkce odpadů v ČR včetně revize prognózy [B5], podoba této metodiky byla průběžně korigována zástupci MŽP s ohledem na její následující využití.

Data o produkci odpadu v ČR jsou shromažďována v každoročním hlášení o produkci a nakládání s odpady dle Zákona o odpadech [C9]. V současnosti je k dispozici datová sada z období 2009–2020. Vzhledem k charakteru těchto dat byl pro prognózování odpadu v ČR zvolen přístup založený na modelování trendu v historických datech s následnou bilancí pro zachování hierarchické struktury. Prognóza dle metodiky [B5] byla implementována v softwaru TiramisO, jehož hlavním uživatelem je MŽP. TiramisO poskytuje prognózy všech kat. č. odpadů do roku 2040 na úrovni ORP, krajů a ČR. Principy uvedené v metodice [B5] jsou však obecně platné a jejich využitím je možné docílit kvalitní prognózy také ve větším detailu územního nebo časového členění, pokud má uživatel k dispozici potřebná historická data, viz metodika [B5].

V navazující činnosti budou řešeny primárně následující body:

- Prognóza produkce odpadu v ČR bude řešena na úrovni obcí. U obecních dat se očekává větší variabilita v historických datech, může být tedy vhodné přizpůsobit kritické meze v rámci pre-processingu. Navíc jsou obecní data specifická poměrně častým výskytem chybějících záznamů o produkci. Bude nutné vyřešit otázku, zda se jedná o nulovou produkci odpadu nebo o chybějící hodnotu, což může mít zásadní vliv na podobu trendu v datech.

- Prognóza produkce odpadu v ČR bude dále doplněna o prognózu nakládání s odpady. Prvotní aplikace metodiky, kde byla produkce odpadu provázaná s jeho zpracováním, byla na úrovni států EU (viz kap. 4.2.1). U časových řad o nakládání s odpady se také častěji vyskytují skokové změny trendu (Příloha 1), které souvisejí s realizací nového zpracovatelského zařízení. Bude tedy nutné věnovat pozornost zejména pre-processingu dat. V případě zohlednění nakládání s odpady ve větším územním detailu je nutné upravit vstupní historická data také s ohledem na transport odpadu mezi územními celky a nesoulad mezi produkcí a nakládáním s odpady v evidovaných datech, viz [A14].

- S ohledem na prognózu nakládání s odpady bude analyzován vliv demografického vývoje a dalších vlivných faktorů na konkrétní metody zpracování odpadu. Kromě toho může být výhodné zohlednit korelace mezi různými metodami nakládání s odpady a produkcí pro model vyrovnávaní dat.

- Konstrukce intervalů spolehlivosti prognózy by měla zohlednit rozptyl reziduí v závislosti na čase. Aktuálně nebyl nalezen vhodný přístup, který by umožnil získat tuto informaci z dostupných dat.

- Pro využití v plánování infrastruktury OH v ČR budou formulovány konkrétní scénáře produkce KO v závislosti na konkrétních změnách systému, např. změna balení potravin, pytlový sběr odpadu, platby za zpracování odpadu dle vyprodukovaného množství atd.

Přístup k prognózování produkce odpadu by měl být průběžně aktualizován v reakci na změny v systému OH.

7 PUBLIKAČNÍ ČINNOST

Články v impaktovaných časopisech

Reference	Hodnocení časopisu podle Web of Science	Podíl na autorství dle systému Apollo
SMEJKALOVÁ, V.; ŠOMPLÁK, R.; NEVRLÝ, V.; BURCIN, B.; KUČERA, T. Trend forecasting for waste generation with structural break. Journal of Cleaner Production, 2020, 266, 121814. DOI: 10.1016/j.jclepro.2020.121814.	Q1	40 %
SMEJKALOVÁ, V.; ŠOMPLÁK, R.; PLUSKAL, J.; RYBOVÁ, K. Hierarchical optimisation model for waste management forecasting. Optimization and Engineering, 2022. DOI: 10.1007/s11081-022-09735-2	Q2	40 %
PAVLAS, M.; ŠOMPLÁK, R.; SMEJKALOVÁ, V.; STEHLÍK, P. Municipal solid saste fractions and their source separation: Forecasting for large geographical area and its subregions. Waste and Biomass Valorization, 2020, 11 (2), 725-742. DOI: 10.1007/s12649-019-00764-0.	Q3	30 %
ŠOMPLÁK, R.; NEVRLÝ, V.; SMEJKALOVÁ, V.; ŠMÍDOVÁ, Z.; PAVLAS, M. Bulky waste for energy recovery: Analysis of spatial distribution. Energy, 2019, 181, 827-839. DOI: 10.1016/j.energy.2019.05.175.	Q1	30 %
KŮDELA, J.; SMEJKALOVÁ, V.; ŠOMPLÁK, R.; NEVRLÝ, V. Legislation-induced planning of waste processing infrastructure: A case study of the Czech Republic. Renewable and Sustainable Energy Reviews, 2020, 132, 110058. DOI: 10.1016/j.rser.2020.110058.	Q1	23 %
ŠOMPLÁK, R.; KŮDELA, J.; SMEJKALOVÁ, V.; NEVRLÝ, V.; PAVLAS, M.; HRABEC, D. Pricing and advertising strategies in conceptual waste management planning. Journal of Cleaner Production, 2019, 239, 118068. DOI: 10.1016/j.jclepro.2019.118068.	Q1	15 %
PAVLAS, M.; ŠOMPLÁK, R.; SMEJKALOVÁ, V.; NEVRLÝ, V.; ZAVÍRALOVÁ, L.; KŮDELA, J.; POPELA, P. Spatially distributed generation data for supply chain models – Forecasting with hazardous waste. Journal of Cleaner Production, 2017, 161, 1317-1328. DOI: 10.1016/j.jclepro.2017.06.107.	Q1	10 %
NEVRLÝ, V.; ŠOMPLÁK, R.; SMEJKALOVÁ, V.; LIPOVSKÝ, T.; JADRNÝ, J. Location of municipal waste	Q1	10 %

containers: Trade-off between criteria. Journal of Cleaner Production, 2020, 278 DOI: 10.1016/j.jclepro.2020.123445.		
PLUSKAL, J.; ŠOMPLÁK, R.; NEVRLÝ, V.; SMEJKALOVÁ, V.; PAVLAS, M. Strategic decisions leading to sustainable waste management: Separation, sorting and recycling possibilities. Journal of Cleaner Production, 2021, 278, 123359. DOI: 10.1016/j.jclepro.2020.123359.	Q1	8 %
ŠRAMKOVÁ, K.; ŠOMPLÁK, R.; NEVRLÝ, V.; JIRÁSEK, P.; SMEJKALOVÁ, V.; POPELA, P. Stratification and multi-representative optimization approach to waste composition analysis. Optimization and Engineering, 2021, 22 (3), 1727-1754. DOI: 10.1007/s11081-021-09645-9.	Q2	5 %
KŮDELA, J.; ŠOMPLÁK, R.; NEVRLÝ, V.; LIPOVSKÝ, T.; SMEJKALOVÁ, V.; DOBROVSKÝ, L. Multi-objective strategic waste transfer station planning. Journal of Cleaner Production, 2019, 230, 1294-1304. DOI: 10.1016/j.jclepro.2019.05.167.	Q1	5 %
ŠOMPLÁK, R.; SMEJKALOVÁ, V.; ROSECKÝ, M.; SZÁSZIOVÁ, L.; NEVRLÝ, V.; HRABEC, D.; PAVLAS, M. Review on waste generation modeling and forecasting methods. Sustainable Cities and Society, 2022. Under review.	Q1	
ŠOMPLÁK, R.; SMEJKALOVÁ, V.; KŮDELA, J. Mixed-integer quadratic optimization for waste flow quantification. Optimization and Engineering, 2022, Under review.	Q2	
PALOVČÍK, J.; JADRNÝ, J.; SMEJKALOVÁ, V.; ŠMÍROVÁ, B.; ŠOMPLÁK, R. Journal of Material Cycles and Waste Management. 2022. Under review.	Q3	

Články indexované v databázi Scopus

Reference	Podíl na autorství dle systému Apollo
SMEJKALOVÁ, V.; ŠOMPLÁK, R.; NEVRLÝ, V.; HOLEC, T. Forecasting of waste production data with changes in credibility and trend. Chemical Engineering Transactions, 2019, 76, 1243-1248. DOI: 10.3303/CET1976208	49 %
SMEJKALOVÁ, V.; ŠOMPLÁK, R.; NEVRLÝ, V.; PAVLAS, M. Design and decomposition of waste prognostic model with hierarchical	40 %

structures. Mendel, 2018, 24(1), 85-92. DOI: 10.13164/mendel.2018.1.085	
SMEJKALOVÁ, V.; ŠOMPLÁK, R.; NEVRLÝ, V.; PAVLAS, M. Heuristic methodology for forecasting of quantities in waste management. Mendel, 2017, 23(1), 185-192. DOI: 10.13164/mendel.2017.1.185	30 %
KŮDELA, J.; ŠOMPLÁK, R.; SMEJKALOVÁ, V.; NEVRLÝ, V.; JIRÁSEK, P. The potential for future material recovery of municipal solid waste: Inputs for sustainable infrastructure planning. Chemical Engineering Transactions, 2020, 81, 1209-1224. DOI: 10.3303/CET2081204	30 %
ŠOMPLÁK, R.; NEVRLÝ, V.; SMEJKALOVÁ, V.; PAVLAS, M.; KUDELA, J. Verification of information in large databases by mathematical programming in waste management. Chemical Engineering Transactions, 2017, 61, 985-990. DOI: 10.3303/CET1761162	30 %
VAN FAN, Y.; NEVRLÝ, V.; ŠOMPLÁK, R.; SMEJKALOVÁ, V. The potential of carbon emission footprint reduction from biowaste in mixed municipal solid waste: EU-27. Chemical Engineering Transactions, 2020, 81, 775-780. DOI: 10.3303/CET2081130	25 %
SMEJKALOVÁ, V.; ŠOMPLÁK, R.; RYBOVÁ, K.; NEVRLÝ, V.; ROSECKÝ, M.; BURCIN, B.; KUČERA, T. Waste production and treatment modelling for EU member states. Chemical Engineering Transactions, 2020, 81, 691-696. doi:10.3303/CET2081116	25 %
ŠOMPLÁK, R.; ŠMÍDOVÁ, Z.; SMEJKALOVÁ, V.; VLASTIMÍR, N. Statistical evaluation of large-scale data logistics system. Mendel, 2018, 24(2), 9-16. DOI: 10.13164/mendel.2018.2.009	25 %
ŠOMPLÁK, R.; SMEJKALOVÁ, V.; NEVRLÝ, V.; PLUSKAL, J.; PAVLAS, M. Implementation of circular economy through the mathematical programming for the complex system evaluation. Chemical Engineering Transactions, 2019, 76, 523-528. doi:10.3303/CET1976088	20 %
NEVRLÝ, V.; VAN FAN, Y.; ŠOMPLÁK, R.; SMEJKALOVÁ, V.; KLEMEŠ, J. J.; LAM, H. L. Optimal location for conference venue in relation to transport emission sustainability strategy. Chemical Engineering Transactions, 2020, 81, 697-702. DOI: 10.3303/CET2081117	16 %
NEVRLÝ, V.; ŠOMPLÁK, R.; KHÝR, L.; SMEJKALOVÁ, V.; JADRNÝ, J. Municipal solid waste container location based on walking distance and distribution of population. Chemical Engineering Transactions, 2019, 76, 553-558. DOI: 10.3303/CET1976093	13 %
HRABEC, D.; ŠOMPLÁK, R.; NEVRLÝ, V.; SMEJKALOVÁ, V. Sustainable model integration of waste production and treatment process based on assessment of GHG. Chemical Engineering Transactions, 2018, 70, 1603-1608. DOI: 10.3303/CET1870268	10 %

MATUŠINEC, J.; HRABEC, D.; ŠOMPLÁK, R.; NEVRLÝ, V.; PECHA, J.; SMEJKALOVÁ, V., REDUTSKIY, Y. Cooking oil and fat waste management: A review of the current state. Chemical Engineering Transactions, 2020, 81, 763-768. DOI: 10.3303/CET2081128	9 %
VÁCLAVKOVÁ, Š.; PLUSKAL, J.; ŠOMPLÁK, R.; TALPA, J.; SMEJKALOVÁ, V. Resolving discrepancies in reported flow amounts in sewage sludge management network datasets by mathematical programming. Chemical Engineering Transactions, 2020, 81, 745-750. DOI: 10.3303/CET2081125	9 %
ERYGANOV, I.; ŠOMPLÁK, R.; NEVRLÝ, V.; SMEJKALOVÁ, V.; HRABEC, D.; HAUGEN, K. K. Application of cooperative game theory in waste management. Chemical Engineering Transactions, 2020, 81, 877-882. DOI: 10.3303/CET2081147	8 %
PLUSKAL, J.; ŠOMPLÁK, R.; SMEJKALOVÁ, V.; NEVRLÝ, V.; TUREK, V. Mixing approach to waste composition and its lower heating value impact on waste-to-energy plant. Chemical Engineering Transactions, 2020, 81, 751-756. DOI:10.3303/CET2081126	5 %

REFERENCE

A – Publikace autora citované v práci

[A1] SMEJKALOVÁ, V.; ŠOMPLÁK, R.; PLUSKAL, J.; RYBOVÁ, K. Hierarchical optimisation model for waste management forecasting. Optimization and Engineering, 2022. doi:10.1007/s11081-022-09735-2.

[A2] SMEJKALOVÁ, Veronika Aproximace prostorově distribuovaných hierarchicky strukturovaných dat: diplomová práce. BRNO: Vysoké učení technické v Brně, Fakulta strojního inženýrství, Ústav Matematiky, 2018. 76 s. Vedoucí práce Ing. Martin Pavlas, Ph.D.

[A3] PAVLAS, M.; ŠOMPLÁK, R.; SMEJKALOVÁ, V.; NEVRLÝ, V.; ZAVÍRALOVÁ, L.; KŮDELA, J.; POPELA, P. Spatially distributed generation data for supply chain models – Forecasting with hazardous waste. Journal of Cleaner Production, 2017, 161, 1317-1328. DOI: 10.1016/j.jclepro.2017.06.107.

[A4] ŠOMPLÁK, R.; SMEJKALOVÁ, V.; ROSECKÝ, M.; SZÁSZIOVÁ, L.; NEVRLÝ, V.; HRABEC, D.; PAVLAS, M. Review on waste generation modeling and forecasting methods. Sustainable Cities and Society, 2022. Under review.

[A5] PAVLAS, M.; ŠOMPLÁK, R.; SMEJKALOVÁ, V.; STEHLÍK, P. Municipal solid waste fractions and their source separation: Forecasting for large geographical area and its subregions. Waste and Biomass Valorization, 2020, 11 (2), 725-742. DOI: 10.1007/s12649-019-00764-0.

[A6] SMEJKALOVÁ, V.; ŠOMPLÁK, R.; NEVRLÝ, V.; PAVLAS, M. Design and decomposition of waste prognostic model with hierarchical structures. Mendel, 2018, 24 (1), 85-92. DOI:10.13164/mendel.2018.1.085.

[A7] SMEJKALOVÁ, V.; ŠOMPLÁK, R.; NEVRLÝ, V.; PAVLAS, M. Heuristic methodology for forecasting of quantities in waste management. Mendel, 2017, 23 (1), 185-192. DOI:10.13164/mendel.2017.1.185.

[A8] SMEJKALOVÁ, V.; ŠOMPLÁK, R.; NEVRLÝ, V.; BURCIN, B.; KUČERA, T. Trend forecasting for waste generation with structural break. Journal of Cleaner Production, 2020, 266, 121814. DOI: 10.1016/j.jclepro.2020.121814.

[A9] ŠOMPLÁK, R.; SMEJKALOVÁ, V.; KŮDELA, J. Mixed-integer quadratic optimization for waste flow quantification. Optimization and Engineering, 2022. Under review.

[A10] ŠRAMKOVÁ, K.; ŠOMPLÁK, R.; NEVRLÝ, V.; JIRÁSEK, P.; SMEJKALOVÁ, V.; POPELA, P. Stratification and multi-representative optimization approach to waste composition analysis. Optimization and Engineering, 2021, 22 (3), 1727-1754. DOI:10.1007/s11081-021-09645-9.

[A11] SMEJKALOVÁ, V.; ŠOMPLÁK, R.; RYBOVÁ, K.; NEVRLÝ, V.; ROSECKÝ, M.; BURCIN, B.; KUČERA, T. Waste Production and Treatment Modelling for EU

Member States. Chemical Engineering Transactions, 2020, 81, 691-696. DOI: 10.3303/CET2081116.

[A12] ŠOMPLÁK, R.; KŮDELA, J.; SMEJKALOVÁ, V.; NEVRLÝ, V.; PAVLAS, M.; HRABEC, D. Pricing and advertising strategies in conceptual waste management planning. Journal of Cleaner Production, 2019, 239, 118068. DOI: 10.1016/j.jclepro.2019.118068.

[A13] KŮDELA, J.; SMEJKALOVÁ, V.; ŠOMPLÁK, R.; NEVRLÝ, V. Legislation-induced planning of waste processing infrastructure: A case study of the Czech Republic. Renewable and Sustainable Energy Reviews, 2020, 132, 110058. DOI: 10.1016/j.rser.2020.110058.

[A14] ŠOMPLÁK, R.; NEVRLÝ, V.; SMEJKALOVÁ, V.; ŠMÍDOVÁ, Z.; PAVLAS, M. Bulky waste for energy recovery: Analysis of spatial distribution. Energy, 2019, 181, 827-839. DOI: 10.1016/j.energy.2019.05.175.

[A15] SMEJKALOVÁ, V.; ŠOMPLÁK, R.; NEVRLÝ, V.; HOLEC, T. Forecasting of waste production data with changes in credibility and trend. Chemical Engineering Transactions, 2019, 76, 1243-1248. DOI: 10.3303/CET1976208

B – Projekty a výstupy projektů

[B1] OPŽP. Příprava podkladů pro oblast podpory odpadového hospodářství 2014–2020. 2015. Operační program Životní prostředí. Cit. 1.6.2022. Dostupné z: https://www.opzp.cz/

[B2] OPŽP. Podklady pro oblast podpory odpadového hospodářství a oběhového hospodářství jako součást Programového dokumentu v Operačním programu Životní prostředí 2021–2027. 2020. Operační program Životní prostředí. Dostupné z: https://www.opzp.cz/

[B3] TIRSMZP719. Prongózování produkce odpadů a stanovení složení komunálního odpadu), doba řešení 1.1.2019 – 30.6.2022. TAČR

[B4] CEVOOH. Centrum environmentálního výzkumu: Odpadové a oběhové hospodářství a environmentální bezpečnost. SS02030008. TAČR. Doba řešení. 1.1.2021 – 31.12.2026

[B5] ŠOMPLÁK, R.; SMEJKALOVÁ, V.; ROSECKÝ, M.; SZÁSZIOVÁ, L.; ŠRAMKOVÁ, K.; KŮDELA, J.; ERYGANOV, I.; BOUDA, Z.; SUZOVÁ, J.; POPELA, P.; PAVLAS, M. Certifikovaná metodika pro provádění dlouhodobé prognózy produkce odpadů v ČR včetně revize prognózy (Výsledek V9). 2021. TIRSMZP719 Produkt byl předán uživateli výsledku: Ministerstvo životního prostředí.

[B6] TiramisO. Prognóza produkce odpadů. Pavlas, M., Šomplák, R., Roupec, J., Talpa, J., Smejkalová V. TIRSMZP719

[B7] PAVLAS, M.; ŠOMPLÁK, R.; SMEJKALOVÁ, V.; ROSECKÝ, M.; KŮDELA, J.; POPELA, P. Výzkumná zpráva popisující přístup k řešení prognózování produkce odpadů v mezinárodním měřítku (Výsledek V5). TIRSMZP719, 2019.

[B8] PAVLAS, M.; ŠOMPLÁK, R.; SMEJKALOVÁ, V.; ROSECKÝ, M.; BOUDA, Z.; SUZOVÁ, J.; ROUPEC, J.; SZÁSZIOVÁ, L.; POPELA, P.; KŮDELA, J. Výzkumná zpráva popisující výběr vhodných metod datové analýzy a matematického modelování prognózy produkce odpadů (Výsledek V6). TIRSMZP719, 2019.

[B9] ŠOMPLÁK, R.; SMEJKALOVÁ, V.; ROSECKÝ, M.; POPELA, P.; KŮDELA, J.; ERYGANOV, I.; ŠRAMKOVÁ, K.; PAVLAS, M. Výzkumná zpráva popisující princip a matematický model prognózování produkce odpadů (Výsledek V7). TIRSMZP719, 2020.

[B10] ŠOMPLÁK, R.; SMEJKALOVÁ, V.; ROSECKÝ, M.; POPELA, P.; KŮDELA, J.; ERYGANOV, I.; ŠRAMKOVÁ, K.; PLUSKAL, J.; PAVLAS, M. Souhrnná komplexní výzkumná zpráva popisující nastavení a řešení zpracování dlouhodobé prognózy produkce odpadů v ČR (Výsledek V8). TIRSMZP719, 2021.

[B11] ŠOMPLÁK, R.; SMEJKALOVÁ, V.; ROSECKÝ, M.; SZÁSZIOVÁ, L.; ŠRAMKOVÁ, K.; KŮDELA, J.; ERYGANOV, I.; BOUDA, Z.; SUZOVÁ, J.; POPELA, P.; PAVLAS, M.: V9 TIRSMZP719; Certifikovaná metodika pro provádění dlouhodobé prognózy produkce odpadů v ČR včetně revize prognózy (Výsledek V9) – PŘÍLOHY. Produkt byl předán uživateli výsledku: Ministerstvo životního prostředí.

[B12] VEVERKA, Z.; PAVLAS, M.; GREGOR, J.; KROPÁČ, J.; BOUDA, Z.; SUZOVÁ, J.: V4 TIRSMZP719; Metodika pro stanovení složení směsného komunálního odpadu z obcí a komunálního odpadu. Produkt byl předán uživateli výsledku: Ministerstvo životního prostředí.

C – Literatura ostatní

[C1] MORSELETTO, P. Targets for a circular economy. Resources, Conservation and Recycling, 2020, 153, 104553. DOI: 10.1016/j.resconrec.2019.104553.

[C2] GAI, L.; VARBANOV, P. S.; FAN, Y. V.; KLEMEŠ, J. J.; ROMANENKO, S. V. Trade-offs between the recovery, exergy demand and economy in the recycling of multiple resources. Resources, Conservation and Recycling, 2021, 167, 105428. DOI: 10.1016/j.resconrec.2021.105428.

[C3] Směrnice Evropského parlamentu a Rady (ES) č. 98/2008 ze dne 19. listopadu 2008 o odpadech a o zrušení některých směrnic (Text s významem pro EHP). [cit. 2020-06-23].

[C4] Směrnice Evropského parlamentu a Rady (EU) 2018/850 ze dne 30. května 2018, kterou se mění směrnice 1999/31/ES o skládkách odpadů (Text s významem pro EHP). [cit. 2020-06-23].

[C5] Směrnice Evropského parlamentu a Rady (EU) 2018/851 ze dne 30. května 2018, kterou se mění směrnice 2008/98/ES o odpadech (Text s významem pro EHP). [cit. 2020-06-23].

[C6] Směrnice Evropského parlamentu a Rady (EU) 2018/852 ze dne 30. května 2018, kterou se mění směrnice 94/62/ES o obalech a obalových odpadech (Text s významem pro EHP). [cit. 2020-06-23].

[C7] Eurostat. European Statistical Office. Cit. 30.5.2022. Dostupné z: https://ec.europa.eu/eurostat/en/

[C8] Informační systém odpadového hospodářství ISOH. CENIA, česká informační agentura životního prostředí [online]. CENIA, česká informační agentura životního prostředí, c 2022 [cit. 2022-05-20]. Dostupné z: https://www.cenia.cz/odpadove-a-obehove-hospodarstvi/isoh/

[C9] Zákon č. 541/2020 Sb. O odpadech. Cit. 20.5.2022. Dostupné z: https://www.zakonyprolidi.cz/cs/2020-541.

[C10] VEJNAR, P. a kol. Matematické vyjádření výpočtu „soustavy indikátorů OH“ v souladu s vyhláškou č. 383/2001 Sb., o podrobnostech nakládání s odpady, v platném znění, 2019 [cit. 2022-07-14]. Dostupné z: https://www.inisoft.cz/uploads/media/default/0001/03/c29f066488e9ca772efa8fbaec6dd18658a93a8d.pdf

[C11] Vyhláška č. 8/2021 Sb. o Katalogu odpadů a posuzování vlastností odpadů (Katalog odpadů) ze dne 12. 1. 2021. In: Sbírka zákonů České republiky. 2021, částka 5 [cit. 2022-05-20]. Dostupné z: https://www.zakonyprolidi.cz/cs/2021-8.

[C12] BEIGL, P.; LEBERSORGER, S.; SALHOFER, S. Modelling municipal solid waste generation: A review. Waste Management, 2008, 28 (1), 200-214. DOI: 10.1016/j.wasman.2006.12.011.

[C13] CHERIAN, J.; JACOB, J. Management models of municipal solid waste: A review focusing on socio economic factors. International Journal of Economics and Finance, 2012, 4 (10), 131-139. DOI: 10.5539/ijef.v4n10p131.

[C14] KOLEKAR, K. A.; HAZRA, T.; CHAKRABARTY, S. N. A review on prediction of municipal solid waste generation models. Procedia Environmental Sciences, 2016, 35, 238-244. DOI: 10.1016/j.proenv.2016.07.087.

[C15] GOEL, S.; RANJAN, V. P.; BARDHAN, B.; HAZRA, T. Forecasting solid waste generation rates. Modelling Trends in Solid and Hazardous Waste Management, 2017, 20, 35-64. DOI: 10.1007/978-981-10-2410-8_3.

[C16] ABDALLAH, M.; TALIB, M. A.; FEROZ, S.; NASIR, Q.; ABDALLA, H.; MAHFOOD, B. Artificial intelligence applications in solid waste management: A systematic research review. Waste Management, 2020, 109, 231-246. DOI: 10.1016/j.wasman.2020.04.057.

[C17] GUO, H.-N.; WU, S.-B.; TIAN, Y.-J.; ZHANG, J.; LIU, H.-T. Application of machine learning methods for the prediction of organic solid waste treatment and recycling processes: A review. Bioresource Technology, 2021, 319, 124114. DOI: 10.1016/j.biortech.2020.124114.

[C18] XU, A.; CHANG, H.; XU, Y.; LI, R.; LI, X.; ZHAO, Y. Applying artificial neural networks (ANNs) to solve solid waste-related issues: A critical review. Waste Management, 2021, 124, 385-402. DOI: 10.1016/j.wasman.2021.02.029.

[C19] ABASSI M. A.; ABDOLI M.; OMIDVAR B.; BAGHVAND A. Results uncertainty of support vector machine and hybrid of wavelet transform – support vector machine models for solid waste generation forecasting. Environmenta Progress & Sustainable Energy, 2014, 33 (1). DOI: 10.1002/ep.11747.

[C20] AGGARWAL, V.; GUPTA, V.; SINGH, P.; SHARMA, K.; SHARMA, N. Detection of spatial outlier by using improved Z-score test. Proceedings of the International Conference on Trends in Electronics and Informatics, 2019, 788-790. DOI: 10.1109/icoei.2019.8862582.

[C21] DE MUTH, J. E. Tests to Evaluate Potential Outliers. APS Advances in the Pharmaceutical Sciences Series, 2019, 40, 197-210. DOI: 10.1007/978-3-030-33989-0_8.

[C22] AYELERU, O. O.; OKONTA, F. N.; NTULI, F. Municipal solid waste generation and characterization in the city of Johannesburg: A pathway for the implementation of zero waste. Waste Management, 2018, 79, 87-97. DOI: 10.1016/j.wasman.2018.07.026.

[C23] COLE, C.; QUDDUS, M.; WHEATLEY, A.; OSMANI, M.; KAY, K. The impact of local authorities' interventions on household waste collection: A case study approach using time series modelling. Waste Management, 2014, 34 (2), 266-272. DOI: 10.1016/j.wasman.2013.10.018.

[C24] DENAFAS, G.; RUZGAS, T.; MARTUZEVIČIUS, D.; SHMARIN, S.; HOFFMANN, M.; MYKHAYLENKO, V.; OGORODNIK, S.; ROMANOV, M.; NEGULIAEVA, E.; CHUSOV, A.; TURKADZE, T.; BOCHOIDZE, I.; LUDWIG, C. Seasonal variation of municipal solid waste generation and composition in four east european cities. Resources, Conservation and Recycling, 2014, 89, 22-30. DOI: 10.1016/j.resconrec.2014.06.001.

[C25] GHINEA, C.; DRĂGOI, E. N.; COMĂNIŢĂ, E.; GAVRILESCU, M.; CÂMPEAN, T.; CURTEANU, S.; GAVRILESCU, M. Forecasting municipal solid waste generation using prognostic tools and regression analysis. Journal of Environmental Management, 2016, 182, 80-93. DOI: 10.1016/j.jenvman.2016.07.026.

[C26] INNOCENT, N. M.; DIEUDONNÉ, B.; JOSE, S. N. Modeling the temporal variations of municipal solid waste generation for future projection in the Douala municipality, Cameroon. Journal of Multidisciplinary Engineering Science and Technology, 2016, 3 (7), 5288–5295.

[C27] INTHARATHIRAT, R.; ABDUL SALAM, P.; KUMAR, S.; UNTONG, A. Forecasting of municipal solid waste quantity in a developing country using multivariate grey models. Waste Management, 2015, 39, 3-14. DOI: 10.1016/j.wasman.2015.01.026.

[C28] ISLAM, M. T.; HUDA, N. E-waste in Australia: Generation estimation and untapped material recovery and revenue potential. Journal of Cleaner Production, 2019, 237. DOI: 10.1016/j.jclepro.2019.117787.

[C29] JIANG, P.; LIU, X. Hidden markov model for municipal waste generation forecasting under uncertainties. European Journal of Operational Research, 2016, 250 (2), 639-651. DOI: 10.1016/j.ejor.2015.09.018.

[C30] KARPUŠENKAITE, A.; RUZGAS, T.; DENAFAS, G. Time-series-based hybrid mathematical modelling method adapted to forecast automotive and medical waste generation: Case study of Lithuania. Waste Management and Research, 2018, 36 (5), 454-462. DOI: 10.1177/0734242X18767308.

[C31] MARANDI, F.; GHOMI, S. M. T. F. Time series forecasting and analysis of municipal solid waste generation in Tehran city. Paper presented at the Proceedings of the 12th International Conference on Industrial Engineering (ICIE), 2016, 14-18. DOI: 10.1109/INDUSENG.2016.7519343.

[C32] MONTECINOS, J.; OUHIMMOU, M.; CHAUHAN, S.; PAQUET, M. Forecasting multiple waste collecting sites for the agro-food industry. Journal of Cleaner Production, 2018, 187, 932-939. DOI: 10.1016/j.jclepro.2018.03.127.

[C33] MWENDA, A.; KUZNETSOV, D.; MIRAU, S. Time Series Forecasting of Solid Waste Generation in Arusha City – Tanzania. Mathematical Theory and Modeling, 2014, 4 (8).

[C34] OWUSU-SEKYERE, E.; HARRIS, E.; BONYAH, E. Forecasting and Planning for Solid Waste Generation in the Kumasi Metropolitan Area of Ghana: An ARIMA Time Series Approach. International Journal of Sciences, 2013, 2, 69–83.

[C35] PETRIDIS, N. E.; STIAKAKIS, E.; PETRIDIS, K.; DEY, P. Estimation of computer waste quantities using forecasting techniques. Journal of Cleaner Production, 2016, 112, 3072-3085. DOI: 10.1016/j.jclepro.2015.09.119.

[C36] RIMAITYTE, I.; RUZGAS, T.; DENAFAS, G.; RAČYS, V.; MARTUZEVICIUS, D. Application and evaluation of forecasting methods for municipal solid waste generation in an Eastern-European city. Waste Management and Research, 2012, 30 (1), 89-98. DOI: 10.1177/0734242X10396754.

[C37] SONG, J.; HE, J. A multistep chaotic model for municipal solid waste generation prediction. Environmental Engineering Science, 2014, 31 (8), 461-468. DOI: 10.1089/ees.2014.0031.

[C38] MAIRIZAL, A. Q.; SEMBADA, A. Y.; TSE, K. M.; RHAMDHANI, M. A. Electronic waste generation, economic values, distribution map, and possible recycling system in Indonesia. Journal of Cleaner Production, 2021, 293. DOI: 10.1016/j.jclepro.2021.126096.

[C39] VU, H. L.; BOLINGBROKE, D.; NG, K. T. W.; FALLAH, B. Assessment of waste characteristics and their impact on GIS vehicle collection route optimization using ANN waste forecasts. Waste Management, 2019, 88, 118-130. DOI: 10.1016/j.wasman.2019.03.037.

[C40] VU, H. L.; NG, K. T. W.; BOLINGBROKE, D. Time-lagged effects of weekly climatic and socio-economic factors on ANN municipal yard waste prediction models. Waste Management, 2019, 84, 129-140. DOI: 10.1016/j.wasman.2018.11.038.

[C41] XU, L.; GAO, P.; CUI, S.; LIU, C. A hybrid procedure for MSW generation forecasting at multiple time scales in Xiamen city, China. Waste Management, 2013, 33 (6), 1324-1331. DOI: 10.1016/j.wasman.2013.02.012.

[C42] YANG, Y.; YUAN, G.; CAI, J.; WEI, S. Forecasting of disassembly waste generation under uncertainties using digital twinning-based hidden markov model. Sustainability (Switzerland), 2021, 13 (10). DOI: 10.3390/su13105391.

[C43] YOUNES, M. K.; NOPIAH, Z. M.; BASRI, N. E. A.; BASRI, H. Medium term municipal solid waste generation prediction by autoregressive integrated moving average. Paper presented at the AIP Conference Proceedings, 2014, 1613, 427-435. DOI: 10.1063/1.4894366.

[C44] ANDERSEN, F. M.; LARSEN, H.V. FRIDA: A model for the generation and handling of solid waste in Denmark. Resources, Conservation and Recycling, 2012, 65, 47-56. DOI: 10.1016/j.resconrec.2012.04.004.

[C45] AWASTHI, A. K.; CUCCHIELLA, F.; D'ADAMO, I.; LI, J.; ROSA, P.; TERZI, S.; WEI, G.; ZENG, X. Modelling the correlations of e-waste quantity with economic increase. Science of the Total Environment, 2018, 613-614, 46-53. DOI: 10.1016/j.scitotenv.2017.08.288.

[C46] CEYLAN, Z. Estimation of municipal waste generation of Turkey using socio-economic indicators by bayesian optimization tuned gaussian process regression. Waste Management and Research, 2020, 38 (8), 840-850. DOI: 10.1177/0734242X20906877.

[C47] CHEN, D. M.; BODIRSKY, B. L.; KRUEGER, T.; MISHRA, A.; POPP, A. The world's growing municipal solid waste: Trends and impacts. Environmental Research Letters, 2020, 15 (7). DOI: 10.1088/1748-9326/ab8659.

[C48] CHUNG, S. S. Projecting municipal solid waste: The case of Hong Kong SAR. Resources, Conservation and Recycling, 2010, 54 (11), 759-768. DOI: 10.1016/j.resconrec.2009.11.012.

[C49] GU, B.; FUJIWARA, T.; JIA, R.; DUAN, R.; GU, A. Methodological aspects of modeling household solid waste generation in Japan: Evidence from Okayama and Otsu cities. Waste Management and Research, 2017, 35 (12), 1237-1246. DOI: 10.1177/0734242X17738338.

[C50] HŘEBÍČEK, J.; KALINA, J.; SOUKOPOVÁ, J.; HORÁKOVÁ, E.; PRÁŠEK, J.; VALTA, J. Modelling and forecasting waste generation – DECWASTE information system. 2017. DOI: 10.1007/978-3-319-89935.

[C51] ARAIZA-AGUILAR, J. A.; ROJAS-VALENCIA, M. N.; AGUILAR-VERA, R. A. Forecast generation model of municipal solid waste using multiple linear regression. Global Journal of Environmental Science and Management, 2020, 6 (1), 1-14. DOI: 10.22034/gjesm.2020.01.01.

[C52] KALINA, J.; HŘEBÍČEK, J.; BULKOVÁ, G. Case study: Prognostic model of czech municipal waste production and treatment. Paper presented at the Proceedings – 7th International Congress on Environmental Modelling and Software: Bold Visions for Environmental Modeling (iEMSs), 2014.

[C53] KORKUT, N.F. Estimations and analysis of medical waste amounts in the city of Istanbul and proposing a new approach for estimation of future medical waste amounts. Waste Management, 2018, 81, 168–176. DOI: 10.1016/j.wasman.2018.10.004.

[C54] KIRAN, M.; SHANMUGAM, P. V.; MISHRA, A.; MEHENDALE, A.; NADHEERA SHERIN, H. R. A multivariate discrete grey model for estimating the waste from mobile phones, televisions, and personal computers in india. Journal of Cleaner Production, 2021, 293. DOI: 10.1016/j.jclepro.2021.126185.

[C55] ORIBE-GARCIA, I.; KAMARA-ESTEBAN, O.; MARTIN, C.; MACARULLA-ARENAZA, A.M.; ALONSO-VICARIO, A. Identification of influencing mucicipal characteristics regarding household waste generation and their forecasting ability in Biscay. Waste Management, 2015, 39, 26–34. DOI: 10.1016/j.wasman.2015.02.017.

[C56] PAN, A.; YU, L.; YANG, Q. Characteristics and forecasting of municipal solid waste generation in China. Sustainability (Switzerland), 2019, 11 (5). DOI: 10.3390/su11051433.

[C57] POPLI, K.; PARK, C.; HAN, S.; KIM, S. Prediction of solid waste generation rates in urban region of Laos using socio-demographic and economic parameters with a multi linear regression approach. Sustainability (Switzerland), 2021, 13(6). DOI: 10.3390/su13063038.

[C58] SOUKOPOVÁ, J.; KALINA, J.; HŘEBÍČEK, J. Mathematical and economic model of municipal waste management using Maple. 32nd International Conference on Mathematical Methods in Economics, 2014.

[C59] SUNAYANA, C.; KUMAR, S.; KUMAR, R. Forecasting of municipal solid waste generation using non-linear autoregressive (NAR) neural models. Waste Management, 2021, 121, 206-214. DOI: 10.1016/j.wasman.2020.12.011.

[C60] WEI, Y.; XUE, Y.; YIN, J.; NI, W. Prediction of municipal solid waste generation in China by multiple linear regression method. International Journal of Computers and Applications, 2013, 35 (3), 136-140. DOI: 10.2316/Journal.202.2013.3.202-3898.

[C61] ABBASI, M.; EL HANANDEH, A. Forecasting municipal solid waste generation using artificial intelligence modelling approaches. Waste Management, 2016, 56, 13-22. DOI: 10.1016/j.wasman.2016.05.018.

[C62] CAMERO, A.; TOUTOUH, J.; FERRER, J.; ALBA, E. Waste generation prediction in smart cities through deep neuroevolution. The History and Science of the Manhattan Project. 2019. DOI: 10.1007/978-3-030-12804-3_15.

[C63] CHHAY, L.; REYAD, M. A. H.; SUY, R.; ISLAM, M. R.; MIAN, M. M. Municipal solid waste generation in China: Influencing factor analysis and multi-model forecasting. Journal of Material Cycles and Waste Management, 2018, 20 (3), 1761-1770. DOI: 10.1007/s10163-018-0743-4.

[C64] KULISZ, M.; KUJAWSKA, J. Prediction of MunicipalWaste Generation in Poland Using Neural Network Modeling. Sustainability, 2020, 12, 10088. DOI: 10.3390/su122310088.

[C65] LU, W.; PENG, Y.; CHEN, X.; SKITMORE, M.; ZHANG, X. The S-curve for forecasting waste generation in construction projects. Waste Management, 2016, 56, 23-34. DOI: 10.1016/j.wasman.2016.07.039.

[C66] NOORI, R.; KARBASSI, A.; SALMAN SABAHI, M. Evaluation of PCA and gamma test techniques on ANN operation for weekly solid waste prediction. Journal of Environmental Management, 2010, 91 (3), 767-771. DOI: 10.1016/j.jenvman.2009.10.007.

[C67] RIBIC, B.; PEZO, L.; SINCIC, D.; LONCAR, B.; VOCA, N. Predictive model for municipal waste generation using artificial neural networks – Case study city of Zagreb, Croatia. International Journal of Energy Research, 2019, 43 (11), 5701-5713. DOI: 10.1002/er.4632.

[C68] SINGH, D.; SATIJA, A. Prediction of municipal solid waste generation for optimum planning and management with artificial neural network – case study: Faridabad city in Haryana state (India). International Journal of System Assurance Engineering and Management, 2018, 9 (1), 91-97. DOI: 10.1007/s13198-016-0484-5.

[C69] SODANIL, M.; CHATTHONG, P. Artificial neural network-based time series analysis forecasting for the amount of solid waste in Bangkok. Paper presented at the 9th International Conference on Digital Information Management (ICDIM), 2014, 16-20. DOI: 10.1109/ICDIM.2014.6991427.

[C70] SONG, J.; HE, J.; ZHU, M.; TAN, D.; ZHANG, Y.; YE, S.; SHEN, D.; ZOU, P. Simulated annealing based hybrid forecast for improving daily municipal solid waste generation prediction. Scientific World Journal, 2014, 1, 834357. DOI: 10.1155/2014/834357

[C71] YUSOFF, S. H.; DIN, U. N. K. A.; MANSOR, H.; MIDI, N. S.; ZAINI, S. A. Neural network prediction for efficient waste management in Malaysia. Indonesian Journal of Electrical Engineering and Computer Science, 2018, 12 (2), 738-747. DOI: 10.11591/ijeecs.v12.i2.pp738-747.

[C72] YUSOFF, S. H.; DIN, U. N. K. A.; MANSOR, H.; MIDI, N. S.; ZAINI, S. A. Design of smart waste bin and prediction algorithm for waste management in household area. Indonesian Journal of Electrical Engineering and Computer Science, 2018, 12 (2), 748-758. DOI: 10.11591/ijeecs.v12.i2.pp748-758.

[C73] DING, Z.; SHI, M.; LU, C.; WU, Z.; CHONG, D.; GONG, W. Predicting renovation waste generation based on grey system theory: A case study of Shenzhen. Sustainability (Switzerland), 2019, 11(16). DOI: 10.3390/su11164326.

[C74] DUMAN, G. M.; KONGAR, E.; GUPTA, S. M. Predictive analysis of electronic waste for reverse logistics operations: A comparison of improved univariate grey models. Soft Computing, 2020, 24 (20), 15747-15762. DOI: 10.1007/s00500-020-04904-w.

[C75] DUMAN, G. M.; KONGAR, E.; GUPTA, S. M. Estimation of electronic waste using optimized multivariate grey models. Waste Management, 2019, 95, 241-249. DOI: 10.1016/j.wasman.2019.06.023.

[C76] FAN, Z.; FAN, Y. Research on prediction of municipal solid waste production based on grey relation analysis and grey prediction model. Paper presented at the IOP Conference Series: Earth and Environmental Science, 2019, 300 (3). DOI: 10.1088/1755-1315/300/3/032070.

[C77] LIU, G.; YU, J. Gray correlation analysis and prediction models of living refuse generation in Shanghai city. Waste Management, 2007, 27 (3), 345-351. DOI: 10.1016/j.wasman.2006.03.010.

[C78] LIU, S.; CHENG, L.; CHEN, P.; XU, S.; GAO, J.; LU, J. Prediction of industrial hazardous waste production based on different models. Paper presented at the IOP Conference Series: Earth and Environmental Science, 2019, 384 (1). DOI: 10.1088/1755-1315/384/1/012026.

[C79] SONG, Y.; WANG, Y.; LIU, F.; ZHANG, Y. Development of a hybrid model to predict construction and demolition waste: China as a case study. Waste Management, 2017, 59, 350-361. DOI: 10.1016/j.wasman.2016.10.009.

[C80] WANG, F.; YU, L.; WU, A. Forecasting the electronic waste quantity with a decomposition-ensemble approach. Waste Management, 2021, 120, 828-838. DOI: 10.1016/j.wasman.2020.11.006.

[C81] WU, H.; DUAN, H.; ZHENG, L.; WANG, J.; NIU, Y.; ZHANG, G. Demolition waste generation and recycling potentials in a rapidly developing flagship megacity of South China: Prospective scenarios and implications. Construction and Building Materials, 2016, 113, 1007-1016. DOI: 10.1016/j.conbuildmat.2016.03.130.

[C82] YAN, J.; LIU, Y.; LI, Z. Present situation of hazardous waste generation in China and grey model prediction. Paper presented at the IOP Conference Series: Earth and Environmental Science, 2020, 467 (1). DOI: 10.1088/1755-1315/467/1/012179.

[C83] ZHANG, Z.; ZHANG, Y.; WU, D. Hybrid model for the prediction of municipal solid waste generation in Hangzhou, China. Waste Management and Research, 2019, 37 (8), 781-792. DOI: 10.1177/0734242X19855434.

[C84] ANDERSEN, F. M.; LARSEN, H.; SKOVGAARD, M.; MOLL, S.; ISOARD, S. A European model for waste and material flows. Resources, Conservation and Recycling, 2007, 49 (4), 421-435. DOI: 10.1016/j.resconrec.2006.05.011.

[C85] DWIVEDY, M.; MITTAL, R. K. Future trends in computer waste generation in India. Waste Management, 2010, 30 (11), 2265-2277. DOI: 10.1016/j.wasman.2010.06.025.

[C86] ESTAY-OSSANDON, C.; MENA-NIETO, A. Modelling the driving forces of the municipal solid waste generation in touristic islands. A case study of the Balearic islands (2000–2030). Waste Management, 2018, 75, 70-81. DOI: 10.1016/j.wasman.2017.12.029.

[C87] SINGH, M.; THIND, P. S.; JOHN, S. An analysis on e-waste generation in Chandigarh: Quantification, disposal pattern and future predictions. Journal of Material Cycles and Waste Management, 2018, 20 (3), 1625-1637. DOI: 10.1007/s10163-018-0726-5.

[C88] ABBASI, M.; ABDULI, M. A.; OMIDVAR, B.; BAGHVAND, A. Forecasting municipal solid waste generation by hybrid support vector machine and partial least square model. International Journal of Environmental Research, 2013, 7 (1), 27-38. DOI: 10.22059/IJER.2012.583.

[C89] DAI, F.; NIE, G.; CHEN, Y. The municipal solid waste generation distribution prediction system based on FIG–GA-SVR model. Journal of Material Cycles and Waste Management, 2020, 22 (5), 1352-1369. DOI: 10.1007/s10163-020-01022-5.

[C90] HU, R.; CHEN, K.; CHEN, W.; WANG, Q.; LUO, H. Estimation of construction waste generation based on an improved on-site measurement and SVM-based prediction model: A case of commercial buildings in China. Waste Management, 2021, 126, 791-799. DOI: 10.1016/j.wasman.2021.04.012.

[C91] OZCLIK, S. T.; BORAY TEK, F. Forecasting and analysis of domestic solid waste generation in districts of istanbul with support vector regression. Paper presented at the 5th International Conference on Computer Science and Engineering (UBMK), 2020, 366-371. DOI: 10.1109/UBMK50275.2020.9219368.

[C92] AL-KHATIB, I. A.; ELEYAN, D.; GARFIELD, J. A system dynamics model to predict municipal waste generation and management costs in developing areas. Journal of Solid Waste Technology and Management, 2015, 41 (2), 109-120. DOI: 10.5276/JSWTM.2015.109.

[C93] MENA-NIETO, A.; ESTAY-OSSANDON, C.; DOS SANTOS S.P. Will the Balearics and the Canary Islands meet the European Union targets for municipal waste? A comparative study from 2000 to 2035. Science of the Total Environment, 2021, 783, 147081. DOI: 10.1016/j.scitotenv.2021.147081.

[C94] CHAERUL, M.; TANAKA, M.; SHEKDAR, A. V. A system dynamics approach for hospital waste management. Waste Management, 2008, 28 (2), 442-449. DOI: 10.1016/j.wasman.2007.01.007.

[C95] ELEYAN, D.; AL-KHATIB, I. A.; GARFIELD, J. System dynamics model for hospital waste characterization and generation in developing countries. Waste Management and Research, 2013, 31 (10), 986-995. DOI: 10.1177/0734242X13490981.

[C96] ESTAY-OSSANDON, C.; MENA-NIETO, A.; HARSCH, N. Using a fuzzy TOPSIS-based scenario analysis to improve municipal solid waste planning and forecasting: A case study of Canary archipelago (1999–2030). Journal of Cleaner Production, 2018, 176, 1198-1212. DOI: 10.1016/j.jclepro.2017.10.324.

[C97] KOLLIKKATHARA, N.; FENG, H.; YU, D. A system dynamic modeling approach for evaluating municipal solid waste generation, landfill capacity and related cost management issues. Waste Management, 2010, 30 (11), 2194-2203. DOI: 10.1016/j.wasman.2010.05.012.

[C98] LEE, C. K. M.; NG, K. K. H.; KWONG, C. K.; TAY, S. T. A system dynamics model for evaluating food waste management in Hong Kong, China. Journal of Material Cycles and Waste Management, 2019, 21 (3), 433-456. DOI: 10.1007/s10163-018-0804-8.

[C99] LONG, F.; SONG, B.; WANG, Q.; XIA, X.; XUE, L. Scenarios simulation on municipal plastic waste generation of different functional areas of Beijing. Journal of Material Cycles and Waste Management, 2012, 14 (3), 250-258. DOI: 10.1007/s10163-012-0066-9.

[C100] AHMED, S.; PANWAR, R. M. Hazardous constituents of E-waste and predictions for India. Proceedings of Institution of Civil Engineers: Waste and Resource Management, 2016, 169 (2), 83-91. DOI: 10.1680/jwarm.15.00008.

[C101] MAHMOOD, S.; SHARIF, F.; RAHMAN, A.; KHAN, A. U. Analysis and forecasting of municipal solid waste in Nankana city using geo-spatial techniques. Environmental Monitoring and Assessment, 2018, 190 (5). DOI: 10.1007/s10661-018-6631-5.

[C102] REZA SABOUR, M.; MOHAMEDIFARD, A.; KAMALAN, H. A mathematical model to predict the composition and generation of hospital wastes in Iran. Waste Management, 2007, 27 (4), 584-587. DOI: 10.1016/j.wasman.2006.05.010.

[C103] YOUSUF, T. B.; RAHMAN, M. Monitoring quantity and characteristics of municipal solid waste in Dhaka city. Environmental Monitoring and Assessment, 2007, 135 (1-3), 3-11. DOI: 10.1007/s10661-007-9710-6.

[C104] LI, K.; MA, H. Prediction of municipal solid waste generation with elman neural network – case study: Shanghai city in China. Paper presented at the Proceedings of 2019 IEEE 3rd Information Technology, Networking, Electronic and Automation Control Conference (ITNEC), 2019, 1174-1177. DOI: 10.1109/ITNEC.2019.8729395.

[C105] JOHNSON, N. E.; IANIUK, O.; CAZAP, D.; LIU, L.; STAROBIN, D.; DOBLER, G.; GHANDEHARI, M. Patterns of waste generation: A gradient boosting model for short-term waste prediction in New York city. Waste Management, 2017, 62, 3-11. DOI: 10.1016/j.wasman.2017.01.037.

[C106] BRAMATI, M. C. Waste production and regional growth of marine activities an econometric model. Marine Pollution Bulletin, 2016, 112 (1-2), 151-165. DOI: 10.1016/j.marpolbul.2016.08.025.

[C107] IBIKUNLE, R. A. Investigating municipal solid waste generation and management in Ilorin for possible integrated waste-management system. Journal of Material

Cycles and Waste Management, 2021, 23(3), 1239-1257. DOI: 10.1007/s10163-021-01189-5.

[C108] IKHLAYEL, M. Differences of methods to estimate generation of waste electrical and electronic equipment for developing countries: Jordan as a case study. Resources, Conservation and Recycling, 2016, 108, 134-139. DOI: 10.1016/j.resconrec.2016.01.015.

[C109] KLAVENIEKS, K.; BLUMBERGA, D. Forecast of waste generation dynamics in Latvia. Paper presented at the Energy Procedia, 2016, 95, 200-207. DOI: 10.1016/j.egypro.2016.09.049.

[C110] LIU, X.; TANAKA, M.; MATSUI, Y. Generation amount prediction and material flow analysis of electronic waste: A case study in Beijing, China. Waste Management and Research, 2006, 24 (5), 434-445. DOI: 10.1177/0734242X06067449.

[C111] YESSENAMANOVA, M. S.; SALYKHOV, R.; TLEPBERGENOVA, A. E.; YESSENAMANOVA, Z. S.; TAUOVA, N. R. Forecast of solid waste generation in Atyrau region. Paper presented at the Journal of Physics: Conference Series, 2021, 1889 (3). DOI: 10.1088/1742-6596/1889/3/032010.

[C112] NGUYEN, X. C.; NGUYEN, T. T. H.; LA, D. D.; KUMAR, G.; RENE, E. R.; NGUYEN, D. D.; CHANG, S. W.; CHUNG, W. J.; NGUYEN, X. H.; NGUYEN, V. K. Development of machine learning - based models to forecast solid waste generation in residential areas: A case study from Vietnam. Resources, Conservation and Recycling, 2021, 167, 105381. DOI: 10.1016/j.resconrec.2020.105381.

[C113] PEETERS, J. R.; ALTAMIRANO, D.; DEWULF, W.; DUFLOU, J. R. Forecasting the composition of emerging waste streams with sensitivity analysis: A case study for photovoltaic (PV) panels in Flanders. Resources, Conservation and Recycling, 2017, 120, 14-26. DOI: 10.1016/j.resconrec.2017.01.001.

[C114] SJÖSTRÖM, M.; ÖSTBLOM, G. Decoupling waste generation from economic growth - A CGE analysis of the Swedish case. Ecological Economics, 2010, 69 (7), 1545-1552. DOI: 10.1016/j.ecolecon.2010.02.014.

[C115] SOKKA, L.; ANTIKAINEN, R.; KAUPPI, P. E. Municipal solid waste production and composition in Finland - changes in the period 1960-2002 and prospects until 2020. Resources, Conservation and Recycling, 2007, 50 (4), 475-488. DOI: 10.1016/j.resconrec.2007.01.011.

[C116] SOLANO MEZA, J. K.; RODRIGO-ILARRI, J.; HERNÁNDEZ, C. P. R.; RODRIGO-CLAVERO, M. A. E. Analytical methodology for the identification of critical zones on the generation of solid waste in large urban areas. International Journal of Environmental Research and Public Health, 2020, 17 (4). DOI: 10.3390/ijerph17041196.

[C117] YANG, J.; FUJIWARA, T.; MATSUOKA, Y.; WANG, W. A systematic approach to projecting industrial solid waste generation by industrial sector in Shanghai. Journal of Material Cycles and Waste Management, 2016, 18 (1), 81-92. DOI: 10.1007/s10163-014-0330-2.

[C118] YOUNES, M. K.; NOPIAH, Z. M.; BASRI, N. E. A.; BASRI, H.; ABUSHAMMALA, M. F. M.; YOUNES, M. Y. Landfill area estimation based on integrated waste disposal options and solid waste forecasting using modified ANFIS model. Waste Management, 2016, 55, 3-11. DOI: 10.1016/j.wasman.2015.10.020.

[C119] YU, B.; WANG, J.; LI, J.; ZHANG, J.; LAI, Y.; XU, X. Prediction of large-scale demolition waste generation during urban renewal: A hybrid trilogy method. Waste Management, 2019, 89, 1-9. DOI: 10.1016/j.wasman.2019.03.063.

[C120] ZHANG, S.; GU, Y.; TANG, A.; LI, B.; LI, B.; PAN, D.; WU, Y. Forecast of future yield for printed circuit board resin waste generated from major household electrical and electronic equipment in China. Journal of Cleaner Production, 2021, 283. DOI: 10.1016/j.jclepro.2020.124575.

[C121] DENICKO ROYNALDI, A.; MARYONO, M. Estimation of waste generation from tidal flood in North Semarang sub-district. Paper presented at the E3S Web of Conferences, 2019, 125. DOI: 10.1051/e3sconf/201912507019.

[C122] SAEED, M. O.; HASSAN, M. N.; MUJEEBU, M. A. Assessment of municipal solid waste generation and recyclable materials potential in Kuala Lumpur, Malaysia. Waste Management, 2009, 29 (7), 2209-2213. DOI: 10.1016/j.wasman.2009.02.017.

[C123] Eunomia Research & Consulting, Öko-Institut, Copenhagen Resource Institute, 2014b. Impact Assessment on Options Reviewing Targets in the Waste Framework Directive, Landfill Directive and Packaging and Packaging Waste Directive, Final Report. Report for the European Comission DG Environment under Framework Contract N°ENV.C.2/FRA/2011/0020, prepared by Hogg et al.

[C124] Impact Assessment. Annex 8: An Overview of the European Reference Model on Waste. Proposal for a Directive of the European Parliament and of the Council amending Directives 2008/98/EC on waste, 94/62/EC on packaging and packaging waste, 1999/31/EC on the landfill of waste, 2000/53/EC on end-of-life vehicles, 2006/66/EC on batteries and accumulators and waste batteries and accumulators, and 2012/19/EU on waste electrical and electronic equipment. 2014.

[C125] ETC/EEA, 2012.Revision of the MSW Generation Projection Equations Based on Additional Data Points for 2009 and 2010, prepared by Andersen et al.

[C126] ROSECKÝ, M.; ŠOMPLÁK, R.; SLAVÍK, J.; KALINA, J.; BULKOVÁ, G.; BEDNÁŘ J. Predictive modelling as a tool for effective municipal waste management policy at different territorial levels. Journal of Environmental Management, 2021, 291, 112584. DOI: 10.1016/j.jenvman.2021.112584.

[C127] KANNANGARA, M.; DUA, T.; AHMADI, L.; BENSEBAA, F. Modeling and prediction of regional municipal solid waste generation and diversion in Canada using machine learning approaches. Waste Management, 2018, 74, 3-15. DOI: 10.1016/j.wasman.2017.11.057.

[C128] BLÁZQUEZ-GARCÍA, A.; CONDE, A.; MORI, U.; LOZANO, J.A. A review on outlier/anomaly detection in time series data. ArXiv, 2020, arXiv:2002.04236. DOI: 10.48550/arXiv.2002.04236.

[C129] ADELEKE, O.; AKINLABI, S.A.; JEN, T.-C.; DUNMADE, I. Prediction of municipal solid waste generation: an investigation of the effect of clustering techniques and parameters on ANFIS model performance. Environmental Technology, 2020, 43 (11), 1634–1647. DOI: 10.1080/09593330.2020.1845819.

[C130] KALINA, J.; HŘEBÍČEK, J.; BULKOVÁ, G. Case study: Prognostic model of Czech municipal waste generation and treatment. Proceedings – 7th International Congress on Environmental Modelling and Software: Bold Visions for Environmental Modeling (iEMSs), 2014, 2, 932-939.

[C131] Prognóza ČNB – jaro 2022. ČNB - Česká národní banka [online]. Copyright c ČNB 2022 [cit. 20.05.2022]. Dostupné z: https://www.cnb.cz/cs/menova-politika/prognoza/

[C132] BLEHA, B.; BURCIN, B.; KUČERA, T.; ŠPROCHA, B.; VAŇO, B. The population prospects of Czechia and Slovakia until 2060. Demografie, 2018, 60 (3), 219-233.

[C133] Projekce obyvatelstva v krajích ČR – do roku 2070. Český statistický úřad [online]. Copyright c ČSÚ 2022 [cit. 20.05.2022]. Dostupné z: https://www.czso.cz/csu/czso/projekce-obyvatelstva-v-krajich-cr-do-roku-2070.

[C134] DE WEERDTA, L.; SASAOC, T.; COMPERNOLLEB, T.; VAN PASSELA, S.; DE JAEGERD, S. The effect of waste incineration taxation on industrial plastic waste generation: A panel analysis. Resources, Conservation & Recycling, 2020, 157, 104717. DOI: 10.1016/j.resconrec.2020.104717.

[C135] Veřejné informace o produkci a nakládání s odpady. Ministerstvo životního prostředí [online]. INISOFT, s.r.o., c 2021 [cit. 2022-05-20]. Dostupné z: https://isoh.mzp.cz/visoh.

[C136] Eurostat - European statistical office [online]. Copyright c Eurostat 2022 [cit. 12.09.2021]. Dostupné z: https://ec.europa.eu/eurostat.

[C137] Vyhláška č. 321/2014 Sb. Vyhláška o rozsahu a způsobu zajištění odděleného soustřeďování složek komunálních odpadů. Cit. 20.5.2022. Dostupné z: https://www.zakonyprolidi.cz/cs/2014-321

[C138] LEBERSORGER, S.; BEIGL, P. Municipal solid waste generation in municipalities: Quantifying impacts of household structure, commercial waste and domestic fuel. Waste Management, 2011, 31 (9-10), 1907-1915. DOI: 10.1016/j.wasman.2011.05.016.

PŘÍLOHY

Příloha 1: Článek [A1] Hierarchical optimisation model for waste management forecasting in EU

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RESEARCH ARTICLE

Hierarchical optimisation model for waste management forecasting in EU

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Abstract

The level of waste management varies significantly from one EU state to another and therefore they have different starting position regarding reaching defined EU targets. The forecast of waste production and treatment is essential information for the expected future EU targets fulfilment. If waste treatment does not meet the targets under the current conditions, it is necessary to change waste management strategies. This contribution presents a universal approach for forecasting waste production and treatment using optimisation models. The approach is based on the trend analysis with the subsequent data reconciliation (quadratic programming). The presented methodology also provides recommendations to include the quality of trend estimate and significance of territory in form of weights in objective function. The developed approach also allows to put into context different methods of waste handling and production. The variability of forecast is described by prediction and confidence intervals. Within the EU forecast, the expected demographic development is taken into account. The results show that most states will not meet EU targets with current trend of waste management in time. Presented methodology is developed at a general level and it is a suitable basis for strategic planning at the national and transnational level.

Keywords Waste forecasting · Circular economy package · Quadratic programming · Trend modelling · Data reconciliation · Confidence intervals

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List of symbols

Sets

$j, \bar{j} \in J$	All territories, i.e. individual states and the EU as a whole
$h, \bar{h} \in H$	Waste handling /production, incineration, recycling, landfilling, treatment/
$t \in T$	Time period of historical data and forecast
$\beta \in B$	Bootstrap resampling

Mathematical symbols

a, b, c	Regression coefficients for trend estimate
$A_{j,\bar{j}}$	Membership matrix for territory hierarchy
$\tilde{k}_{ii}$	Diagonal element of regression matrix
$l_{t,j,h}$	Binary parameter taking into account results from data pre-processing
$m_{t,j,h}$	Forecasted result of waste production or handling after data reconciliation
$\tilde{m}_{t,\beta}^{j,h}$	Forecasted result of bootstrap generated data
n	Number of points in time series used for trend estimate
$p_{t,j,h}$	Trend value for territorial unit j and waste handling h
q	Number of parameters in regression used for trend estimates
$\tilde{t}$	Order of predicting year
$t_{\mathrm{n}-q}(1-\alpha/2)$	$(1-\alpha/2)$-Quantile of Student's t-distribution with $n-q$ degree of freedom
$T_{j,h}$	Total number of available points in time series after data pre-processing
$U_{h,\bar{h}}$	Membership matrix for waste production and handling hierarchy
$v_{j,h}$	Weight characterising the size of the producent
$w_{j,h}$	Weight characterising the quality of data fitting
$x_{i,j,h}$	Historical data point in time series
$\tilde{x}_{t,\beta}^{j,h}$	Generated data for confidence interval bootstrap construction
$\in_t^{j,h}$	Data residuals from evaluated trend
$\in_{t,\beta}^{j,h}$	Selected residual from the set of data residuals in bootstrap
$\tilde{\in}_t^{j,h}$	Scaled data residuals from evaluated trend
σ_t^2	Variance estimate of prognosis based on bootstrap repetition
$\tilde{\sigma}^2$	Variance estimate of residual component
$\varepsilon_{t,j,h}$	Error included into trend to maintain links in the system
$\varepsilon_{t,j,h}^{+}$	Positive part of error
$\varepsilon_{t,j,h}^{-}$	Negative part of error
$\delta_{t,j,h}$	Multiplier of trend in data reconciliation

Abbreviations

BE	Belgium
CEP	Circular economy package
CZ	Czechia

DK	Denmark
ES	Spain
EU	European Union
FI	Finland
IT	Italy
LR	Linear regression
LT	Lithuania
LV	Latvia
MSW	Municipal solid waste
RO	Romania
SE	Sweden
TSA	Time-series analysis
WM	Waste management

1 Introduction

Waste management (WM) in the EU is currently undergoing a transition from a linear economy to a circular economy (Morseletto 2020). The WM modification is motivated by the need to treat large amounts of waste and save the environment. Appropriate waste treatment could also replace and save some limited primary resources (Gai et al. 2021). The smooth and sustainable transition to the circular economy and the transformation of WM is enshrined in legislation by Circular economy package (CEP), essential for municipal solid waste (MSW) are directives: Directive (EU) (2018)/850, Directive (EU) (2018)/851, Directive (EU) (2018)/852. The goal of CEP is to maintain the value of the product as long as possible based on Waste management Hierarchy, Directive (2008)/98/EC. The key years for CEP are the years 2025, 2030 and 2035. The major milestones contained in CEP are recycling targets and landfilling target, see Fig. 1.

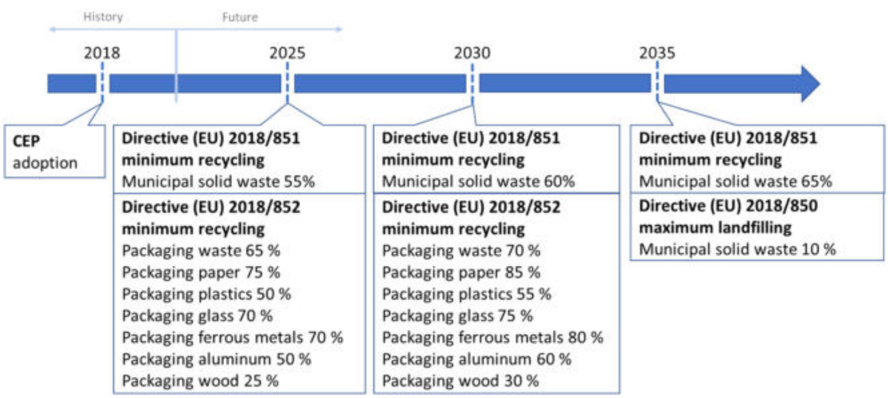

Fig. 1 Targets of Circular Economy Package

The EU's goals are set at state level, but each EU country has a different starting position for meeting the CEP targets. Significant differences are observed in terms of MSW generation and ways of treatment. The level of waste generation is coupled with economic development (Wilson et al. 2015). As a key information can be considered the waste composition, which shapes future WM development (Šramková et al. 2021). The Fig. 2 illustrates the time evolution of EU MSW treatment in the period 1995–2018. The construction of the ternary graph is based on principle presented by Pomberger et al. (2017) and shows the ways of MSW treatment in percentage. An obvious trend of reduction of landfilling and increase in material recovery can be seen. A slight increase in incineration of waste can be observed. The incineration, in other words energy recovery, of waste in Waste-to-Energy plants represents efficient method, how to deal with non-recyclable components, and thus constitutes an important countermeasure against global warming (Maki et al. 2021). The area where the goals in 2035 are met (the last monitored year in CEP) is marked in green. The right part of the Fig. 2 shows the percentage change in waste production related to the initial year 1995.The historical development of WM at the state level and also at the EU level as a whole the initial information for estimating future development in this article. It can be stated that there are considerable differences between individual states. Most states already show a gradual development to reduce landfilling and increase material recovery, thus approaching the CEP target. The question is whether this gradual development will reach the required goal in time, i.e., in 2035. This information will be provided by the forecast of the expected development of waste treatment on the basis of the current trend. A complete visualisation of

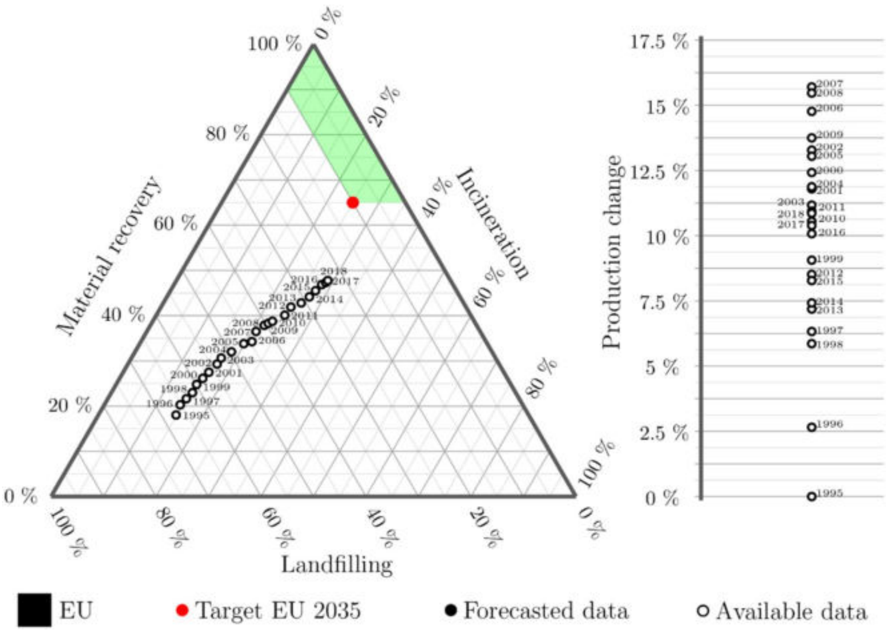

Fig. 2 Waste production and processing in the EU, data 1995–2018 (Eurostat 2020)

historical data with a follow-up forecast at the state level is available in Sect. 5 and Appendix 2.

This contribution presents a methodology for forecasting waste production and treatment at the state level in EU. Input information is historical data on WM. The methodology uses trend analysis of historical data with subsequent data reconciliation to maintain the link between waste production and treatment. At the same time, the expected demographic development of individual states is considered. Demography is a factor that is well predictable and at the same time has a significant impact on the absolute amount of produced waste (Smejkalová et al. 2020b). The knowledge of expected future MSW production and treatment is valuable information for WM planning. In addition, the forecasting of baseline scenario identifies countries, which need the systematic change to achieve the defined targets.

2 Literature review

Waste production and treatment forecasting is an essential input for planning in WM. The waste treatment models rarely appear, see Table 1. The waste production models can be distinguished into prediction models and forecasting models. Prediction models deal with description of current or future waste production using factors influencing it. In this way, it is possible to estimate the waste production for example in the locality without available data according to influencing factors. Simultaneously it is possible to model expected development in future. In contrast, forecasting models focus on estimates for the future waste production using only historical data without external intervation. The difference between prediction and forecasting models is if the estimation is modelled using links in the system (prediction) or using historical development (forecasting). There is currently no comprehensive review for forecasting models. Quality review for prediction models was provided by Beigl et al. (2008). A subsequent article (Lebersorger and Beigl 2011) by the same authors follows up on the mentioned shortcomings in the review by creating a regression model, which desribes links between WM and socio-economic factors. These links can be valuable for forecasts in a field of WM. As another way for forecasting is time series analysis (TSA) and its combination with other methods. An interesting example, how to obtain value in unmeasured point, can be the use of surrounding values (Lanzi et al. 2009). Further in Table 1 is a summary of articles that have dealt with the forecasts in the EU during recent years.

The waste forecasts listed in the Table 1 deal with production of MSW as a whole and also its fractions (paper, plastic, glass, etc.). However, only Andersen and Larsen (2012) and Estay-Ossandon and Mena-Nieto (2018) also provided a forecast of waste treatment, see column “Treatment”. Lack of forecasts of waste treatment methods are considered a significant shortcoming and research gap. Territorial level ranges from the municipal to the state level, so data are in various details. Only at the level of municipalities the data are available in greater detail than on the annual basis (month, week). Forecasts are usually targeted at a long prediction horizon compared to the number of historical data used.

Table 1 Literature review—MSW forecasting for EU member states

State	Source	Treatment (yes/no)	Territory level	Data detail	Number of historical data	Forecast length	Confidence intervals	Method
EU	Andersen et al. (2007)	No	State	Year	–	15	No	General regression
BE	Peeters et al. (2017)	No	Region	Year	18	25	Scenarios	Distribution delay forecasting
CZ	Pavlas et al. (2017)	No	Micro-region	Year	6	6	No	TSA—trend analysis, data reconciliation*
	Pavlas et al. (2020)	No	Micro-region	Year	6	10	No	TSA—trend analysis, data reconciliation*
	Hřebíček et al. (2017)	No	State	Year	6	6	Yes	LR
	Smejkalová et al. (2020a)	No	Micro-region	Year	9	14	No	TSA—trend analysis, credibility model
DK	Andersen and Larsen (2012)	Yes	State	Year	15	12	No	LR
FI	Sokka et al. (2007)	No	State	Year	43	18	Scenarios	IPAT equation
IT	Bramati (2016)	No	Region	Year	10	13	Scenarios	SEM = Simultaneous equations model
LV	Klavenieks and Blumberga (2016)	No	State	Year	10	7	Scenarios	LR
LT	Denafas et al. (2014)	No	Municipality	Month	24	12	Yes	TSA
	Karpušenkaitė et al. (2018)	No	state	Year	10	7,14	No	TSA
	Rimaitytė et al. (2012)	No	Municipality	Week	416	10	No	LR, TSA
RO	Ghinea et al. (2016)	No	Municipality	Year	16	15	No	TSA
ES	Estay-Ossandon and Mena-Nieto (2018)	Yes	Region	Year	16	16	Scenarios	SD
	Oribe-Garcia et al. (2015)	No	Municipality	Year	15	13	No	CA, LR, factor models
SE	Sjöström and Östblom (2010)	No	State	Year	13	24	No	Computable general equilibrium analysis

Remark: *methods involving optimisation

In most cases, the forecast is modeled using statistical approaches which vary through contributions, but LR and TSA are applied repeatedly. Therefore, these two are classical approaches. LR describes the links between waste production and influential factors from various fields (economics, sociology, demography and others). TSA has different forecasting approach, it uses historical data to describe development over time, which is then extrapolated to the future. Optimization methods are marked * in Table 1, these are just two papers. Both of them use data reconciliation to ensure links in the hierarchical structure of territorial units (Pavlas et al. 2017) and links between waste fractions (Pavlas et al. 2020). Forecasts for states outside Europe include the use of optimisation only exceptionally. Usually the optimisation is used for estimated suitable parameters in the model, as was the case study of e- waste forecasting production in Australia (Islam and Huda 2019). A study presented by (Dai et al. 2020) described the links between influencing factors and waste production in China. These links involving nonlinear dependencies were estimated using SVM, coefficients for the model were found by minimizing risk function using a genetic algorithm. The regression risk and the loss function were minimized by solving the quadratic optimization problem in the study for USA presented by (Song et al. 2014). Simulated annealing was used by (Song et al. 2014) for combine three models.

Estimate of variability or expected deviations from forecasted data are an important additional information about all predictions. It can be expressed by confidence intervals. As literature review shows, the variability evaluation and modelling is usually omitted. Some publications tried to desribe potential future development using many scenarios. Only two papers presented construction of confidence intervals, but they aproach only waste production. To maintain links between production and treatment, advanced statistical and optimisation methods are needed.

Many publications have shown that there is a link between waste production and some factors, such as population size, income, education etc. The methods for searching links between waste production (treatment) and economic or demoghraphic data presume sufficient quality of explanatory parameters, which is not usually available. It represents significant limitations for these approaches for prediction of WM, especially for long-term prediction. Quality forecasts of influential factors are therefore needed. In addition, most contributions are presented for only one EU state. As an exception, Andersen et al. (2007) applied a model of dependence on economic and demographic factors for the 25 EU states. The inclusion of influential factors in the forecast (economics, sociology, demography) will be discussed further in Sect. 4.

TSA has a significant representation among the approaches used for forecasting waste production. The choice of method for time series analysis depends on many factors, but the length of the time series is crucial. WM usually offers only short-time series of data. In this case, it is possible to successfully model the trend component in the historical data by mathematical curves. It may be advantageous to use S-curves, as a logistic trend or a Gompertz curve Ghinea et al. (2016). These types of S-curves are asymptotically limited and it is therefore necessary to determine in advance the potential that the modelled quantity can reach. Sometimes the development of a time-series is disrupted by an external factor that changes its trend (legislation, change in waste collection, new materials etc.). Smejkalová et al. (2020a) introduced an approach correcting the S-curve trend in data using credibility theory. With this approach, it is possible to take into account a change in the trend even if the individual territories react to the intervention with different intensity. TSA models generally do not include hierarchy, which is ensured by approach presented by Pavlas et al. (2020). On the other hand, there were no criteria, which take into account the model quality. The explanatory predictor like demoghraphic development was also not considered.

In most cases, WM plans are available in the national language of the country, making it difficult to study. The summarized forecasts within selected WM plans are available in Appendix 1, which can help readers with analysis of approaches in other countries. Based on the study of selected WM plans it is clear that the forecast are often modelled on very short time-series of historical data. The definition of MSW is not the same for all EU member states. The inconsistent definition may cause also differences in the fulfilment of EU targets. The existence of non-uniform definition of MSW can be also substantiated by the fact that MSW production varies greatly among countries (Eurostat 2020). The different definitions do not represent significant limitation if they are consistent within historical data. The MSW treatment will be assessed according to the national definition at EU level. Even in WM plans, there is often no MSW treatment forecast. However, this is an essential information for planning of MSW treatment infrastructure to ensure proper waste management. This contribution presents a uniform methodology for production and waste treatment forecasts using data from the Eurostat database (Eurostat 2020).

3 Contribution and novelty

In order to achieve the CEP targets, it is necessary to react in time to the changes. EU member states have currently different levels of WM. Some of them are already on track to meet targets with their current form of WM. In other cases, changes in WM will be needed to meet the CEP targets in a timely manner. It is essential to identify the appropriate form of WM for each individual state. Key information will be provided by the forecast of MSW production and treatment. Based on the results of the forecast it is possible to assess whether it is necessary to change the current form of WM.

This contribution presents an approach for forecasting the MSW production and treatment. The input data is information on the annual amount of MSW in the history. The available data set plays a crucial part of successful forecast. The methodology uses TSA and trend evaluating, individual time series are solved on basis of available data and its properties. Therefore, more regression functions are introduced in this paper, which should take into account different development in the history more precisely. It also enables finding the trend in different units measures and unify them afterwards in data reconciliation. The methodology is based on the assumption of maintaining the link between production and treatment of waste—all produced waste must be treated in some way. This link is crucial from a planning point of view but has not been considered in previous publications.

The data reconciliation is based on the method by Pavlas et al. (2020) using the principles of quadratic programming. But the methodology is significantly extended. Due to different nature of the task, two approaches for errors, and thus the form of the objective function to minimize, are introduced to keep mass balance in the system. The additive and multiplicative approaches are presented with individual advantages and recommendations in specific situations based on experience with optimisation models and solvers on real data sets. In addition to data reconciliation, the weights are newly addressed, which are developed to consider the quality of trend estimate and the significance of individual territory. Another novelty is the description of uncertain development by the construction of confidence and prediction intervals, which provide additional information about variability of collected data and parameters estimate in regression-based trend evaluation. With respect to the forecast methodology, standard statistics cannot be used for confidence interval and its construction is based on random sampling—the bootstrap method. The intervals also reflect the result from data reconciliation (deviation from trend) and the length of forecast.

Literature review has shown that optimization is used only rarely for forecasting in waste management. This contribution presents approach based on non-linear regression, quadratic optimisation and experience with real data sets is used for EU forecasting. The expected demographic development of the state is taken into account. The methodology is a comprehensive approach to forecasting that is applicable to all EU member states and makes it possible to compare developments in individual EU member states. Part of the case study is a summary of the results and expected developments for EU member states and it also evaluates the recommendations for intervention in the way of MSW treatment for individual countries. The results can serve as a basis for adequate WM plans at national and EU level.

4 Time series analysis

The forecast of waste production and treatment carries several challenges. As review has shown, WM data are often available only annually. Unfortunately, the annual data do not provide a sufficiently long time series. In addition, the relatively long prediction horizon, which is usually modelled in the field of WM, must be considered. The reason is that infrastructure modification is a long-term issue that needs to be covered by a forecast already in the planning phase. The text in this section describes the proposed methodology for forecasting waste production and treatment. In this paper, waste treatment is also newly included in the model. The approach allows the inclusion of significant influencing factors where relevant data can be provided. However, the main idea is the analysis of time series with subsequent data reconciliation taking into account the links in the system.

4.1 Available data and influencing factors

Waste production and treatment methods have been shown to be influenced factors, see Smejkalová et al. (2020b). According to regression models, waste production is specifically influenced by some economic variables, education and age composition of the population. The same is true for the method of waste treatment (Smejkalová et al. 2020b). In order to be able to use these links for the forecast of waste production and treatment, it is necessary to have forecasts of all important factors.

Demographic forecasts are published for all EU member states in databases at European level (Eurostat 2020). In other areas (economics, sociology), mostly forecasts created by national institutions for specific countries are available. Economic forecasts are made only for short periods due to dynamic and unpredictable changes. For example, GDP is forecasted in German to 2023 (Deutsche Bundesbank Eurosystem 2021), in Austria to 2024 (Federal Ministry of Republic of Austria 2021) and in Czechia to 2023 (Czech National Bank 2021) and due to the current turbulent economic development the forecasts are probably not accurate. The basic precondition for the use of any factors is that their forecast covers the entire forecasting horizon, at least until 2035 with regard to the CEP. In the sufficient prediction horizon, only demographic forecasts are available. Another feature of economic and social forecasts are very wide confidence intervals if the uncertainty in the forecast is expressed at all. Therefore, it is not eligible to consider them in WM forecast.

Historical data, period 1995–2018, annual detail (Eurostat 2020):

- MSW production [kt],
- MSW treatment [kt],
- MSW material recycling [kt],
- MSW composting [kt],
- MSW energy recovery [kt],
- MSW incineration [kt],
- MSW landfilling [kt],
- Population [person].

Forecast, period 2019–2035, annual detail:

- Population [person].

MSW treatment considers all treatment methods in aggregated form. The approach to forecasting consists of five steps: data pre-processing, extrapolation of trend in historical data, inclusion of expected demographic development, data reconciliation to maintain the links in the system and confidence intervals.

4.2 Data pre-processing

The available datasets were aggregated, if desired, to allow comparison with EU targets. Specifically, it is waste recycling, which includes material recycling and composting. Furthermore, incineration will generally be referred to as incineration and energy recovery of waste. From the point of view of the targets, information on the energy production of waste incineration is not essential at this time. Although, according to the Waste management hierarchy (Directive 2008/98/EC) this is the preferred treatment method. Furthermore, the term incineration will be understood as MSW energy recovery + MSW incineration, similarly recycling will be understood as MSW material recycling + MSW composting. Other datasets were not aggregated.

Diverse algorithms on data pre-processing were developed and published in the past to identify significant deflections and changes in the data. The review was provided on outlier detection by Blázquez-García et al. (2020), and changepoint detection by Aminikhanghahi and Cook (2017). Individual methods are suitable for a certain type of data and there is no known general method. Individual time series for waste production and treatment were expertly analysed to identify outliers and changepoints. There are outliers in the WM data that are not significant at the state level. This is an advantage for this application and outlier was detected only for treatment in Finland in the year 2015. This point was omitted for following steps of the calculation. At the state level, changes in the system can be evident, which will be reflected in changepoints. As part of pre-processing, it is desirable to reveal these points in time series.

This EU state-level application includes a total of 145 time series from WM field, 5 variables (after the required aggregations) for 29 territories (28 states and EU as a whole). The case study is being carried out for the current 27 Member States of the European Union and the United Kingdom. These 145 time series were gradually assessed individually by experts. On the basis of a visual assessment, it was decided whether a changepoint occurs. Experience in waste management has been taken into account. This is especially the energy recovery, when new facilities are gradually built and there are step changes. However, these changes were not considered as anomalies in the data, but the trend of this series is modelled. The changepoints was identified for landfilling in 3 time series (Germany, Netherland, Austria) and for recycling in 2 time series (Bulgaria, Romania). For the next part of the calculation, the time series before the changepoint was neglected and the time series analysis was applied only to the part of the time series after the change. If there is a missing point in the data, it is considered an unavailable value and is not replaced in any way.

4.3 Extrapolation of trend in historical data

Every citizen produces waste, so MSW production and overall treatment is affected by demographic trends. For this reason, historical data on MSW production and overall treatment are converted from absolute quantities to kg/capita, so these values are extrapolated per capita. The specific treatment method is extrapolated as a rate of the total amount of waste treatment and the interconnection between methods is already included in trend estimate. This adjustment ensures the positive impact on trend quality, because any data oscillations can be smoothed out.

The approach draws on the idea that the development of the observed variables in history will continue in the future, provided that the current conditions are maintained. It is therefore a forecast of the so-called scenario business-as-usual. Historical data are modelled by a suitable curve. Three trend functions are considered for historical data fitting: power function, logistic function and average. Primarily a trend in the form of a power function was considered (Eq. (1)).

$$p_t = a + bt^c, \tag{1}$$

where p is a dependent variable. Trend p is fitted for the following dependent variables: production [kg/cap], treatment [kg/cap], recycling [%], incineration [%] and landfilling [%]. The symbol t denotes the year, which is an independent variable. The regression coefficients sought are a, b, c. The nonnegativity of trend is ensured only after regression because this constrain represents difficulties. Any negative value of evaluated trend is set to zero.

If the coefficient $c > 1$ applies, an exponential increase (or decrease) in the trend can be expected. In order to avoid the development of a too growing (or shrinking) trend and thus an unrealistic estimate of the development, in the case of $c > 1$, the model was approached by a logistic function, see Eq. (2). To use this function, it is necessary to normalise the input data to 0–1 range. The historical data should be normalised by minimum and maximum values that can be reached on the basis of the estimate. If such values are not available, it is recommended to use 1.5 times the maximum value of historical data for the upper limit and 0.5 times the minimum value of historical data for the lower limit.

$$p_t = \frac{1}{1 + e^{-(a+bt)}}. \tag{2}$$

The notation remains the same as for Eq. (1). The regression coefficients are a, b.

The non-linear regression was solved by non-linear optimisation, where finding a global solution is not guaranteed and therefore a suitable setting of the initial points is essential (e.g. by linearisation of equations). The choice of solver also plays key role (Chu et al. 2013). In the case, that there is no way to model the trend quality, the trend is modelled as an average in historical data. The average is modelled in the three following cases:

1. If a small amount of data remains after pre-processing, so the trend cannot be modelled by a curve. The authors recommend modelling the trend only by an average in the case of less than five points of historical data.
2. The trend model using above functions (1)or (2) has low quality. The criterion for this approach was the coefficient of determination $R^2 < 0.1$.
3. Trend is modelled by average to avoid using a complicated model if the change from a simple model (average in the data) is very small. The criterion for the average model is as follows:

$$\frac{\left|p_{\bar{i}} - \bar{x}\right|}{\bar{x}} < 0.05, \tag{3}$$

where $\bar{i}$ is the last year of the forecasting horizon and $\bar{x}$ is the average of historical data. Subsequently, the trend model p_t is recalculated back to the absolute amount of waste produced in order to apply the data reconciliation model.

5 Data reconciliation to maintain the links in the system

Historical data on WM includes hierarchical links that result from the nature of the data. The idea of data reconciliation comes from the fact that the trend estimates p are not in logical compliance (i.e., the sum of estimated production of states is not equal to estimated production of EU). Models based on this idea are commonly used for systems, where the values are measured with some errors and at the same time laws of physics applied (Galan et al. 2019). The goal of this paper is to obtain high-quality estimate of future waste production and treatment with respect to links in the system and at the same time, with minimal deviations from already estimated values obtained from trend extrapolation.

5.1 Mathematical model

The mathematical model for data reconciliation is based on quadratic optimisation and it is defined by objective function and set of boundaries. The objective function minimises the square of errors, which are influenced by weights. These errors represent the deflection from evaluated trends. The minimisation is done with condition of fulfilment mass balance, which ensure the hierarchy. To evaluate the error $\varepsilon_{j,h}$, it can be based on the additive (A) or multiplicative (B) approach. In the case of additive approach (A), some problems may occur due to disproportion of input data (i.e. orders of magnitude different values). Multiplicative approach (B) is more complicated due to its solvability caused by non-linear dependencies. In some cases, the suitable chosen solver (KNITRO, Conopt or Ipopt) can figure out this problem. Another solution is reducing the scale of task for considered links in balance conditions. The constraint conditions and objective function for the data balancing model are presented below. The time index is omitted in all equations because the model is developed for one period. Individual periods are balanced independently of each other.

The Eq. (4) reflects the territorial hierarchy. It means in practise that the sum of production in countries is equal to EU production. The relationship between territories is defined by hierarchy matrix $A_{j,\bar{j}}$.

$$m_{j,h} = \sum_{\bar{j} \in J} A_{j,\bar{j}} m_{\bar{j},h}, \quad \forall j \in J, \forall h \in H. \tag{4}$$

The hierarchy from the point of view of WM respects the links between MSW production and treatment. This means that the MSW production is equal to the waste treatment and at the same time the individual methods of waste treatment (recycling, incineration, landfilling) are equal to the total amount of MSW treatment. The Eq. (5) ensures the required relationships by using matrix $U_{h,\bar{h}}$, which defines specific links.

$$m_{j,h} = \sum_{\bar{h} \in H} U_{h,\bar{h}} m_{j,\bar{h}}, \quad \forall j \in J, \forall h \in H. \tag{5}$$

As a next part, the data errors must be defined. Below are two options for introducing model errors: additive (A) and multiplicative (B) form. The use of an additive or multiplicative form of the model depends on the specific task. The additive model (A) is unsuitable for tasks with a large difference in the size of input values. However, its advantage is that it is less computationally intensive and, in addition, it copes well with zero trends. The multiplicative model (B) works with a percentage change, thus eliminating the problem of different data sizes. On the other hand, it is a more computationally intensive variant. Moreover, it is unsuitable in the case of zero trend values, because the percentage change from zero still remains at zero.

Conditions (9) and (10) are valid for both methods (A) and (B). The Eq. (6) connects the estimated amounts of waste $p_{j,h}$ with variables $m_{j,h}$ and errors $\varepsilon_{j,h}$ in additive form. The Eq. (7) states link between amounts of waste $p_{j,h}$ and variables $m_{j,h}$ using multiplier $\delta_{j,h}$. The Eq. (8) describes the deflection from trend function. The logarithm ensures symmetry of multiplier used, i.e. $\delta_{j,h} = 0.5$ has the same impact on objective function as $\delta_{j,h} = 2$. However, the logarithm function can make the model implementation more difficult and significantly influence the computing time, even the solvability. The formula $\delta_{j,h} + \varepsilon_{j,h} = 1$ can be used instead of the logarithm, however the change of bigger amount is preferred (the same percentage change has bigger impact to satisfy mass balance). It can be partially maintained by appropriate weight (see Eq. (14)). Another limitation of multiplicative approach (B) is input zero values in production or waste handling. Such cases should be solved by additive approach (A). The Eq. (9) describes the division of error into positive and negative parts. This division of the error enables to implement other criteria, such as the sum of absolute error values, but can also be used to add additional constrains or process the results. The formulas in Eq. (10) represent the nonnegativity of specific variables.

$$\text{(A)} \quad m_{j,h} = p_{j,h} + \varepsilon_{j,h}, \quad \forall j \in J, \forall h \in H, \tag{6}$$

$$\text{(B)} \quad m_{j,h} = p_{j,h}\delta_{j,h}, \quad \forall j \in J, \forall h \in H, \tag{7}$$

$$\text{(B)} \quad \varepsilon_{j,h} = log\delta_{j,h}, \quad \forall j \in J, \forall h \in H, \tag{8}$$

$$\varepsilon_{j,h} = \varepsilon^+_{j,h} - \varepsilon^-_{j,h}, \quad \forall j \in J, \forall h \in H, \tag{9}$$

$$\varepsilon^+_{j,h}, \varepsilon^-_{j,h}, \delta_{j,h}, m_{j,h} \geq 0, \quad \forall j \in J, \forall h \in H. \tag{10}$$

The aim of the forecast is to maintain these links. Compliance with constraints is required with the smallest possible change from the trend in the historical data. This is achieved by the minimisation task of mathematical programming. The formula Eq. (11) represents the objective function with weights $v_{j,h}$ and $w_{j,h}$.

$$\sum_{j\in J}\sum_{h\in H}\left(v_{j,h}w_{j,h}\right)^2\left[\left(\varepsilon^+_{j,h}\right)^2 + \left(\varepsilon^-_{j,h}\right)^2\right]. \tag{11}$$

The goal is to minimise the sum of squared errors related to each territorial unit and type of handling. The individual time-series are influenced by the weights $v_{j,h}$

and $w_{j,h}$, which are described below. This correction achieves the final forecast of production and WM for the-business-as usual scenario. Presented model is further used for every forecasted year. It can be beneficial to limit the maximal change from the trend $p_{j,h}$, these are mainly cases that do not have a clear trend. For this condition, the estimation of waste production resp. treatment potential, if available, can be used. However, it is necessary to monitor the solvability of the model.

5.2 Ensuring the significance of input data

The goal of the first weight $v_{j,h}$ is to ensure the significance of all input parameters. In the system of hierarchical arrangement, orders of magnitude of different values naturally occur. The same problem can be observed in the case of two countries of different sizes. The weights incorporation ensures that the error is minimised for each country with same rate, in other words, it is a kind of data normalisation. The weights are therefore defined as inverse value for each input data, see following formula Eq. (12), where $\bar{t}$ is the last year of historical data. The reason is to ensure equal weight for all modelled years. This measure will be particularly important for declining trend, so as not to put too little weight on trends approaching zero. In the case where the trend is zero in year $\bar{t}$, the weight $v_{j,h}$ is set to big M. This ensures that if the trend has reached zero in the historical data, a restart is not expected in the forecast.

$$\text{(A)} \quad v_{j,h} = \begin{cases} \frac{1}{p_{j,h,\bar{t}}}, & \text{for}\, p_{j,h,,\bar{t}} > 0, \forall h \in H, \forall j \in J \\ M, & \text{for}\, p_{j,h,,\bar{t}} = 0, \forall h \in H, \forall j \in J. \end{cases} \tag{12}$$

Thanks to this system of weights, each value in the model has the same significant level. The recommendation for some cases, where the big difference between hierarchical levels is observed, is to consider the possibility of preference on higher territorial division. It can be achieved for additive approach (A) by using weights in the form defined by Eq. (13).

$$\text{(A)} \quad v_{j,h} = \begin{cases} \frac{1}{\sqrt{p_{j,h,\bar{t}}}}, & \text{for}\, p_{j,h,,\bar{t}} > 0, \forall h \in H, \forall j \in J \\ M, & \text{for}\, p_{j,h,,\bar{t}} = 0, \forall h \in H, \forall j \in J. \end{cases} \tag{13}$$

In the case of multiplicative approach (B), it is recommended to implement weights in the form defined by Eq. (14), which also makes preference on bigger amounts. However, there is no goal to normalise data, because the essence of the multiplicative approach is already a percentage change.

$$\text{(B)} \quad v_{j,h} = \sqrt{\frac{p_{j,h,\bar{t}}}{\max\limits_{j} p_{j,h,\bar{t}}}}, \quad \forall h \in H, \forall j \in J. \tag{14}$$

These modified weights are very useful in that cases when more different models are used for forecasting estimate. Due to specific links in the system, some territory or waste handling must be modelled by diverse procedure or individual approach and this weight can help to maintain all dependencies with reasonable error from trend in every partial territory. Otherwise, there could be the tendency to modify region with greater values or higher territory division because it is more favourable in context of relative change in objective function.

5.3 The quality of trend estimate

The weight $w_{j,h}$ considers the quality of historical data fitting. Individual time series of historical data show different variability. The more reliable estimate of a trend can be observed in the case of stable and clear development in the history. It is desirable to preserve the set trend also in the future. In the case of more variable development, the trend is more difficult to be estimated and such time series are considered as less trustworthy in the process of data reconciliation. The weight $w_{j,h}$ quantify the quality of the data fitting and implement this information into the model. The weight is defined by Eq. (15) and Eq. (16) with range of values from 0.5 to 1.

$$w_{j,h} = \frac{1 - \frac{SMAPE_{j,h}}{\max\left(SMAPE_h^{0,9}; SMAPE_{j,h}\right)}}{2} + 0.5, \tag{15}$$

$$SMAPE_{j,h} = \frac{1}{T_{j,h}} \sum_{i=1}^{T_{j,h}} \frac{\left|p_{i,j,h} - x_{i,j,h}\right| l_{i,j,h}}{\left(\left|x_{i,j,h}\right| + \left|p_{i,j,h}\right|\right)/2}. \tag{16}$$

The symbol $x_{i,j,h}$ represents real data related to waste handling in year i for time series in territory j a waste handling h. Index i means years with available historical data. Next, the $p_{i,j,h}$ represents the trend for the point $x_{i,j,h}$ and the symbol $l_{i,j,h}$ in a binary parameter taking into account results from data preprocessing. If the parameter $l_{i,j,h}$ is equal to 0, the point was removed and has no impact on $SMAPE_{j,h}$. Otherwise, the parameter $l_{t,j,h}$ is equal to 1. The symbol $T_{j,h}$ is defined as total number of available points in time series after data preprocessing. $SMAPE_h^{0,9}$ means 90. percentile of set of values of $SMAPE_{j,h}$. The weight $w_{j,h} = 0.5$ is set for the time series with higher value of $SMAPE_{j,h}$ than 90. percentile. The same value of the weight ($w_{j,h} = 0.5$) is defined for these time series, where no trend is modelled, and historical data was fitted by mean. The key requirement for weight calculation is to have same units for each time series in the model.

With respect to the nature of the data reconciliation, it cannot be expected that the overall error for approach with weight $w_{j,h}$ is better than without it. Necessary adjustments for ensuring the mass balance are in sum the same. The difference lies in which time series are adjusted to maintain links in the system. The goal is to modify those time series, which show more variability. On the contrary, it is not suitable to change data, which shows long-term and obvious trend.

5.4 Confidence and prediction intervals

The important additional information is variability of estimated values. The confidence interval represents the uncertainty of parameters estimate. It provides an insight into likely future direction of the trend. On the other hand, it does not provide the variability of specific values around the trend. These values can deviate from the trend, especially for data set with big variability. The prediction interval determines the uncertainty for individual data sample. It is usually significantly wider and shows the variability around the trend. This additional information reflects bigger variability in future estimated value. The construction of intervals estimates is complicated due to territory hierarchy and data reconciliation. Thanks to implemented errors, which preserve the links in the system, the standard methods are not directly usable. Therefore, the construction is based on scenarios, which are calculated by model-based bootstrap with resampling errors. The error from data reconciliation and the length of prediction are implemented. The wider intervals can be expected in the case of bigger deviations and longer forecast. The procedure is as follows, where t denoted forecasted years:

- Step 1: The above-mentioned methodology is performed to get the estimate $m_{t,j,h}$ for each period t, which is based on base scenario, i.e. point estimate.
- Step 2: The data residuals $\epsilon_t^{j,h}$ from evaluated trend are determined. These residuals form a set, from which the values are selected for parametric bootstrap. The residuals should be centred by subtracting the average of residuals from each residual of a time series. It is also recommended to take into account the number of parameters in regression used for trend estimates and apply scaled residuals defined by Eq. (17).

$$\tilde{\in}_t = \frac{\in_t}{\sqrt{1 - \frac{q}{n}}}. \tag{17}$$

The symbol n is number of points in time series used for trend estimate and q is number of parameters in regression used for trend estimates. As another way based on non-linear regression is to use standardised residuals, which are defined by Eq. (18).

$$\tilde{\tilde{\in}}_t = \frac{\in_t}{\sqrt{1 - \tilde{k}_{ii}}}. \tag{18}$$

The element $\tilde{k}_{ii}$ is diagonal element of regression matrix, which rows contain gradients of the trend function with respect to a specific parameter in the point estimate of this parameter. This formulation can lead to unfavourable results if historical data represents short time series much more than Eq. (17). Therefore, it is recommended to use previous formula, because available data represents one of the biggest problems of forecasting.

- Step 3: The generation of new random sample is performed for β bootstrap. The residuals are selected from the set defined in previous step for each point of time series. It is selection with repetition. The data for β bootstrap is defined as $\tilde{x}^{j,h}_{t,\beta} = p_{t,j,h} + \tilde{\in}^{j,h}_{t,\beta}$,where $p_{t,j,h}$ is trend and $\tilde{\in}^{j,h}_{t,\beta}$ is a residual from range defined in step 2.
- Step 4: The methodology for trend analysis and data reconciliation is performed for each generated scenario β. The result is future development estimate $\tilde{m}^{j,h}_{t,\beta}$ for bootstrap β. The recommendation is to perform at least 30 bootstrap repetitions.
- Step 5: The correction $\frac{n+\tilde{t}}{n}$ is introduced to take into account the fact, that the methodology is based on TSA, which is neglected in bootstrap principle. It can be expected that the residuals are positively corelated, which leads to greater variance. It represents caution in the cases, where long prediction is performed with short available time series. The symbol $\tilde{t}$ is order of predicting year. Thanks to this correction, longer prediction has wider interval as well as fewer available points in historical data.
- Step 6: Based on the newly obtained values of $\tilde{m}^{j,h}_{t,\beta}$, confidence intervals for the obtained estimates are constructed. The approximate confidence interval for the trend in the data is determined by Eq. (19).

$$\left(m_t - t_{n-q}\left(1-\frac{\alpha}{2}\right)\sqrt{\frac{n+\tilde{t}}{n}\sigma_t^2}, m_t + t_{n-q}\left(1-\frac{\alpha}{2}\right)\sqrt{\frac{n+\tilde{t}}{n}\sigma_t^2}\right), \tag{19}$$

where $t_{n-q}\left(1-\frac{\alpha}{2}\right)$ is $\left(1-\frac{\alpha}{2}\right)$-quantile of Student's t-distribution with $n-q$ degree of freedom. The symbol σ_t^2 represents the variance estimate of prognosis $\tilde{m}^{j,f}_{t,\beta}$ based on bootstrap repetition. The prediction interval is defined by Eq. (20), where $\tilde{\sigma}^2$ is variance estimate of residual component. Both variance estimates should consider the number of degrees of freedom equal to $n-q$.

$$\left(m_t - t_{n-q}\left(1-\frac{\alpha}{2}\right)\sqrt{\frac{n+\tilde{t}}{n}\left(\sigma_t^2+\tilde{\sigma}^2\right)}, m_t + t_{n-q}\left(1-\frac{\alpha}{2}\right)\sqrt{\frac{n+\tilde{t}}{n}\left(\sigma_t^2+\tilde{\sigma}^2\right)}\right). \tag{20}$$

For EU countries, the authors do not have a sufficient dataset to validate the approach. There are 145 time series and only 29 time series for waste production or particular waste treatment. Therefore, it is not possible to statistically evaluate the quality of the model on such a small data set. For this reason, the computation of the prediction intervals was tested with WM data of Czech Republic (ISOH 2021), where the authors could obtain relevant number of time series. Unfortunately, the length of time series is too short for long-term assessment and the principle was evaluated only for one-year forecast. Overall dataset contains 206 regions and 17 waste types, which results to 3502 time series. The 90% prediction intervals cover 85% of data points. The value was obtained by median from results of individual waste types. The median approach is less sensitive to waste types outliers, which can occur in cases with unexpected legislative intervention or inaccuracies in available data set. Similar underestimated results were obtained for intervals with different value of significance. The 70% intervals cover 62% of data points and the 50%

intervals cover 49%. The intervals should be wider from the essence of it, on the other hand, it can be considered satisfactory because the deviance is not great. The testing of this approach confirms the benefit of data reconciliation when real data is on average closer to reconciled data than the trend. The future research related to confidence and prediction intervals is needed to reveal improvements and the diagnostic of this approach should be repeated with additional data.

6 Results

The forecast of MSW production and treatment at the state level showed the expected development of WM for the so-called business as usual scenario. The Fig. 3 shows the waste production and treatment forecast for the EU. The results were obtained by additive approach (A) of data reconciliation due to occurrence of zero values. The additive approach works well because time series trend differences are commensurate with the size of the task. For each time-series (production, recycling, incineration, landfilling), four data series are displayed in a given colour. The first of these is historical data, these are the input data for the forecasting approach. The trend in this data is modelled by a curve, which is shown by a solid line in each time-series. Trend in data for MSW recycling and landfilling were modelled by power function (Eq. (1)). Data on MSW incineration show a slightly exponential character, so trend was modelled by logistic function (Eq. (2)). Production data oscillate around the average value, so value of R^2 is very low. Thus, the trend was modelled by the average in the data per capita. The Fig. 3 shows the absolute amount predicted for the EU, where the demographic forecast is already included. The trend model enters the data reconciliation. The Fig. 3 is shown at the EU level, so data reconciliation is also

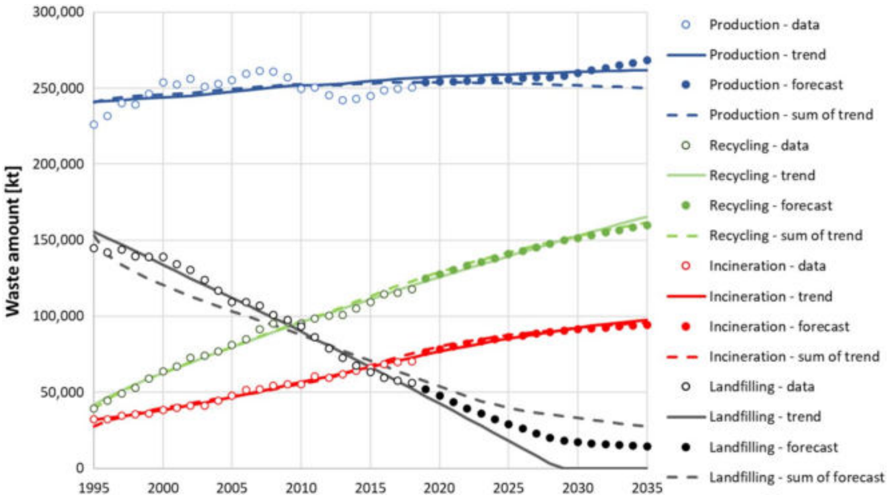

Fig. 3 Waste production and treatment forecast for EU

influenced by the trends of lower territorial units—states. The sum of trends at the national level is shown by the dashed line.

The resulting forecast after data reconciliation is shown in solid dots. It is obvious that the results of data reconciliation for recycling and incineration are concentrated around two trends: on the basis of EU data (trend) and on the basis of the sum of trends for EU states (sum of trend). Limiting the decline in landfilling due to non-negativity needs to limit changes in other series. The approach due to landfilling accelerated MSW production in forecast. The landfilling deceleration should affect other types of MSW treatment rather than production. In the further research, it would be appropriate to modify the model in step-by-step data reconciliation or to implement correlations between time series.

The resulting forecast is supplemented by prediction intervals. They provide a necessary information about variability and show the credibility of forecasted data. If in any series the confidence or prediction interval reached a value lower than zero, it was limited to zero. The intervals for waste production and each type of waste treatment are shown for EU level in Fig. 4. It is obvious that intervals for waste treatment are relatively narrower in context of waste production. It supports the explanation of principle of data reconciliation described in Fig. 3, where production has the bigger deviation from trend.

The step increase in the incineration is caused by historical development. The incineration is usually affected by the construction of new plant with large capacity, which is also projected into forecast. In the case of recycling, the growth slowdown can be observed around the year 2008. It can be affected by bad economic situation in the world caused by the global economic crisis. In the subsequent research, it

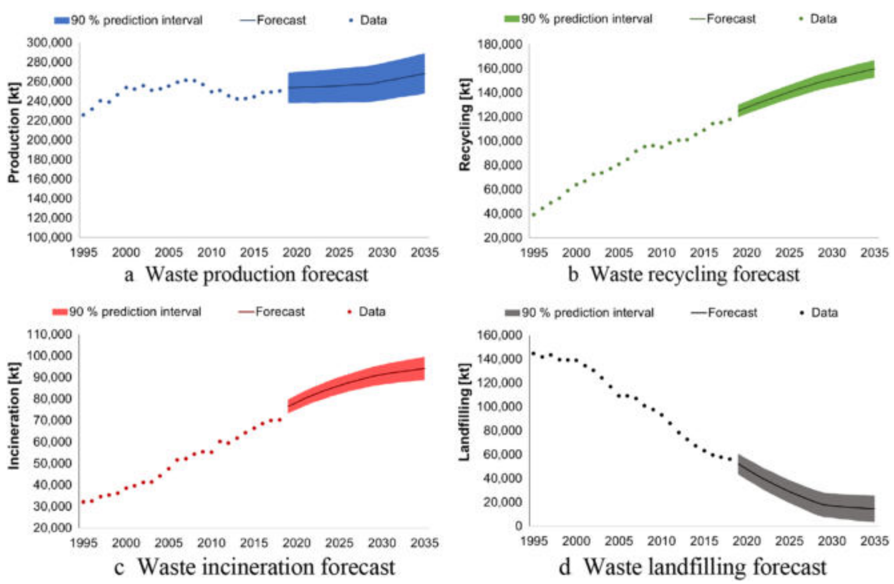

Fig. 4 WM development for EU in selected historical and forecasted years with confidence and prediction intervals

could be beneficial to focus on data cleansing based on social and economic factors. These are difficult to forecast, but their influence could be found in a historical context.

The results of the forecast are compared with the EU's targets. The outputs of the forecast at state level were divided into three categories for individual countries, see Table 3, and marked with symbols defined in the Table 2. The Table 3 shows the numerical results of the forecast. Percentage recovery of recycling and landfilling of MSW is available in the last year with historical data from 2018 and the EU targets key years 2025, 2030, 2035. The last column „Meeting EU targets " uses the symbols if the country will meet the EU's targets according to the legend in the Table 2.

It is clear that only one country, Germany, in 2018 met the EU targets set for 2035 contained in the CEP, see Table 3. If the current trend of WM in the EU states is maintained in the future, based on the results, other 7 countries are expected to meet the EU's recycling targets for the key years. The question is whether these states can continue the established trend into the future until 2035. Limited equipment capacities, waste separation efficiency, etc. may be an obstacle to maintain the historical trend also to the future. With respect to the uncertainty and presented prediction intervals, there is probability that 18 countries will meet 65% recycling rate and 10% landfilling rate for positive scenario. Of course, prediction intervals apply also to opposite side and therefore the number of countries can be smaller. Historical and forecasted data in selected years are visualised in Appendix 2 for the EU and its members.

A lot of EU states face a situation where their current state of WM is failing to meet given milestones, especially in context of recycling. However, a relative diversion from landfilling can be observed, which is replaced mostly by incineration. If the targets set out in the CEP are not met, the EU states will be subjected to sanctions. Nevertheless, there are tools that can influence the way waste is handled and redirect waste in the desired direction. It is the responsibility of the state to ensure suitable conditions for the desired waste treatment, in particular, build the necessary equipment. As introduced by Smejkalová et al. (2020b), MSW production and treatment is affected by some economic, sociological and demographic variables. Focusing on these influencing factors can contribute to the transformation of WM. It is highly recommended to update results each year and flexibly respond to actual development and prediction.

Table 2 Indication of forecast results

Symbol	Explanation
	The EU's targets are met based on forecast (year 2035) of the current situation—there are no necessary interventions
	The EU's targets are met based on the positive scenario (upper 90% prediction interval (PI) of recycling and lower 90% PI incineration and landfilling) of the forecast. The better values to meet EU goals are presented
	The EU's targets will not be met with the current form of WM, not even within prediction intervals. Necessary interventions in the system

Table 3 Results of MSW production and treatment forecast for EU states, comparison with EU targets

	Recycling			Landfilling			Meeting EU targets	
Locality	2018	2035	PI 2035	2018	2035	PI 2035	Recycling	Landfilling
EU	48 %	60 %	64 %	23 %	5 %	1 %	✗	✓
Austria	59 %	47 %	63 %	2 %	0 %	0 %	✗	✓
Belgium	55 %	55 %	67 %	1 %	0 %	0 %	✓	✓
Bulgaria	37 %	51 %	93 %	60 %	40 %	0 %	✓	✓
Croatia	28 %	66 %	100 %	72 %	33 %	0 %	✓	✓
Cyprus	17 %	41 %	81 %	82 %	57 %	19 %	✓	✗
Czechia	35 %	75 %	92 %	49 %	0 %	0 %	✓	✓
Denmark	48 %	48 %	68 %	1 %	0 %	0 %	✓	✓
Estonia	31 %	40 %	89 %	24 %	0 %	0 %	✓	✓
Finland	42 %	30 %	43 %	1 %	0 %	0 %	✗	✓
France	44 %	63 %	67 %	21 %	0 %	0 %	✓	✓
Germany	68 %	67 %	76 %	0 %	0 %	0 %	✓	✓
Greece	19 %	34 %	77 %	80 %	64 %	23 %	✓	✗
Hungary	37 %	77 %	93 %	49 %	0 %	0 %	✓	✓
Ireland	43 %	63 %	86 %	24 %	0 %	0 %	✓	✓
Italy	55 %	70 %	74 %	24 %	0 %	0 %	✓	✓
Latvia	29 %	65 %	87 %	68 %	31 %	11 %	✓	✗
Lithuania	59 %	76 %	84 %	27 %	0 %	0 %	✓	✓
Luxembourg	50 %	59 %	65 %	6 %	0 %	0 %	✓	✓
Malta	7 %	9 %	16 %	93 %	91 %	84 %	✗	✗
Netherlands	56 %	52 %	64 %	1 %	0 %	0 %	✗	✓
Poland	34 %	61 %	78 %	42 %	0 %	0 %	✓	✓
Portugal	30 %	61 %	82 %	51 %	2 %	0 %	✓	✓
Romania	12 %	45 %	90 %	82 %	42 %	0 %	✓	✓
Slovakia	36 %	52 %	85 %	55 %	37 %	15 %	✓	✗
Slovenia	75 %	77 %	100 %	12 %	0 %	0 %	✓	✓
Spain	36 %	48 %	76 %	51 %	32 %	13 %	✓	✗
Sweden	46 %	43 %	53 %	1 %	0 %	0 %	✗	✓
United Kingdom	45 %	57 %	71 %	15 %	0 %	0 %	✓	✓

7 Conclusion

In order to meet the EU's strict targets, it is necessary to make the adjustments in WM in a timely manner. The need to intervene in the current system can be revealed by a forecast of expected development. This article presented a methodology for the forecast of MSW production and treatment. It is based on non-linear regression, quadratic optimisation and experience with real data sets, which leads to building a comprehensive tool with wide range of uses. The methodology is a generally applicable approach that can be applied to all EU member states. As results show, it is possible to estimate the expected way of waste treatment and thus the fulfilment of EU targets. The forecast revealed that with current developments in WM, most EU member states are not on track to meet EU targets in time. Even under a positive scenario, not all states are expected to meet the EU targets. This crucial information should help to initiate efforts to modernize WM.

In the follow-up, it would be appropriate to make forecasts also on greater detail of individual states (e.g., regions or municipalities). Modification of WM can then take place with a link to a specific area. The influence of demographic development and other influencing factors on specific treatment methods is another challenge that should be addressed in this area in the future. In addition, it would be beneficial to consider correlations between different waste treatment methods and production for data reconciliation model. Then it is possible to model scenarios that lead to the achievement of goals. Scenarios can identify regions that have the potential to improve WM and thus help national assessment. The cornerstone of the model is also the data availability, so future work will be focused on data collection related to specific waste treatment and territory detail. Construction of prediction intervals should take into account residuals variance depending on time. From the optimisation point of view, the future research can improve the model performance, solvability and starting points with respect to other solvers. The verification of the presented approaches could be evaluated with respect to data heteroskedasticity and other characteristics. Of course, the application of this approach on real data can reveal another links and dependencies, which can lead to extensions of the methodology and recommendations originating from the experience.

Appendix 1: The summarized forecasts within selected waste management plans

Czech Republic (Ministry of the Environment of Czech Republic 2014).

- MSW definition: Group 20 from all producers and 15 01 from citizens based on Waste catalogue (ANION CS, 2021)
- Treatment: yes
- Territory level: state
- Data detail: year
- Number of data: 4
- Forecast length: 12
- Method: Design of 3 models: 1. linear regression, 2. exponential trend, 3. multidimensional linear model.

Austria (Federal Ministry for Climate Protection, Environment, Energy, Mobility, Innovation and Technology 2017).

- MSW definition: Municipal waste is waste from private households and other types of waste which, on account of its nature or composition, is similar to domestic waste. This includes fractions such as mixed municipal waste (residual waste), bulky waste or biogenic waste collected separately.

There is no reference to the waste catalogue in the document.

- Treatment: no
- Territory level: state
- Data detail: end state
- Number of data: no information
- Forecast length: 6
- Method: No information

Germany (LAGA 2021).

There is no national waste management planning in Germany. Instead, each Federal State develops a waste management plan for its area.

(a) **Berlin** (Senate Department for Environment, traffic and climate protection 2011)

- MSW definition: MSW is waste that, based on its origin, can be allocated to private households and is collected as part of public waste collection. MSW also includes waste from commercial industry and wastewater treatment plants
- Treatment: no
- Territory level: Federal state
- Data detail: 2 milestones (2015, 2020)
- Number of data: 1
- Forecast length: 9
- Method: Setting progressive targets to be met and will have an impact on waste production. Inclusion of demographic projection.

(b) **Nordrhein-Westfalen** (Ministry for Climate Protection, Environment, Agriculture, Nature and Consumer Protection of the State of North Rhine-Westphalia 2015)

- MSW definition: Household waste is waste and packaging that is usually produced predominantly in private households and collected as part of public waste collection or from Take-back systems according to the Packaging Ordinance or Packaging Act, the so-called dual system. This typical household waste includes household and bulky waste, organic and green waste, separately collected valuable waste or packaging (including paper, light packaging, glass) as well as waste that is collected as part of municipal pollutant collections.
- Treatment: no
- Territory level: District, administrative districts and municipalities
- Data detail: year
- Data detail: End state
- Number of data: 1
- Forecast length: 14

- Method: Population projection combined with assumption about per capita waste production.

(c) **Baden-Württemberg** (Ministry of Environment Climate and Energy 2015)

- MSW definition: The document does not directly contain a definition of MSW, but the federal states have usually the same definition of MSW, see Nordrhein-Westfalen.
- Treatment: no
- Territory level: Federal state
- Data detail: year
- Number of data: 19
- Forecast length: 10
- Method: Determination of two scenarios for each type of waste. Scenarios are based on the expansion of the involved part of the population, the use of more efficient methods of collection, greater promotion, etc. Involvement of the demographic projection, the percentage decrease in the number of inhabitants is considered.

(d) **Hesse** (Hessian Ministry for the Environment, Climate Protection, Agriculture and Consumer Protection 2015)

- MSW definition: See Nordrhein-Westfalen.
- Treatment: no
- Territory level: Federal state
- Data detail: 5 years
- Number of data: 3
- Forecast length: 12
- Method: Population forecast and assumption of economic growth and fulfillment of goals in waste management.

Poland (Ministry Climate and Environment of Poland 2021).

- MSW definition: Municipal waste is waste generated in households and waste generated in retail trade, enterprises, office buildings and educational institutions as well as health care and public administration institutions, and the nature and composition of this waste is similar to that of waste generated in households.

  There is no reference to the waste catalogue in the document.

- Treatment: no
- Territory level: Region, state
- Data detail: 2 milestones (2025, 2030)
- Number of data: 1
- Forecast length: 16
- Method: Based on population forecast and two waste generation indexes—it is still assumed the same year-on-year growth in production (0.6% or 1.0%) and a decrease in population.

Slovakia (Ministry of the Environment of Slovakia 2015).
Waste management plan does not include any forecast.

- MSW definition: Code 20 in Waste catalogue
  Finland (Launonen 2019).
- MSW definition: Municipal waste means waste generated in permanent dwellings, holiday homes, residential homes and other forms of dwelling, including sludge in cess pools and septic tanks, as well as waste comparable in its nature to household waste generated by administrative, service, business and industrial activities.
- Treatment: yes
- Territory level: state
- Data detail: End state
- Number of data: 1
- Forecast length: 8
- Method: The first scenario makes use of the waste volumes in 2015 as indicated in the waste statistics. The scenario presumes that the generation of waste has been successfully halted at the level of 2015. The second scenario makes use of the moderate waste quantity growth forecast to 2023 of the Forecasting waste volumes -project, in which future municipal waste quantities were modelled.

Switzerland–Canton Zürich (Kanton Zürich 2021).

- MSW definition: waste from households, commercial and service companies with less than 250 full time employees.
- Treatment: no
- Territory level: Canton
- Data detail: year
- Number of data: 6
- Forecast length: 18
- Method: No information

Appendix 2: The waste management development for EU and its members

See Figs. 5, 6, 7, 8, 9, and 10.

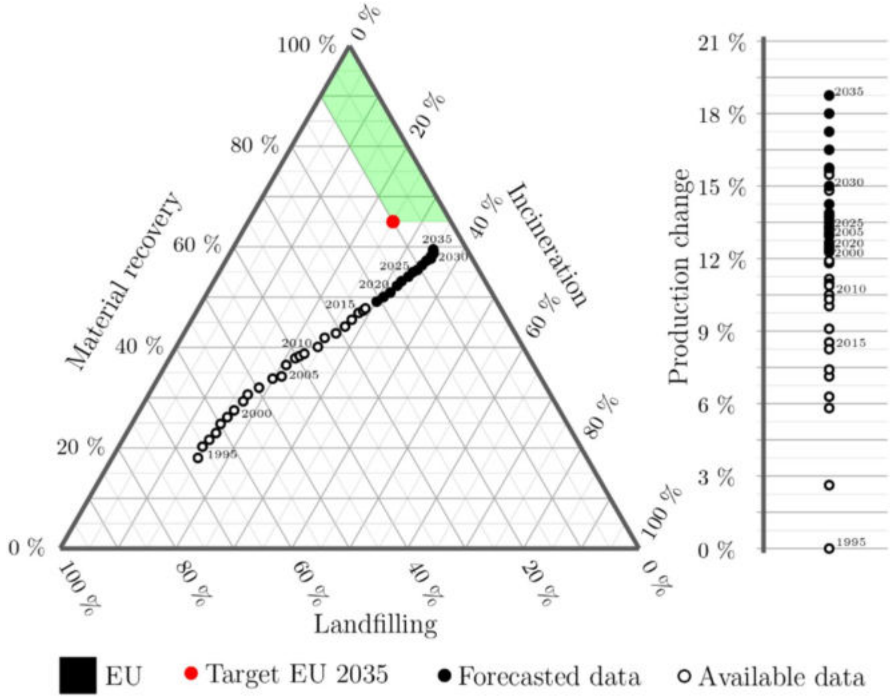

Fig. 5 Waste management development for EU

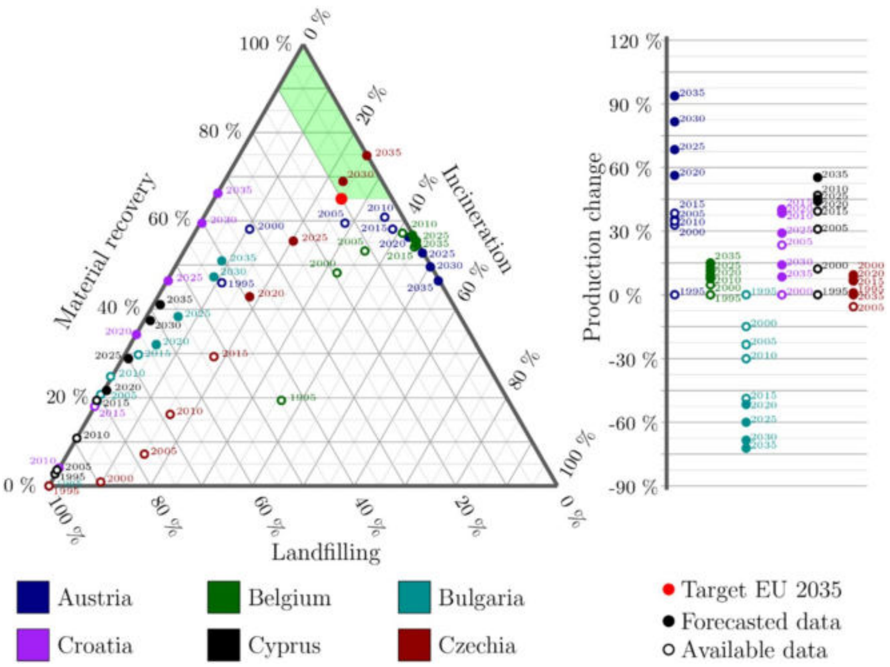

Fig. 6 Waste management development for Austria, Belgium, Bulgaria, Croatia, Cyprus and Czechia

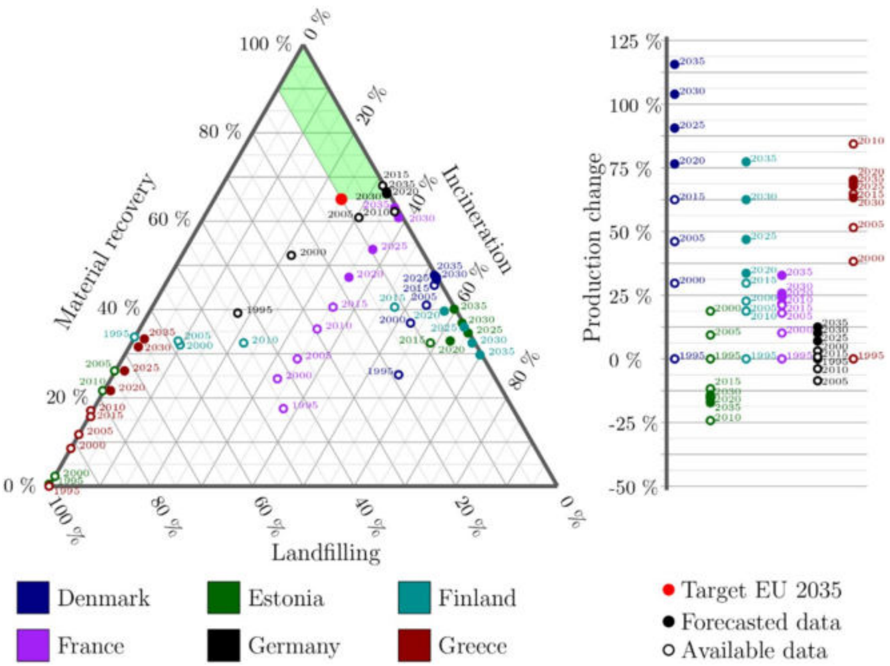

Fig. 7 Waste management development for Denmark, Estonia, Finland, France, Germany and Greece

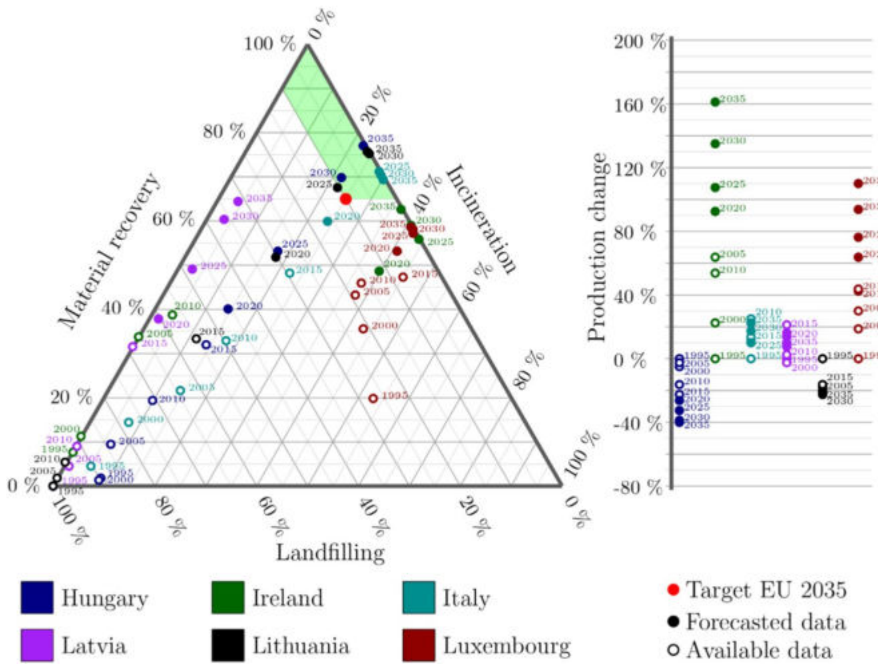

Fig. 8 Waste management development for Hungary, Ireland, Italy, Latvia, Lithuania and Luxembourg

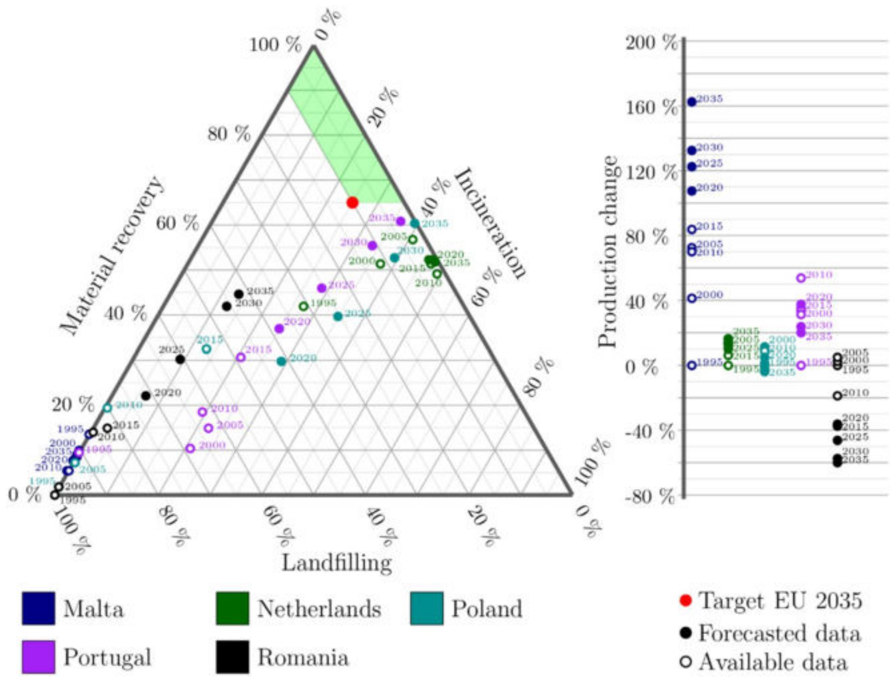

Fig. 9 Waste management development for Malta, Netherlands, Poland, Portugal and Romania

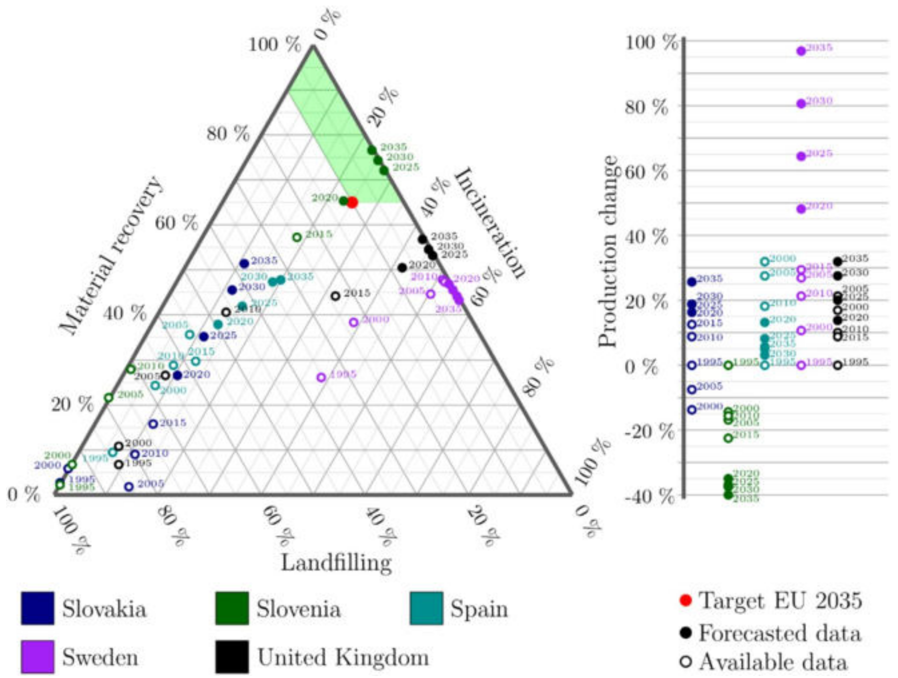

Fig. 10 Waste management development for Slovakia, Slovenia, Spain, Sweden and United Kingdom

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Author contributions All authors contributed to the presented study. Conceptualisation was provided by RŠ. The data collection and formal analysis was performed by VS and KR. Development of methodology and creation of models were performed by VS and RŠ. Validation of results was performed by VS, RŠ and JP. The figures and overall visualisation were performed by VS and JP. The first draft of the manuscript was written by VS, RŠ and JP. All authors read and approved the final manuscript.

Data availability The demographic data and data about municipal solid waste used in the case study are available from the database of the Eurostat – European statistical office and Waste Management Information System of Czech Republic called ISOH (ISOH 2021).

References

Aminikhanghahi S, Cook DJ (2017) A survey of methods for time series change point detection. Knowl Inf Syst 51:339–367. https://doi.org/10.1007/s10115-016-0987-z

Andersen FM, Larsen HV (2012) FRIDA: a model for the generation and handling of solid waste in Denmark. Resour Conserv Recycl 65:47–56. https://doi.org/10.1016/j.resconrec.2012.04.004

Andersen FM, Larsen H, Skovgaard M, Moll S, Isoard S (2007) A European model for waste and material flows. Resour Conserv Recycl 49:421–435. https://doi.org/10.1016/j.resconrec.2006.05.011

ANION CS (2021) Katalog odpadů. Sbírka zákonů ČR v aktuálním konsolidovaném znění. https://www.zakonyprolidi.cz/cs/2021-8. Accessed 7 April 2021

Beigl P, Lebersorger S, Salhofer S (2008) Modelling municipal solid waste generation: a review. Waste Manag 28:200–214. https://doi.org/10.1016/j.wasman.2006.12.011
Blázquez-García A, Conde A, Mori U, Lozano JA (2020) A review on outlier/anomaly detection in time series data. ArXiv, abs/2002.04236
Bramati MC (2016) Waste production and regional growth of marine activities an econometric model. Mar Pollut Bull 112:151–165. https://doi.org/10.1016/j.marpolbul.2016.08.025
Chu E, Keshavarz A, Boyd S (2013) A distributed algorithm for fitting generalized additive models. Optimizing and Engineering 14:213–224. https://doi.org/10.1007/s11081-013-9215-9
Czech National Bank (2021) Prognosis of CNB. https://www.cnb.cz/cs/menova-politika/prognoza/. Accessed 12 Nov 2021
Dai F, Nie G-h, Chen Y (2020) The municipal solid waste generation distribution prediction system based on FIG-GA-SVR model. J Mater Cycles Waste Manag 22:1352–1369. https://doi.org/10.1007/s10163-020-01022-5
Denafas G, Ruzgas T, Martuzevičius D, Shmarin S, Hoffmann M, Mykhaylenko V, Ogorodnik S, Romanov M, Neguliaeva E, Chusov A, Turkadze T, Bochoidze I, Ludwig Ch (2014) Seasonal variation of municipal solid waste generation and composition in four East European cities. Resour Conserv Recycl 89:22–30. https://doi.org/10.1016/j.resconrec.2014.06.001
Deutsche Bundesbank Eurosystem (2021). https://www.bundesbank.de/en/tasks/monetary-policy/economic-analyses/forecasts-625856. Accessed 12 Nov 2021
Directive (EU) 2018a/850 of the European Parliament and of the Council of 30 May 2018a amending Directive 1999/31/EC on the landfill of waste (Text with EEA relevance), Accessed 23 June 2020
Directive (EU) 2018b/851 of the European Parliament and of the Council of 30 May 2018b amending Directive 2008/98/EC on waste (Text with EEA relevance), Accessed 23 June 2020
Directive (EU) 2018c/852 of the European Parliament and of the Council of 30 May 2018c amending Directive 94/62/EC on packaging and packaging waste (Text with EEA relevance)
Directive 2008/98/EC of the European Parliament and of the Council of 19 November 2008 on waste and repealing certain Directives (Text with EEA relevance)
Estay-Ossandon Ch, Mena-Nieto A (2018) Modelling the driving forces of the municipal solid waste generation in touristic islands. A case study of the Balearic Islands (2000–2030). Waste Manag 75:70–81. https://doi.org/10.1016/j.wasman.2017.12.029
Eurostat (2020) European statistical office. https://ec.europa.eu/eurostat Accessed 12 Sept 2021
Federal Ministry for Climate Protection, Environment, Energy, Mobility, Innovation and Technology (2017) Bundes-Abfallwirtschaftsplan. https://www.bmk.gv.at/themen/klima_umwelt/abfall/aws/bundes_awp/bawp.html. Accessed 15 Apr 2021
Federal Ministry of Republic of Austria (2021) Austrian Stability Programme. https://ec.europa.eu/info/sites/default/files/2021-austria-stability-programme_en.pdf Accessed 12 Nov 2021
Gai L, Varbanov PS, Fan YV, Klemeš JJ, Romanenko SV (2021) Trade-offs between the recovery, exergy demand and economy in the recycling of multiple resources. Resour Conserv Recycl 167:105428. https://doi.org/10.1016/j.resconrec.2021.105428
Galan A, de Prada C, Gutierrez G, Sarabia D, Grossmann IE, Gonzalez R (2019) Implementation of RTO in a large hydrogen network considering uncertainty. Optim Eng 20:1161–1190. https://doi.org/10.1007/s11081-019-09444-3
Ghinea C, Drăgoi EN, Comăniţă ED, Gavrilescu M, Câmpean T, Curteanu S, Gavrilescu M (2016) Forecasting municipal solid waste generation using prognostic tools and regression analysis. J Environ Manage 182:80–93. https://doi.org/10.1016/j.jenvman.2016.07.026
Hessian Ministry for the Environment, Climate Protection, Agriculture and Consumer Protection (2015) Abfallwirtschaft in Hessen. https://umwelt.hessen.de/umwelt-natur/kreislauf-abfallwirtschaft/abfallwirtschaft-hessen. Accessed 22 Apr 2021
Hřebíček J, Kalina J, Soukopová J, Horáková E, Prášek J, Valta J (2017) Modelling and forecasting waste generation—DECWASTE information system. IFIP Adv Inf Commun Technol 507:433–445. https://doi.org/10.1007/978-3-319-89935-0_36
Islam MT, Huda N (2019) E-waste in Auastralia: generation estimation and untapped material recovery and revenue potential. J Clean Prod 237:117787. https://doi.org/10.1016/j.jclepro.2019.117787
ISOH (2021) Waste Management Information System of Czech Republic. https://www.cenia.cz/odpadove-a-obehove-hospodarstvi/isoh/. Accessed 15 October 2021

Karpušenkaitė A, Ruzgas T, Denafas G (2018) Time-series-based hybrid mathematical modelling method adapted to forecast automotive and medical waste generation: case study of Lithuania. Waste Manag Res 36:454–462. https://doi.org/10.1177/0734242X18767308

Klavenieks K, Blumberga D (2016) Forecast of waste generation dynamics in Latvia. Energy Procedia 95:200–207. https://doi.org/10.1016/j.egypro.2016.09.049

LAGA (2021) Publikationen/Informationen/Übersicht über Abfallwirtschaftspläne der Länder—Bund/Länder-Arbeitsgemeinschaft Abfall. https://www.laga-online.de/Publikationen-50-Informationen-Uebersicht-ueber-Abfallwirtschaftsplaene-der-Laender.html. Accessed 8 Apr 2021

Lanzi L, Airoldi A, Chirwa C (2009) Application of an iterative global approximation technique to structural optimizations. Optim Eng 10:109–132. https://doi.org/10.1007/s11081-008-9044-4

Launonen K (2019) JÄTEHUOLTOSUUNNITELMA. Bachelor's thesis. Vaasa University of Applied Sciences. https://www.theseus.fi/bitstream/handle/10024/171932/J%C3%A4tehuoltosuunnitelma.pdf?sequence=2&isAllowed=y. Accessed 12 Apr 2021

Lebersorger S, Beigl P (2011) Municipal solid waste generation in municipalities: Quantifying impacts of household structure, commercial waste and domestic fuel. Waste Manag 31:1907–1915. https://doi.org/10.1016/j.wasman.2011.05.016

Maki S, Ohnishi S, Fujii M, Goto M, Sun L (2021) Technical and economic analysis of potential steam supply from waste treatment plants to industries in Aichi Prefecture, Japan. Optim Eng 22:1755–1782. https://doi.org/10.1007/s11081-021-09637-9

Ministry Climate and Environment of Poland (2021) Krajowy plan gospodarki odpadami 2022 przyjęty w 2016 r. https://bip.mos.gov.pl/pl/strategie-plany-programy/krajowy-plan-gospodarki-odpadami/krajowy-plan-gospodarki-odpadami-2022-przyjety-w-2016-r/. Accessed 9 Apr 2021

Ministry for Climate Protection, Environment, Agriculture, Nature and Consumer Protection of the State of North Rhine-Westphalia (2015) Abfallwirtschaftsplan Nordrhein-Westfalen. https://www.umwelt.nrw.de/fileadmin/redaktion/Broschueren/abfallwirtschaftsplan_nrw_broschuere.pdf. Accessed 21 Apr 2021

Ministry of Environment, Climate and Energy (2015) Abfallwirtschaftsplan Baden-Württemberg. https://um.baden-wuerttemberg.de/fileadmin/redaktion/m-um/intern/Dateien/Dokumente/2_Presse_und_Service/Publikationen/Umwelt/AWP_BW_TPSiedlAbfaelle.pdf. Accessed 22 Apr 2021

Ministry of the Environment of Czech Republic (2014) Plán odpadového hospodářství České republiky pro období 2015–2024. https://www.mzp.cz/C1257458002F0DC7/cz/poh_cr_prislusne_dokumenty/$FILE/OODP-POH_CR_2015_2024_schvalena_verze_20150113.pdf. Accessed 6 Apr 2021

Ministry of the Environment of Slovakia (2015) Program odpadového hospodárstva SR na roky 2016–2020. https://www.minzp.sk/files/sekcia-enviromentalneho-hodnotenia-riadenia/odpady-a-obaly/registre-a-zoznamy/poh-sr-2016-2020_vestnik.pdf. Accessed 7 Apr 2021.

Morseletto P (2020) Targets for a circular economy. Resour Conserv Recycl 153:104553. https://doi.org/10.1016/j.resconrec.2019.104553

Oribe-Garcia I, Kamara-Esteban O, Martin C, Macarulla-Arenaza AM, Alonso-Vicario A (2015) Identification of influencing municipal characteristics regarding household waste generation and their forecasting ability in Biscay. Waste Manag 39:26–34. https://doi.org/10.1016/j.wasman.2015.02.017

Pavlas M, Šomplák R, Smejkalová V, Nevrlý V, Zavíralová L, Kůdela J, Popela P (2017) Spatially distributed production data for supply chain models—Forecasting with hazardous waste. J Clean Prod 161:1317–1328. https://doi.org/10.1016/j.jclepro.2017.06.107

Pavlas M, Šomplák R, Smejkalová V, Stehlík P (2020) Municipal solid waste fractions and their source separation: forecasting for large geographical area and its subregions. Waste Biomass Valoriz 11:725–742. https://doi.org/10.1007/s12649-019-00764-0

Peeters JR, Altamirano D, Dewulf W, Duflou JR (2017) Forecasting the composition of emerging waste streams with sensitivity analysis: a case study for photovoltaic (PV) panels in Flanders. Resour Conserv Recycl 120:14–26. https://doi.org/10.1016/j.resconrec.2017.01.001

Pomberger R, Sarc R, Lorber KE (2017) Dynamic visualisation of municipal waste management performance in the EU using ternary diagram method. Waste Manag 61:558–571. https://doi.org/10.1016/j.wasman.2017.01.018

Rimaitytė I, Ruzgas T, Denafas G, Račys V, Martuzevicius D (2012) Application and evaluation of forecasting methods for municipal solid waste generation in an eastern-European city. Waste Manag Res 30:89–98. https://doi.org/10.1177/0734242X10396754

Senate Department for Environment, traffic and climate protection (2011) Abfallwirtschaftsplan für das Land Berlin 2011–Teilplan Siedlungsabfälle. https://www.berlin.de/sen/uvk/_assets/umwelt/kreislaufwirtschaft/strategien/abfallwirtschaftsplaene/awp_siedlungsabfaelle_2011.pdf. Accessed 21 Apr 2021

Sjöström M, Östblom G (2010) Decoupling waste generation from economic growth—A CGE analysis of the Swedish case. Ecol Econ 69:1545–1552. https://doi.org/10.1016/j.ecolecon.2010.02.014

Smejkalová V, Šomplák R, Nevrlý V, Burcin B, Kučera T (2020a) Trend forecasting for waste generation with structural break. J Clean Prod 266:121814. https://doi.org/10.1016/j.jclepro.2020.121814

Smejkalová V, Šomplák R, Rybová K, Nevrlý V, Rosecký M, Burcin B, Kučera T (2020b) Waste production and treatment modelling for EU member states. Chem Eng Trans 81:691–696. https://doi.org/10.3303/CET2081116

Sokka L, Antikainen R, Kauppi PE (2007) Municipal solid waste production and composition in Finland—Changes in the period 1960–2002 and prospects until 2020. Resour Conserv Recycl 50:475–488. https://doi.org/10.1016/j.resconrec.2007.01.011

Song J, He J, Zhu M, Tan D, Zhang Y, Song Ye, Shen D, Zou P (2014) Simulated annealing based hybrid forecast for improving daily municipal solid waste generation prediction. Hindawi Publ Corp. https://doi.org/10.1155/2014/834357

Šramková K, Šomplák R, Nevrlý V, Jirásek P, Smejkalová V, Popela P (2021) Stratification and multi-representative optimization approach to waste composition analysis. Optim Eng 22:1727–1754. https://doi.org/10.1007/s11081-021-09645-9

Wilson DC et al. (2015) Global waste management outlook. UNEP

Zürich K (2021) Amt für Abfall, Wasser, Energie und Luft. https://awel.zh.ch/internet/baudirektion/awel/de/abfall_rohstoffe_altlasten/abfallplanung_2019_2022/_jcr_content/contentPar/downloadlist/downloaditems/massnahmenplan_abfal.spooler.download.1544091158985.pdf/massnahmenplan_abfallwirtschaft_2019_2022_A4.pdf. Accessed 20 Apr 2021

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Spatially distributed production data for supply chain models - Forecasting with hazardous waste

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ABSTRACT

This paper introduces a novel approach to forecasting future commodity production in hundreds of nodes, which represents a key input for many applications of supply-chain models. A mathematical model was proposed to handle the problem of forecasting with spatially distributed and uncertain data. It is derived from the principle of regression analysis and extended by a data reconciliation technique. Additional areal constraints guarantee mass conservation in a tree-like structure, which reflects the organisational arrangement of an investigated region. The proposed model was tested through a case study, where future production of hazardous waste suitable for thermal treatment was forecasted in 206 base-nodes, 14 superior nodes and one apex. Based on an extensive investigation of historical data, it was revealed that extrapolations carried out at different levels of the hierarchical organisational structure lead to inconsistent forecasts. The differences between forecasts reached up to 50%. In addition to this, mass conservation was violated. Significant corrections were performed by computations utilizing the formulated model. The corrections ranged from between 0% and 12% for 90% of nodes. There were 17 nodes, where massive adjustments of up to 30% were inevitable.

1. Introduction

This contribution addresses issues of quantitative input data processing prior to a supply chain model (SCM) calculation. As is explained later on, it tackles the interconnected problem of extrapolation and subsequent data reconciliation. The paper focuses on prognosis with the preservation of hierarchical and waste code aggregations in the field of hazardous waste management. For this reason, this article starts with a short review of recent achievements which are relevant to the topic of the paper.

1.1. Quantitative data and their forecasted values as key inputs for supply chain model applications

SCMs represent an effective concept to optimise processes where resources and raw materials are first transformed into desired products and then moved on to the customers. SCM are employed at several stages of process development covering both strategic and tactical issues, i.e. investment planning and operation.

Any SCM requires spatially distributed production data (related to the region of interest). The higher the level of detail, the more nodes which are included in the calculation network and the more data which are needed. Many research articles relevant to SCM and devoted to the various areas of transporting raw materials, fuels, waste, and so on have been published in the last few years. This confirms a broad range of applications for this supportive approach handling various commodities. For example, Balaman and Selim (2016) presented a comprehensive decision model for the sustainable design of biomass-based renewable energy supply chains. The aim was to locate and size facilities. The proposed model was based on mixed integer linear programming (MILP).

A P-graph is another interesting approach related to SCM. In the paper Varbanov and Fiedler (2008) a procedure for the evaluation of energy conversion systems is presented. In Vance et al. (2015), the effort is extended with another sustainability metric, emergy. A

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Monte Carlo simulation was used in Tan et al. (2017) to evaluate the robustness of a network to variations in system parameters.

Among other areas, SCMs are also relevant to waste management (WM). Since this contribution is dedicated to hazardous waste, the paper focuses on this field in particular. In Ghiani et al. (2014), the reverse problem was proposed, where the product, which is now the waste of different types and its individual fractions, is first collected and then transported to places of its intermittent or final treatment. The transport of residual solid waste was optimised by Chatzouridis and Komilis (2012). One of their key questions was whether a transfer station should be built or not. A complex problem was presented in Šomplák et al. (2014) which described the competitive environment in the field of waste management and where the collection phase was excluded. The issue of collecting and processing hazardous waste was dealt with by Zhao et al. (2016). Their case study described the situation in Sichuan province in China and used an approach based on multi-objective MILP. Samanlioglu (2013) described a task focusing on the location of processing plants and determined the flow of hazardous waste in selected areas in Turkey. The problem was described by a multi-objective location-routing model, where the objective was to minimise the cost and risk to the population.

The mentioned papers perform economic optimisations of the processes, where the operational cost (or annualised cost in the case of investment planning of an overall system) is minimised.

In this context, our review revealed that a typical paper published in this area dominantly focuses on the introduction of the mathematical model, highlighting new contributions and features. The practical impact is typically presented through case studies. Whereas the region of interest is commonly well described (the network may be reconstructed by using online maps and more advanced geographical information systems), the quantitative data addressing the production of the commodity in each of the nodes are often only briefly mentioned. Typically, current commodity availability is provided based on the latest reported data or an average value from the few last years at the highest regional level. This value is distributed down to all nodes of the network, for example using a socio-economic parameter (e.g. population, in the case of household waste). Based on our knowledge, none of the papers dedicated to SCMs and its applications stressed the issues of simultaneous forecasting a commodity's availability in the future for all nodes in the investigated network. This may be acceptable in the case of stable commodity availability. The use of current or average data represents a strong simplification because data develop over time and future investments are planned by the SCM. On the other hand, forecasting, especially based on short-time series (a typical case in SCM applications, not only in waste management), represents an independent problem (see Section 1.2) which was studied by many authors in different fields. The complexity of the problem, even if applied to one time series, is enormous, which hinders its routine use as demanded by SCM.

1.2. Short-time series forecasting

From a mathematical point of view, there are several approaches toward estimating beyond the observed data which can be called a basic time series analysis (TSA). Frequently used techniques are provided by regression analysis, so in the context of this paper, TSA represents regression analysis based techniques for extrapolation, where the sole explanatory parameter is time.

Andow and Kiritani (2016) studied the population dynamics of 17 species of saproxylic beetles in a specific location by using classical autoregressive integrated moving average (ARIMA) models. It is a frequently used technique for data fitting or predicting which generalises an autoregressive moving average model (ARMA), see Hamilton (1994). These techniques are not appropriate for a short TSA.

The waste management area usually suffers from a rather short available dataset (regarding time and one year as a basic time interval). This has a negative impact on prediction quality, especially when using traditional methods. Forecasting is often devoted to municipal solid waste (MSW) and its fractions.

The work presented by Ghinea et al. (2016) used a small dataset prognostic tool, regression analysis and time series analysis for forecasting MSW generation in Iasi (Romania) in 2023, when data from 2001 to 2013 were used. This study also focused on predicting the amount of solid waste fractions (paper, plastic, metal, glass, biodegradable and other waste). A different methodology was used in the study Intharathirat et al. (2015), which presented an analysis of possibilities for determining the prediction interval for MSW production. This was over a long-term period and used optimised multivariate grey models. Only 13 samples were available here. Another approach for forecasting based on a set of limited samples was presented in Xiang and Daoliang (2007), where grey fuzzy dynamic modelling (combining two forecasting techniques - grey dynamic model and the fuzzy goal regression model) was used for the prediction of solid waste generation in a fast-growing urban area - Beijing (China).

Since the time series (the available data for each node) encompasses only a few points (seven in our case study), any attempt at a rigorous time series analysis of such data is going to result in a heavily skewed estimate of the real underlying trend.

From the previously mentioned points, a current SCM developer and user working in the waste management area has to cope with short-time series. From a statistical point of view, the accuracy of extrapolation models is rarely guaranteed with a high level of confidence if the series consists of only a few points. This limits the direct use of the obtained forecasts in SCM applications. On the other hand, these models still provide important information about the trend. They are acceptable from an engineering point of view as no other models are available and they offer an improvement to existing approaches which rely on only the most recent reported data.

All of these approaches forecast data for a single node and commodity in terms of SCM terminology. Moreover, none of these extrapolation techniques reflects mass conservation, where, for example, the sum of values in regions equals the value in a higher territorial unit. As a result, this leads to inconsistencies (see Section 2). For this purpose, the utilization of a reconciliation technique appears promising.

1.3. Data reconciliation

Data reconciliation is a frequently used technique for data balancing and identifying gross errors. It primarily uses mathematical programming techniques, where the weighted least square errors are minimised, while balance constraints are satisfied. One of its first applications was in the field of chemical engineering, where the data reconciliation problem was presented by Crowe et al. (1983). A further extension of his research was proposed in Crowe (1996). Many other works have attempted to apply this method in various industries.

The energy system application in Yong et al. (2016) considers complete heat exchanger networks within the data reconciliation scope. Two methods are compared: i) an iterative method using local non-linear programming (NLP) and ii) a simultaneous method applying global NLP. In Weiss et al. (1996), an iterative gross error detection method was proposed, followed by data reconciliation using weighted least squares on a non-linear and on a linearized model of an industrial pyrolysis reactor. Jiang et al. (2014)

presented another mathematical method to evaluate the minimum isolable magnitude with a required probability for data reconciliation based on gross error identification. The importance of adequately treating the possible heteroscedasticity of measurement errors was demonstrated in Vocciante et al. (2014). A two-step approach for error detection and data reconciliation is provided by Sun et al. (2011). A simultaneous calculation of reconciled values and gross error detection was described in Korpela et al. (2016) using the Welsch-estimator and NLP methods. Martins et al. (2010) proposed a water balance tool for data reconciliation in industrial processes. They presented a new method based on the idea that an estimated assumption can be made for any flow rate based on the best available information (the quality of information). Valdetaro and Schirru (2011) used a metaheuristic (inspired by naturally occurring events) to simultaneously tune the model objective function, detect outliers and compute the data reconciliation. Zhang et al. (2010) propose sequential sub-problem programming strategies for data reconciliation and parameter estimation with multiple data sets. Based on objective and model parameters, the construction of a series of sub-problems is performed to solve the optimum of the original optimisation problem. A paper from Manenti et al. (2011) describes the integrated solution of different model-based optimisation levels to face the problem of inferring and reconciling online plant measurements practically. This was under the condition of poor measure redundancy in measurements due to the lack of instrumentation installed in the field. The question of choosing an adequate objective function for gross error detection and data reconciliation in chemical processes was studied in Özyurt and Pike (2004).

To sum up, articles in this field mostly focus on presenting new approaches for optimisation tasks, specifically reducing the computational complexity of the models or gross error detection. A common feature of data reconciliation papers is a fully defined covariance matrix which reflects the accuracy of the measurement devices. In this case, a covariance matrix which reflects the regression's quality is needed. Moreover, multiple values for a particular node must be allowed, where each of these values can have a different contribution in the matrix.

1.4. Contribution and novelty

The user of the SCM tool has to frequently cope with short-time series. Each of the mentioned approaches for extrapolation is interesting and have their strengths and weaknesses. In general, they provide only rough estimates instead of precise values and they are of very low practical relevance. Low confidence intervals, in addition with the complexity of extrapolation even when done for one time series (i.e. one node and one commodity, see Section 2.2), represent an obvious hindrance to effective forecasting in SCMs, where such extrapolation is needed in hundreds of nodes.

This paper introduces an approach towards improving forecasting in SCM applications. It is considered to be a pre-processing phase, prior to the main SCM calculations. The principle proposed is structured as follows:

1. Extrapolation – Non-linear regression is applied to all nodes of an investigated area to obtain initial estimates on future commodity production. As follows from Section 1.1 and 1.2, such an approach has not been published yet nor has it been practically applied to SCM. In this paper, we propose an extrapolation model which was tested for a particular waste type – hazardous waste. An iterative calculation is formulated with altered starting values, overcoming the problem of local solutions.
2. Reconciliation – the results of the extrapolation are handled as initial estimates, which are subject to further adjustments. Our method proposes exploiting mass conservation equations associated with a tree-like organisational and code aggregation structure in the reconciliation process. First, the problem of inconsistent forecasting and mass-balancing in a tree diagram is introduced. Then a mathematical model for data reconciliation is formulated and explained (see Section 3). The application of reconciliation in the field of reverse flow models and data forecasting is considered to be novel.

The whole procedure is tested through a complex case study, where hazardous waste produced in many small particular regions is forecasted, balanced and analysed. This paper was motivated by an extensive project for the Ministry of Environment of the Czech Republic carried out by the authors in 2015. The task was to allocate future capacities for hazardous waste treatment in the Czech Republic using the application of an advanced network flow model, called NERUDA (Ferdan et al., 2015). This waste is mainly produced by the industrial sector. Detailed historical data on production in particular micro-regions was provided by the authorities.

2. Extrapolation and inconsistent forecasts

In this section, specific aspects of simultaneous forecasting in a tree-like structure are introduced for locations of a large geographical area divided into many sub-areas and their parts.

2.1. Areal aggregation within a hierarchical organisational structure

Generally, the geographical area of the investigated region is organised according to a tree-like structure. It is illustrated in Fig. 1 and the real administrative arrangement for the Czech Republic may be derived from supplementary materials. The diagram, if based on real data, describes the relationship between nodes located at different levels of a hierarchical structure.

The idea, further explored in this contribution in more detail, is to utilise relationships within this tree-like structure to produce more convenient forecasted values, especially for those nodes where there are poor results from extrapolation regression models.

Following the tree diagram, the historical base data (i.e., data for nodes located at L2 level according to Fig. 1) may be aggregated to generate production at higher levels. This is highlighted by the sums in Fig. 1 for the apex node (L0) and one L1 level node. This summation is later labelled as “areal aggregation”. This areal aggregation is commonly used in practise where data for higher organisational levels (regions, country, see L1 and L0 level in Fig. 1, respectively) are reported as sums of production in all subordinate nodes. It also means that mass is conserved in the system around the particular node and its descendants as highlighted by the boundaries in Fig. 1. In Section 3, there is only one set with all nodes and tree structure is included in hierarchical matrix.

Whereas base level data often fluctuate, this variability is often suppressed by areal aggregation at a higher level (compare Fig. 2 a) and b) for instance).

2.2. Extrapolation

The creation of extrapolation models for all territorial units (i.e. L2, L1 and L0 levels) represents the initial step in the procedure. Trend analysis applied to historical data was used for non-linear regression model building and subsequent forecasting of the amount of waste produced. The model used is generally defined as:

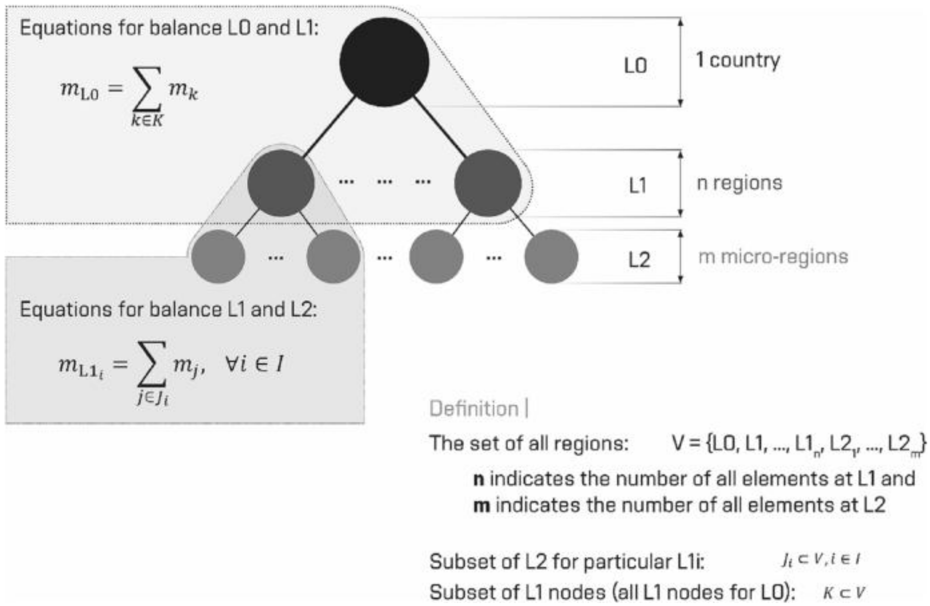

Fig. 1. Locations represented by nodes and organised in a tree structure with several levels, where mass conservation is required.

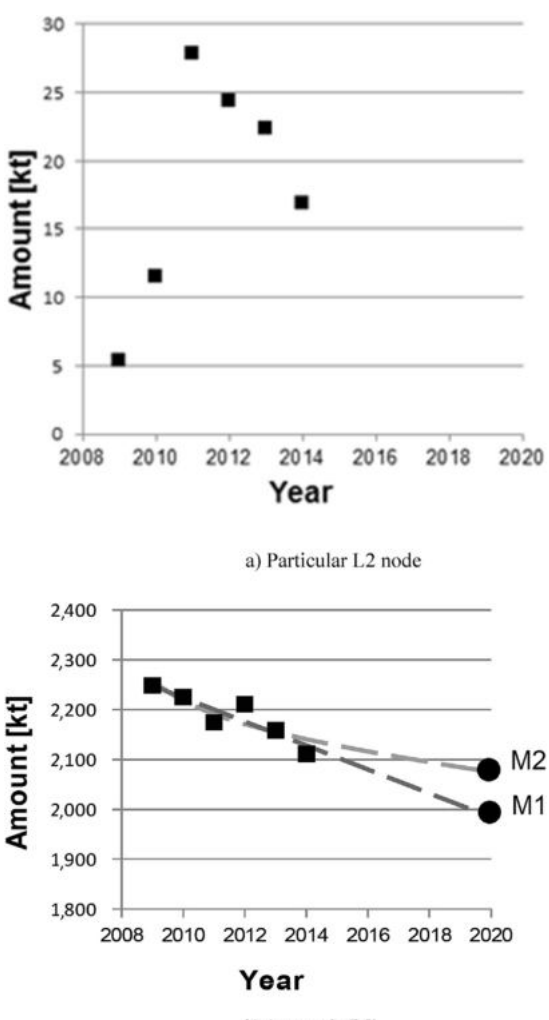

Fig. 2. Various data quality based on the level of detail, an example for particular waste stream. a) Particular L2 node. b) Apex node (L0).

$$M = a + bt^c, \tag{1}$$

where t is an independent variable whose values are the year(s) of waste production, M is the dependent variable giving the amount of produced waste in year t, and a, b, c are regression parameters to be estimated. Additionally, $M \geq 0$ is valid.

This type of model was judged to be suitable for the studied area of hazardous waste and input data is summarised in the supplementary materials. However, an alternative model could be more convenient for other types of data. For example, logistic function is very suitable for streams were a surge in the amount is observed as a response to recently introduced incentives and new legislation.

2.2.1. Setup of the algorithm's starting values

The minimization of the sum of square errors (looking for the least sum of squares) in the non-linear regression model (1) does not guarantee convexity of the objective function. Only a locally optimal solution can be found. Some pre-processing effort has to be made to achieve suitable starting values for the locally convergent Marquardt-Levenberg similar algorithm to find a globally optimal solution, see, e.g., Bazaraa et al. (2014). Therefore, the extrapolation was repeated in several iterations. Parameter a was established on the basis of the most recently reported data (in our case it was from the year 2015, see supplementary materials). Parameter b was set to zero. A uniform probability distribution of U(-3,3) was used to generate c values. This interval was estimated by our investigation to be the most suitable since it covers most observed trends in WM. The mentioned scheme was utilised to repeatedly generate the algorithmic starting values of c. For each of the s iterations, the quality of the regression was measured in a standard way as the sum of least square errors ε_{is}:

$$\forall i \in I: \qquad \varepsilon_{is} = \sum_{t=2009}^{2015} (m_{it} - M_{its})^2 \tag{2}$$

where t is the year based on the utilised regression model, m_{it} is historical input data for years t (2009–2015) and nodes i, and M_{its} is a computed value of waste production in the year t, node i and specific iteration s.

The results were compared and an extrapolation model (coefficients a, b, c), experiencing minimum ε_{is} denoted as $\varepsilon_{i,opt}$ is awarded as an initial estimate for the next calculation by the reconciliation model proposed in Section 3.

For future computations, this pre-processing can also be optimised to improve the regression models as their number can be quite large for SCM applications and hundreds of nodes. Due to the extreme time requirements, the selection of initial estimates and number of iterations may be subject to further enhancement. For example, the initial values can be obtained by choosing three typical points and a solving system of non-linear equations to get the solution values (not necessarily unique) of three regression parameters.

2.2.2. An evaluation of the extrapolation model's quality

To evaluate the quality of the extrapolation model, we proposed the following parameter Q_i:

$$Q_i = \frac{\frac{1}{N}\sum_{t=T1}^{T2} m_{it}^2}{\varepsilon_{i,opt}} \tag{3}$$

where T1 and T2 represent the first and last year, respectively, where the time series is available, $N = \mathrm{T2} - \mathrm{T1}$, because it is the number of years for which data are available.

The quality of an individual extrapolation model is expressed by $\varepsilon_{i,opt}$ and Eq. (2). These absolute values are not suitable for comparing nodes with completely different production. Therefore, normalisation expressed by Eq. (3) is implemented, where the average of square productions serves this purpose. The higher the $Q_{i,}$, the better the extrapolation model which was achieved.

2.3. Discussion on aggregation and forecasting

At this point, extrapolating models on future production are available not only in micro-regions (L2), but also in all regions (L1) and for the whole country (L0). There is less data variation at L1 and L0 levels and extrapolation provides models with a better fit (for example, expressed by Q_i). In other words, TSA for larger geographical areas provides more robust predictions. This is illustrated later in the case study.

The mentioned areal aggregation may be applied not only to historical data but also to extrapolated values. This opens up alternative ways how to build extrapolation models for nodes situated at higher hierarchical levels in the tree structure.

This idea is illustrated in Fig. 3. The starting point, located in the origin of our coordinate system, is established by the historical data for nodes at level L2 (micro-regions). There are three basic moves possible in the direction of the three axes (see edges highlighted in red). These moves are associated with two types of actions: i) forecasting ($\rightarrow$ symbol) and ii) aggregation ($\sum$ symbol). A move upwards along the vertical axis represents aggregation for various types of waste. This type of aggregation is mentioned in Section 4, where the procedure of grouping waste codes was applied to define investigated streams. There are two alternatives left: For example, we can take the local forecasts first (base level extrapolation, L2) and follow the horizontal edge. Then, we can move in parallel with the depth axis to aggregate the L2 forecasts with the hierarchical spatial structure. The displayed situation is relevant for aggregation towards the country level (L0) forecasts, which means that all forecasts for all L2 nodes were summed. The alternative path starts with the aggregation of region-related information and is followed by the forecasting model computations at country level data. In general, the moves may be ordered arbitrarily. In addition to the previous steps, intermediate levels (e.g. L1) can be included as points where the direction is changed. This leads to many combinations and possibilities how to build the final model.

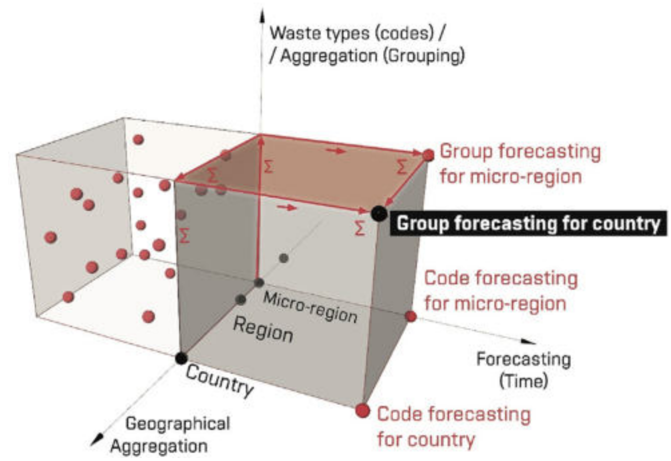

Fig. 3. Visualisation of the consistent forecasting procedure, where the order of aggregation ($\sum$) and forecasting ($\rightarrow$) operations do not influence the result.

Fig. 3 also illustrates the desired state where the same forecasted value is obtained irrespective of the movements along the box's edges. The group forecast we require for a country is depicted by the vertex highlighted in bold. It also means that the final forecast is subject to the areal constraint that represents a mass conservation, as introduced above.

Unfortunately, it is not possible to guarantee that all models will be equivalent from a mathematical point of view. This is due to the treatment of uncertainty in computations, the necessity to use the non-linear regression models and non-commutative properties of aggregation and forecasting steps discussed above. This is also illustrated in Fig. 2 b), where two different extrapolation models were obtained, resulting in values M1 and M2 for the year 2020. Model M1 starts at bottom level data and forecasts for all L2 nodes are performed. Following the mass conservation (applied to future forecasts), we aggregate the extrapolation's results to obtain a forecast at L0 level. Alternatively, forecasting on top level data was performed for M2.

We conclude that the result may depend on the order of the operations, geographically-based sums and level–related extrapolation, because the different models differ by their presence, realisations, and treatment of random errors, which are interpreted as a source of uncertainties. This finding was considered to be a key-driver to develop a reconciliation technique, where results from extrapolation are treated as initial estimates.

2.4. Forecasting improvements by implementing the reconciliation technique

A variety of spatially distributed forecasts (sub-models) for production at every considered node were obtained separately by the mentioned basic TSA (based on non-linear regression models). For nodes at higher organisational levels (i.e. L0 and L1 in Fig. 4), the forecasted values may obviously differ for the various sub-models (see M1 and M2 in Figs. 2 and 4 for instance). They are considered to be initial estimates from now. In the next step, they are subject to further processing by the reconciliation-based model, leading to consistent and unified, final forecasts (see red stripes and R in Fig. 4).

From a computational point of view, the balancing itself is

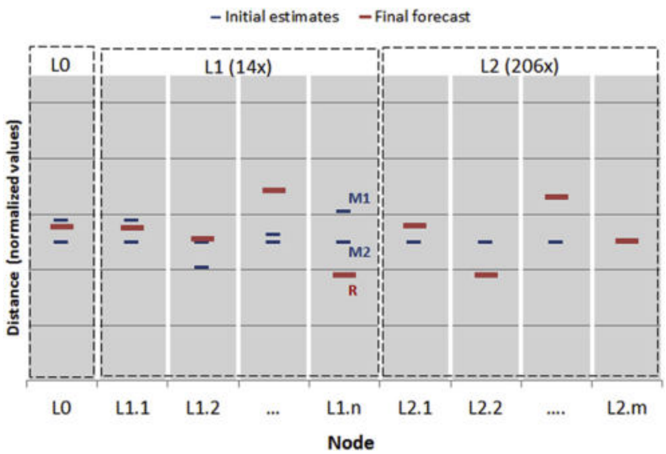

Fig. 4. The principle of model adjustments and final forecasted values.

inspired by the frequently used engineering principle of least squares of differences. The same technique is used in many other areas as summarised in Section 1.3.

A common denominator for the studies mentioned in this section is that the process they describe is a steady state, the topology of the model, mass and energy conservation equations (linear or non-linear) and that the covariance matrix of the measurement errors is directly known or can be determined from historical process data. The problem addressed in this paper differs in these regards. Instead of a rigorous process and an identified precision of measurements, a several forecasts are prepared for future values (possibly from different models/approaches) and the mass balance-like constraints correspond to certain consistency requirements (i.e. that the resulting forecasted values for higher hierarchical structures should equal the sum of the forecasts of its components). The variability of error for the different forecasts (i.e. in the data coming into the model) is unknown to us, hence the introduction of different weights is proposed.

Furthermore, weight parameters are derived and utilised to equalise the differences between nodes together with an area-hierarchical relationship approach. We have to emphasise that this approach allows us to also use other (e.g., more robust) optimisation criteria and structural modifications to the related constraints. This will be presented in forthcoming papers.

In the mentioned articles about data reconciliation, weights for each measurement are usually determined on the basis of the quality of the data measurement and collection, which is generally not always available. In our case, there are multiple models for one node. The data are tied to each other and each change affects all the other elements of the system for industrial processes. For each of measurements, errors are additionally present and the assumption is their mutual independence.

In the case of this paper, the production of waste is predicted, while the value is estimated separately in each location and it has no effect on other elements of the system. These values are tied up in the final model, where the data reconciliation is performed. The aim is to obtain the maximum from the historical data, while the desire is to exploit a suitable regression model for predicting a trend (usually non-linear). The key input parameters for the entire balance task are weights and their choice. This respects the character of the historical data with regard to their predictability (the existence of trends in historical data with minimal variability in the data). For this purpose, a new approach for evaluating the quality of the models is proposed.

3. Reconciliation model

Since extrapolations performed for all nodes are inconsistent in terms of mass conservation in a tree-like structure, reconciliation represents the next logical step. Data reconciliation is basically mathematical programming and it has been found by the authors to be a proper approach to deal with the initial estimates and their adjustments.

3.1. Mathematical model

Before building a model, the following notation is provided with a description:

<u>sets and indices</u>

$i \in I$ index of territorial units (nodes)
$d \in D$ index of particular data set (extrapolation models)
$h \in H$ index specifying particular area-hierarchical constraint

<u>parameters</u>

A_{hi} matrix reflecting the hierarchy of territorial units (nodes) and waste codes grouping
M_{id} two-dimensional parameter containing data for node i and data set d (values from extrapolation models for all nodes)
p_{id} $\{0,1\}$ indicator of data availability for node i and data set d
w_i^I weights for node i
w_d^D weights for data set d

<u>variables</u>

R_i amount waste for node i
e_{id}^+ positive part of an error in data for node i and data set d
e_{id}^- negative part of an error in data for node i and data set d

With this notation, we have built the following mathematical model:

$$\min_{\{e_{id}^+, e_{id}^-\}} \sum_{i \in I} \sum_{d \in D} w_d^D w_i^{I^2} \left(\left(e_{id}^-\right)^2 + \left(e_{id}^+\right)^2 \right) \tag{4}$$

Subject to

$$\sum_{i \in I} A_{hi} R_i = 0 \qquad \forall h \in H \tag{5}$$

$$p_{id}\left(M_{id} + e_{id}^+ - e_{id}^- - R_i\right) = 0 \qquad \forall i \in I, \forall d \in D \tag{6}$$

$$e_{id}^+, e_{id}^- \geq 0 \qquad \forall i \in I, \forall d \in D \tag{7}$$

$$R_i \geq 0 \qquad \forall i \in I \tag{8}$$

Eq. (4) represents the objective function, which summarises all positive and negative squared errors with weights w_i^I for each node and weights w_d^D for data set d, which are used to balance differences. The use of the square of the weight w_i^I and their construction is explained further on in Section 3.2.

Eq. (5) follows the idea that some lower nodes i (from L2 or L1) are part of a bigger node (from L1 or L0 respectively) and can also connect waste codes into groupings. This feature is included in matrix A_{hi}, where h defines a row and corresponds with a particular area-hierarchical constraint. Each row consists of numbers $\{-1;0;1\}$, where -1 defines a bigger node for an index i_L and $\{0;1\}$ number indicates if it belongs to it or not for the rest of nodes with corresponding indices.

There is Eq. (6) which connects the input data M_{id} with the decision variable R_i and the respective error between them, which is separated into a positive and negative part (e_{id}^+, e_{id}^-). The error is separated to allow easy implementations of the other forms of criteria, such as the sum of absolute values of errors. The binary indicator parameter p_{id} determines whether Eq. (6) with indices i and d is used or not, which is based on the parameter's data availability M_{id}, see Eq. (9).

Eq. (7) defines non-negative bounds on variables e_{id}^+ and e_{id}^- .

Eq. (8) states the variable R_i as non-negative.

The binary indicator parameter p_{id} is defined as follows:

$$\forall i \in I, \forall d \in D: \quad p_{id} = \begin{cases} 0, & \text{if } M_{id} \text{ not available or incorrect} \\ 1, & \text{otherwise.} \end{cases} \tag{9}$$

Use of the least square method is motivated by expert based advice and by experience with computer science heuristics in engineering. The least square method in its traditional applications, results in a description where the sum of the square distances between each of the input data (and the related forecasted or model-based value) is minimised. The application is illustrated in Fig. 4 for our case. The initial models (see M1, M2 and all other blue points in Fig. 4) obtained from TSA and RA are split into groups related to the points specified by year and location. In other words, each of the groups which is represented by a grey vertical bar in Fig. 4 is associated with one unknown parameter, which describes the point-related waste production. For example, M1 and M2 stand for initial estimates for production in a particular node. Considering each of the vertical bars, the initial estimates have to be balanced (corrected) to provide a final forecast, labelled R (the thicker red segment of the horizontal straight line). However, the task cannot be solved in a decomposed way for each of the bars due to the additional area-hierarchical constraints and related reasons mentioned above. It is handled by the above-mentioned optimisation model involving both balancing and the discussed constraints (Eq. (5)). In this context, Fig. 5 shows a simplified example of the unknown "hazardous waste amount", previously displayed as the first bar on the left in Fig. 4. The final corrected forecast (the R point on the horizontal axis) is obtained by balancing values from the two initial models (points M1 and M2). The result, R, is shifted to the left from M1 and M2 due to the effect of the area-hierarchical constraints. In our complex interconnected system, the correction in the first bar introduces secondary deviations in all the other bars. This effect is illustrated by the visualisation of a "penalty function based constraint relaxation" for the model in Fig. 5.

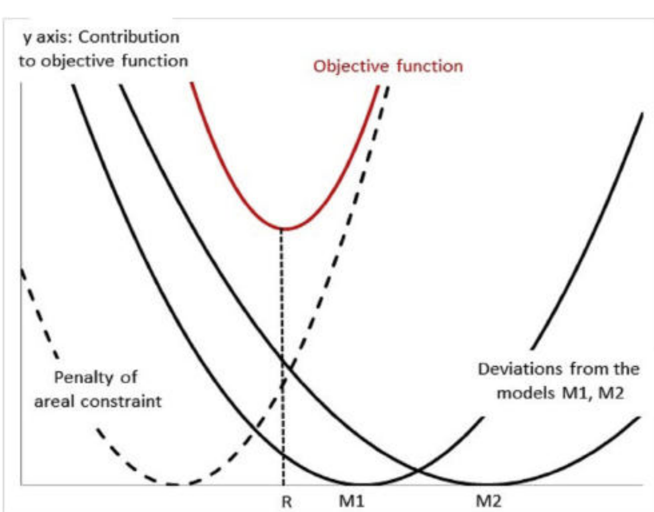

Fig. 5. The balancing principle illustrated as an optimisation task for specific node.

One important task is to discuss whether the optimal solution obtained by classical locally convergent algorithms for the model Eqs. (4)–(8) is a global one. It is a non-linear optimisation model. Because the node-related non-linear regression models are separated from the optimisation model in this text as the related computations are realised in advance, we can enlist the following facts:

Each optimisation problem can be characterised from the viewpoint of linearity and convexity. In the introduced model the sum of squared errors is minimised. These errors are the differences between the input data and the resulting modelled forecast. The minimised objective function is a quadratic convex (see Fig. 5 for an example). In addition, the areal constraints are linear.

For the above reasons, the minimization of a convex quadratic objective function (on a convex set specified by linear constraints) assures the global optimum, which was proved in Giaquinta and Modica (2012), for instance. Well-developed algorithms from the field of quadratic programming can be utilised to solve this problem.

3.2. Locality-dependent weights

With respect to the fact that territorial units have different areas, populations, and different waste productions, the estimated errors influence the objective function with various significance from a waste management specialist's point of view. The model without weights gives preference to the reduced error in bigger territorial units in order to minimalize square errors. Errors in smaller territorial units may increase, which is the impact of heteroscedasticity. For this reason, it is necessary to design a system of weights for individual errors in order to be able to minimise the impacts of these errors almost uniformly.

Based on these requirements, the goal in the weights construction process is to make all input data equally significant in the objective function. Several approaches have been applied to solving these problem and related tests have been performed. Finally, these weights were constructed in order to normalize errors from input data. In this case, the effect was achieved by using a square of weights w_i^I in the objective function (Eq. (4)) for each territorial unit, where the weights are the inverse of the average. The weights for all territorial units then look as follows:

$$\forall i \in I: \qquad w_i^I = \begin{cases} \dfrac{\sum_{d \in D} p_{id}}{\sum_{d \in D} M_{id}} & \text{for nonzero } \sum_{d \in D} M_{id} \\ 0, & \text{for } \sum_{d \in D} M_{id} = 0 \end{cases} \tag{10}$$

When utilizing weights according to Eq. (10), the importance of errors in the objective function gets normalized.

The weights w_d^D are generally set according to the quality of the extrapolation model.

3.3. Computational tests of proposed model

To illustrate and discuss benefit of the model, we present a special test case at the end of this section. For our explanatory example, we consider two input data sets specifying waste production. The hierarchical regional structure (see Fig. 1) is taken into the account as defined for the Czech Republic. This means 1 × L0, 14 × L1 and 206 × L2 (see supplementary materials). The first data set, M1, represents the original input data from 2015, as received from the authorities (presented in Section 4 and in supplementary materials). For each of L0 and L1 nodes, the areal constraint is satisfied in this dataset. The second data set, M2, is generated by incorporating a random error into M1. The multiplier from normal probability distribution, N(1, 0.01) was repeatedly generated and applied. As a result, areal constraints were violated since it is not possible to guarantee that the values in the L1 node are the sum of values for emulate random errors in all its L0 nodes. In fact, we are describing a multiplicative model. Areal constraints are violated for M2 but not for M1. Both M1 and one instance of M2 entered the core calculation. There were two initial estimates for every node and the algorithm was tested to see how it addresses these initial estimates to produce the final result, R.

Before analysing the result, let us briefly comment on the anticipated results and their interpretation. Considering each node separately, the average value presented by the dashed line between M1 and M2 would become the expected result without areal constraints. Both models are handled with the same weight and there is no other information in such reduced computations. On the other hand, different new relationships between data are involved (see Fig. 5) and some other results can be obtained that are more challenging for interpretation. There are four possible expected results, labelled R1 to R4 as visualised in Fig. 6.

The cases R1 and R2, those near to the original M1 data, are favoured. Such a result is better than a simple average. In addition, it ignores M2, which is loaded by error and prefers the original M1 value. On the other hand, R3 and R4 are not welcome as they are worse than the average of M1 and M2 (see K = 0.5 in Fig. 6). These cases are unwanted when large errors and, hence, distances between M1 and M2 appear. Let us emphasise that for small errors (i.e. small distances between M1 and M2 inputs), even R3 and R4 are not far away from M1, and hence, they are usually acceptable. The following expert-based empirical criterion was introduced to analyse the discussed problem:

$$K = \frac{(|R - M1|)}{\max(|R - M1|, |M2 - M1|, |R - M2|)}. \tag{11}$$

In the case of the result between M1 and M2, K will be around 0.5 and will indicate the model's choice difficulty.

The test results are displayed in Fig. 7 a), where M2 was generated repeatedly for 100 scenarios, followed by computations of optimal solution for model Eqs. (4)–(8) for each of scenarios. Fig. 7 a) and b) separately displays the results for regions L0 and L1 and L2 nodes.

The asymmetry of results in Fig. 7 a) vindicates the benefit of proposed model by detecting errors on L0 and L1 levels. Additional information from areal constraints is positively utilised L0 and L1 nodes, where it was available. Most results are located close to M1 in the region of R1 or R2, i.e. K is close to 0. When we have L2 nodes,

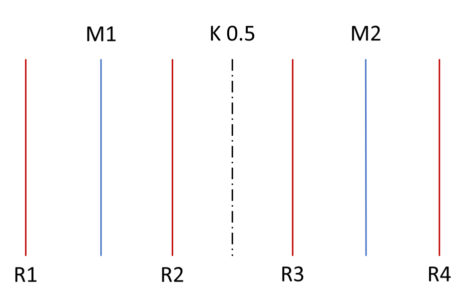

Fig. 6. A qualitative presentation of possible results.

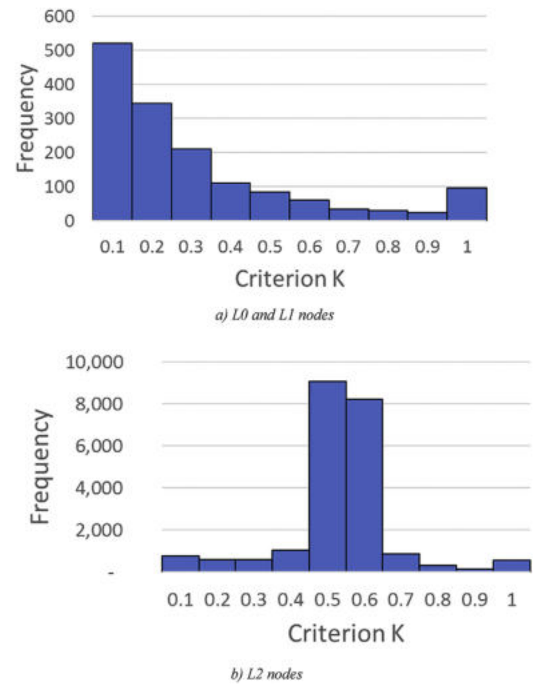

Fig. 7. An evaluation of the input data's set preference. a) L0 and L1 nodes. b) L2 nodes.

we can see the piece-wise uniform preference of the input data. The symmetry in the data is inherent and a typical 0.5 value was expected. There is no additional information provided by areal constraints for any L2 node since these nodes have no descendants. Therefore, both the M1 and M2 model are considered with similar importance. Only some L2 nodes were shifted from K = 0.5 if this helped to satisfy the areal constraint at L1 or L0 level (see the shift in R to the left in Fig. 5).

Without going into detail, we can also mention some other observations which resulted from the comprehensive testing:

- The increased standard deviations of the errors do not change the results qualitatively.
- If a systematic error is not included, then the M1 impact on the total error is about 23%.
- The largest impact on errors came from L0 and L1 levels, while L2 deals with smaller numbers and, hence, its influence is not so significant.
- The results of the test examples show that the introduced model Eqs. (4)–(8) is also suitable for cases containing systematic errors in data sets. A systematic error shifts the result while all areal constraints are still satisfied and the objective function is minimised.
- Based on our investigation, the key factor for the quality of a resulted forecast is the relationship between a random and systematic error. The empirical conclusion says that with the increase of systematic errors (compared to random errors), the tendency is more to the neutral position between the input data (K = 0.5).

There are three final comments to be made about our tests. First, in the examples where the data shift influenced by a systematic error was greater than the standard deviation of a random error, the results do not show better values than the average for M1 and M2's input data, without areal constraints. Secondly, some iteration results look better for the average of the input data (K > 0.5) is specific for particular generated data. Finally, when repeatedly generating from the same probability distributions, the average results (for K) would converge to 0.5, i.e., the qualitatively same R result for the resulting model and with an increasing importance of the random error (compared to a systematic error), the total results obtained from calculations are much better than the averaging of input data used overall.

4. Case study

Following on from the previous discussion about the proposed model and solution algorithm's behaviour for explanatory input data, we shall further focus on its use for a real-world case. The software implementation of the extrapolation approach and model introduced in Section 3 and related solution algorithm is called JUSTINE.

We may distinguish many types of hazardous waste according to its physical state, composition, heating value and hazardous traits (toxicity, etc.). In our specific case, we dealt with 380 categories, denoted by specific codes according to the European waste code system (European Parliament and the Council, 2000). Each of these fulfilled one of the hazardous properties defined by European Parliament and the Council (2008). Data were available for production in the last 7 y (time row 2009 to 2015) for each of the codes. The territory under investigation was the Czech Republic (L0), composed of 206 nodes, representing micro-regions (L2.X, where X denotes a specific micro-region). Each micro-region belongs to one of the 14 regions (L1.Y, where Y denotes a specific region). A time series for production of each code was available at the lowest considered level L2, i.e. for each of the micro-regions. To make the situation simpler and to avoid handling such a large amount of data, codes of similar properties were grouped into the following streams of hazardous waste (HW).

- HW for incineration (INC)
- HW for stabilization
- HW for biodegradation
- HW for a demulgation/neutralization line
- HW for incineration or stabilization
- HW for demulgation/neutralization or stabilization.

This grouping is represented in Fig. 3 by the upward move from the origin of the coordinate system and was done based on possible methods of treatment process for the individual code. There is no overlapping between the groups, i.e. each of the codes belongs to only one group. Since there is no space to provide expanded details on every group, one of the six groups, titled “INC HW for incineration” is used as an example in this case study and the subject of the following text. Other groups are mentioned too if it was a necessity to comment on results in a broader perspective.

4.1. Input data and pre-processing

For illustration, Table 1 shows input data for the INC stream. A full dataset for this stream is included in the supplementary materials. Total production is mentioned for the whole country, a selected region identified as L1.5 (Liberec region) and in all 10 descendants of this region in the year 2009–2015. Whereas production at country level decreased by 23% in this period, one can observe a completely different trend in the L1.5 region. Here production rose by 59%, especially due to a surge in the L2.86 micro-region (Liberec), which represents the most populated and industrialised city in the whole region. In contrary to municipal solid waste, the production of HW is dominantly bound to the industrial sector. There is no correlation between population and INC production. Nevertheless, we provide some basic information for comparison:

- The Czech Republic: 10.55 million citizens, gross domestic product GDP in 2015 was 169,000 EUR.
- L1.5 Region: population in 2015 was 439,640 citizens.

At first, the data related to Table 1 were verified and extreme values were identified. They were considered to be incorrect and were excluded from further computations. To avoid the subjective role of an expert's opinion in excluding these outliers, Dixon's statistical test was utilised and a significance level 0.05 was set. Original values are shown in parentheses (see Table 1). The values identified as extreme outliers were substituted by the average of neighbouring values. For example, the value for L2.63 (Jilemnice) in 2011 was replaced by the average values from 2010 to 2012, i.e., $(334 + 174)/2 = 254$. For the extreme values at the beginning or the end of the considered time period, the neighbouring value was used, e.g., the value for Turnov L2.177 from 2015 was replaced with the value from 2014.

Although Dixon's test was suitable for most of the case study's data, several limitations of its use appeared. The test fails for two significant outliers in the short-time series (see Table 2) and the same may happen in for the symmetry for minimum and maximum data outliers. The following Table 2 repeats the INC waste production data of Tanvald micro-region (L2.168), where Dixon's test did not help to identify the steep growth in the waste production. According to the results of the commonly used Q-Test, the experienced value was 0.181, which is well below the threshold value of 0.507 (for details see Dean and Dixon, 1951). Consequently, it influences the whole region L1.5. This impact on the waste production trend in the Liberec region puts the focus on the necessity to continue the discussion on data verification. In this case, the use of an outlier detection technique that is suitable for a TSA test is recommended.

4.2. Extrapolation

Extrapolation models for all territorial units, i.e. L0, L1 and L2 nodes, were generated, applying the non-linear regression model and iterative processes mentioned in Section 2.2.

In addition, the quality of extrapolation models Q_i according to Eq. (2) was evaluated for all time-series involved in our case study. The results confirmed the assumption of a better model fit for higher territorial units (L0, L1) compared to base nodes (L2) as was mentioned in section 2. Table 3 summarises Q_i to the average Q achieved at different territorial levels. Not only INC, but also all other streams mentioned at the beginning of this section were included in the assessment.

The value of Q_i may be further utilised as weights w_d^D associated with every initial estimate (M1) entering the calculation (see Section 3, Eq. (4)). Weighting was not applied in our case study as it is a subject for future computational development and testing. As mentioned in Section 2.2, the higher the Q_i, the better extrapolation model achieved and further used for constructing the weights w_d^D. A future research challenge is to establish a minimum threshold value of w_d^D. If this is not done, weights close to zero cause massive corrections by the reconciliation and, in fact, lead to unrealistic solutions.

4.3. Balanced results

The results of the extrapolation are summarised for our region in Table 4. Further details can be found in supplementary materials. First, initial guesses for 2020 were calculated by the extrapolation models. In addition to this, alternative initial estimates were

Table 1
Hazardous waste for incineration (INC); production data in the investigated region [t/y].

Node name	Node ID	Superior node	Year						
			2009	2010	2011	2012	2013	2014	2015
Czech Republic	L0	N/A	437,748	334,739	385,367	271,165	292,015	322,050	338,407
Liberec region	L1.5	L0 (CZE)	8,645	9,958	12,098	10,560	11,377	10,501	13,718
Česká Lípa	L2.21	L1.5	2,806	2,213	2,090	3,441	2,387	2,423	2,701
Frýdlant	L2.35	L1.5	717	1,049	2,419	979	1,749	1,610	1,121
Jablonec/Nisou	L2.57	L1.5	1,181	1,193	935	1,138	1,051	1,592	1,103
Jilemnice	L2.63	L1.5	235	334	254 (662)	174	225	174	261
Liberec	L2.86	L1.5	2,738	4,022	4,917	3,896	4,868	3,440	6,359
Nový Bor	L2.114	L1.5	235	263	170	162	252	213	268
Semily	L2.152	L1.5	154	372	269	238	301	227	518
Tanvald	L2.168	L1.5	95	72	128	127	118	318	373
Turnov	L2.177	L1.5	454	393	482	368	388	465	465 (951)
Železný Brod	L2.205	L1.5	29	47	26	37	38	40	62

Table 2
Dixon's test applied to INC HW production in the Tanvald micro-region L2.168.

Production [t/y]							Q-Test result	Q-Test threshold
2009	2010	2011	2012	2013	2014	2015		
95	72	128	127	118	318	373	0.181	0.507

Table 3
The average values of Q achieved for various territorial units.

Level	L0	L1	L2
Q value [-]	26.5	9.3	2.2

determined for territories at a higher level (L1, L0) in accordance with Section 2. In fact, M2 represents the sum of M1 forecasts for all descendant locations. Referring back to Fig. 3, the following sequence of the symbol may be used for M1 ($\sum$; $\rightarrow$) and M2 ($\rightarrow$; $\sum$). The difference between M1 and M2 was also evaluated for comparison.

In this case, there are nearly negligible differences of 0.2% and 0.7% between M1 and M2 for L0 and L1.5. However, there is no guarantee that similar positive results would be obtained in all L1 regions. This is documented in the next Fig. 8 and Fig. 9. Whereas for most of L1, the difference is very low (up to 2%), there are a few where the gap is significantly higher. The highest was identified in L1.11, where the difference is more than 50% (for details, see supplementary materials). At the same time, the quality of the M1 model expressed by Q is significantly lower compared to other L1 regions. (See Fig. 8 and supplementary materials).

The results confirm that it is not possible to secure, from a mathematical point of view that all models will equal due to the uncertainty-related reasons discussed above. This real-life data case justifies the application of the proposed computational tool, which can handle different models at different territorial units. Such a model was proposed in Section 3 and used on our data.

For our tree-like structure, there were 206 M1 models for 206 L2 locations. Their confidence level expressed by Q_i was different. In addition, forecasted values for 14 L1 and one L0 region entered the core-calculation. On the other hand, M2 models were not used as initial estimates since they were substituted by areal constraints (see Eq. (5)), which represents a mass conservation equation for a region and all of its sub-regions. It is of the same meaning as M2.

The calculation was made on a computer with Intel(R) Core(TM) i7- CPU @ 3.40 GHz.

Table 4
Forecasted production of INC stream for the year 2020.

Node name	Node ID	Superior node	Trend 2020 [t/y] M1 ($\sum$; $\rightarrow$)	Criterion quality M1 [-], Q	Trend 2020 [t/y] M2 ($\rightarrow$; $\sum$)	Difference M1 and M2	Prediction 2020 [t], R	Difference R and M1
ČR	L0	N/A	312,483	3.4	313,722	−0.2%	320,221	2.4%
Liberecký kraj	L1.5	L0	12,786	6.1	12,614	0.7%	12,542	−1.9%
Česká Lípa	L2.21	L1.5	2,694	1.1	N/A	N/A	2,679	−0.6%
Frýdlant	L2.35	L1.5	1,524	0.3	N/A	N/A	1,515	−0.6%
Jablonec/Nisou	L2.57	L1.5	1,236	1.3	N/A	N/A	1,229	−0.6%
Jilemnice	L2.63	L1.5	199	0.7	N/A	N/A	198	−0.6%
Liberec	L2.86	L1.5	5,378	0.9	N/A	N/A	5,347	−0.6%
Nový Bor	L2.114	L1.5	220	0.9	N/A	N/A	219	−0.6%
Semily	L2.152	L1.5	534	0.3	N/A	N/A	531	−0.6%
Tanvald	L2.168	L1.5	335	0.1	N/A	N/A	333	−0.6%
Turnov	L2.177	L1.5	427	2.7	N/A	N/A	425	−0.6%
Železný Brod	L2.205	L1.5	67	0.6	N/A	N/A	67	−0.6%

Note: The difference between models M1 and M2 was determined as $|M1 - M2|$ divided by the average from M1 and M2. This was also done for R and M1.

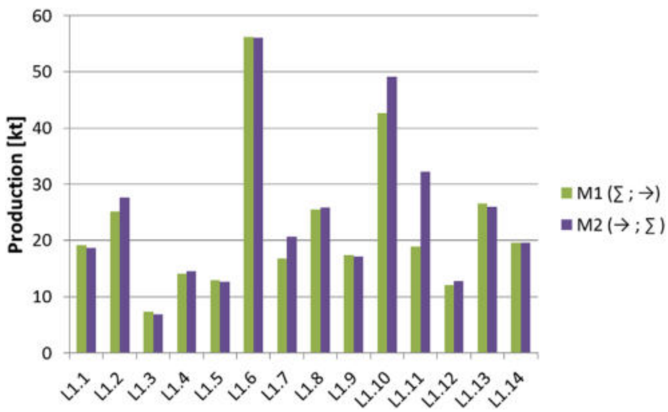

Fig. 8. The difference between the values of the models' prediction for L1.

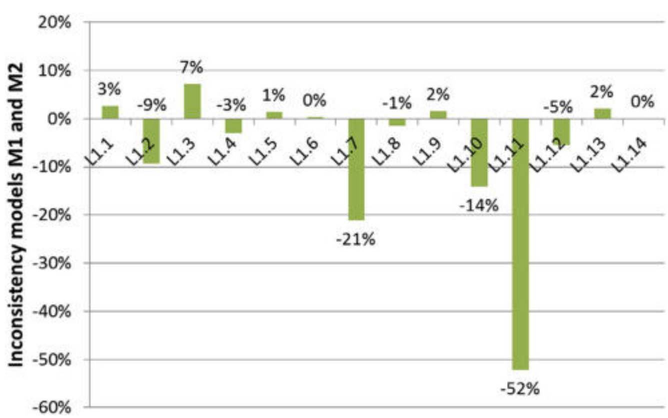

Fig. 9. Inconsistency in models M1 and M2 for L1 level.

The computational times for the areas (L0, L1 and L2 – together 221 nodes) and 6 categories (total 380 waste codes) were as follows:

- Forecasting future waste production (see Section 2) –386 $(380 + 6) \times 221$ $(206 + 14 + 1)$ computations performed in total with 10 different starting values with an average time of 0.543 s results in a total calculation time of 5.4 d.
- Reconciliation of forecasted values (see Section 3) – only one calculation with input data loading time 240 s and solving time 150 s.

The result (i.e. the final corrected forecast) for the studied region is depicted in Table 4 in column R. Initial estimates for L0 (country) were increased. Even though there was a very small difference between M1 and M2, this was necessary. In other words, much more serious deviations at L1 and L2 level were prevented. The results also revealed a significant correction minus of 1.9% for L1.5 (Liberecký kraj). As a result, corrections in all micro-regions belonging to L1.5 were kept at a minimum. The same correction of minus 0.6% results from applied normalisation by utilization of weights (see Eq. (10)).

Significant changes were made, as can be further examined in the supplementary materials. The corrections ranged from between 0% and 10% for 86% of nodes with average of 3%. The adjustments for the rest of nodes ranged from between 10% and 31.2% and were caused due to the especially low quality of extrapolation models.

Taking into account all types of waste, the corrections ranged from between 0% and 12% for 90% of nodes. There were 17 nodes where massive adjustments up to 30% were inevitable.

5. Conclusion and future work

A complex approach to handling the problem of spatially distributed, incomplete and uncertain data forecasting was proposed. It combines several steps which provide data quality assessment, trend series analysis (to provide extrapolated future values) and initial estimate corrections via a data reconciliation model.

The investigated problem was considered at different territorial levels (regions, micro-regions and their parts), where an organisational structure is described by a tree diagram. Areal data aggregation was performed in accordance with this tree diagram for both historical data and forecasted values. Considering the different levels of detail, additional constraints called “areal constraints” were introduced and used as a main element in the reconciliation model. These constraints, which are linear, represent mass conservation equations in the tree structure and they cause corrections of the forecasts in nodes where historical data and regression models are uncertain. The objective function to be minimised is based on the least square principle traditionally implemented in industrial data reconciliation.

The principles and benefits of the proposed model and related computational algorithm were implemented into software called JUSTINE and its benefits were explained through a case study in waste management, where future amounts of hazardous waste suitable for thermal treatment was forecasted for 206 micro-regions, 14 regions and the whole country of the Czech Republic. The case study revealed that extrapolations carried out at different levels of the hierarchical organisational structure lead to inconsistent forecasts. The differences were subject to the qualities of extrapolation models, which were measured by a newly developed criteria Q.

The proposed approach is suitable for many applications of supply-chain and network flow models where future amounts of commodities (the flow of which is optimised) are to be forecasted for a lot of nodes.

Our case study dealt with several waste streams. They were without interactions. The proposed algorithm also handles issues comprising several interconnected streams, where components overlap between streams. Municipal solid waste represents a good example as it consists of several fractions, such as paper, plastics, biowaste, mineral, and so on.

Future work will focus on extending the model to handle such a multi-commodity problem.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jclepro.2017.06.107.

References

Andow, D.A., Kiritani, K., 2016. Density-dependent population regulation detected in short time series of saproxylic beetles. Popul. Ecol. 58 (4) http://dx.doi.org/10.1007/s10144-016-0558-x.

Balaman, Ş.Y., Selim, H., 2016. Sustainable design of renewable energy supply chains integrated with district heating systems: a fuzzy optimization approach. J. Clean. Prod. 133, 863–885. http://dx.doi.org/10.1016/j.jclepro.2016.06.001.

Bazaraa, M.S., Sherali, H.D., Shetty, C.M., 2014. Nonlinear Programming: Theory and Algorithms, third ed. Wiley, Hoboken, New Jersey, USA. ISBN: 978-1-118-85756-4.

Chatzouridis, C., Komilis, D., 2012. A methodology to optimally site and design municipal solid waste transfer stations using binary programming. Resour. Conserv. Recycl. 60, 89–98. http://dx.doi.org/10.1016/j.resconrec.2011.12.004.

Crowe, C.M., Campos, Y.A.G., Hrymak, A., 1983. Reconciliation of process flow rates by matrix projection. Part I: linear case. AIChE J. 29 (6), 881–888. http://dx.doi.org/10.1002/aic.690290602.

Crowe, C.M., 1996. Data reconciliation - progress and challenges. J. Process Control 6 (2–3), 89–98. http://dx.doi.org/10.1016/0959-1524(96)00012-1.

Dean, R.B., Dixon, J.W., 1951. Simplified statistics for small numbers of observations. Anal. Chem. 23 (4), 636–638. http://dx.doi.org/10.1021/ac60052a025.

European Parliament and the Council, 2000. Commission Decision of 3 May 2000 Establishing a List of Hazardous Waste. Official Journal of the European Communities, 6.9.2000 (L 226). eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32000D0532&from=EN (Accessed 23 December 2016).

European Parliament and the Council, 2008. Directive 2008/98/EC on Waste and Repealing Certain Directives. Official Journal of the European Union. L 312, 19.11. 2008. eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2008:312:0003:0030:en:PDF (Accessed 23 December 2016).

Ferdan, T., Šomlák, R., Zavíralová, L., Pavlas, M., Frýba, L., 2015. A waste-to-energy project: a complex approach towards the assessment of investment risks. Appl. Therm. Eng. 89 (1), 1127–1136. http://dx.doi.org/10.1016/j.applthermaleng.2015.04.005.

Ghinea, C., Dragoi, E.N., Comanita, E.D., Gavrilescu, M., Campean, T., Curteanu, S., Gavrilescu, M., 2016. Forecasting municipal solid waste generation using prognostic tools and regression analysis. J. Environ. Manag. 182, 80–93. http://dx.doi.org/10.1016/j.jenvman.2016.07.026.

Ghiani, G., Laganà, D., Manni, E., Musmanno, R., Vigo, D., 2014. Operations research in solid waste wanagement: a survey of strategic and tactical issues. Comput. Oper. Res. 44, 22–32. http://dx.doi.org/10.1016/j.cor.2013.10.006.

Giaquinta, M., Modica, G., 2012. Mathematical Analysis Foundations and Advanced Techniques for Functions of Several Variables. Birkhäuser, USA, New York. ISBN: 978-081-7683-108.

Hamilton, J.D., 1994. Time Series Analysis. Princeton University Press, Princeton, New Jersey, USA. ISBN: 9780691042893.

Intharathirat, R., Salam, P.A., Kumar, S., Untong, A., 2015. Forecasting of municipal solid waste quantity in a developing country using multivariate grey models. Waste Manag. 39, 3–14. http://dx.doi.org/10.1016/j.wasman.2015.01.026.

Jiang, X., Liu, P., Li, Z., 2014. Gross error isolability for operational data in power plants. Energy 74, 918–927. http://dx.doi.org/10.1016/j.energy.2014.07.071.

Korpela, T., Suominen, O., Majanne, Y., Laukkanen, V., Lautala, P., 2016. Robust data reconciliation of combustion variables in multi-fuel fired industrial boilers. Control Eng. Pract. 55, 101–115. http://dx.doi.org/10.1016/j.conengprac.2016.07.002.

Manenti, F., Grottoli, M.G., Pierucci, S., 2011. Online data reconciliation with poor redundancy systems. Ind. Eng. Chem. Res. 50 (24), 14105–14114. http://dx.doi.org/10.1021/ie202259b.

Martins, M.A.F., Amaro, C.A., Souza, L.S., Kalid, R.A., Kiperstok, A., 2010. New objective function for data reconciliation in water balance from industrial processes. J. Clean. Prod. 18 (12), 1184–1189. http://dx.doi.org/10.1016/j.jclepro.2010.03.014.

Özyurt, D.B., Pike, R.W., 2004. Theory and practice of simultaneous data reconciliation and gross error detection for chemical processes. Comput. Chem. Eng. 28 (3), 381–402. http://dx.doi.org/10.1016/j.compchemeng.2003.07.001.

Samanlioglu, F., 2013. A multi-objective mathematical model for the industrial hazardous waste location-routing problem. Eur. J. Oper. Res. 226 (2), 332–340. http://dx.doi.org/10.1016/j.ejor.2012.11.019.

Šomplák, R., Pavlas, M., Kropáč, J., Putna, O., Procházka, V., 2014. Logistic model-based tool for policy-making towards sustainable waste management. Clean Technol. Environ. Policy 16, 1275–1286. http://dx.doi.org/10.1007/s10098-014-0744-5.

Sun, S., Huang, D., Gong, Y., 2011. Gross error detection and data reconciliation using historical data. Procedia Eng. 15, 55–59. http://dx.doi.org/10.1016/j.proeng.2011.08.012.

Tan, R.R., Aviso, K.B., Foo, D.C.Y., 2017. P-graph and Monte Carlo simulation approach to planning carbon management networks. Comput. Chem. Eng. http://dx.doi.org/10.1016/j.compchemeng.2017.01.047 (in press), Corrected Proof.

Valdetaro, E.D., Schirru, R., 2011. Simultaneous model selection, robust data reconciliation and outlier detection with swarm intelligence in a thermal reactor power calculation. Ann. Nucl. Energy 38 (9), 1820–1832. http://dx.doi.org/10.1016/j.anucene.2011.06.001.

Vance, L., Heckl, I., Bertok, B., Cabezasa, H., Friedler, F., 2015. Designing sustainable energy supply chains by the P-graph method for minimal cost, environmental burden, energy resources input. J. Clean. Prod. 94, 144–154. http://dx.doi.org/10.1016/j.jclepro.2015.02.011.

Varbanov, P., Fiedler, F., 2008. P-graph methodology for cost-effective reduction of carbon emissions involving fuel cell combined cycles. Appl. Therm. Eng. 28 (16), 2020–2029. http://dx.doi.org/10.1016/j.applthermaleng.2008.02.007.

Vocciante, M., Mantelli, V., Aloi, N., Dovì, V.G., Reverberi, A.P., 2014. Process data reconciliation in the presence of non-uniform measurement errors. Clean Technol. Environ. Policy 16 (7), 1287–1294. http://dx.doi.org/10.1007/s10098-014-0824-6.

Weiss, G.H., Romagnoli, J.A., Islam, K.A., 1996. Data reconciliation - an industrial case study. Comput. Chem. Eng. 20 (12), 1441–1449. http://dx.doi.org/10.1016/0098-1354(95)00241-3.

Xiang, Z., Daoliang, L., 2007. Forecasting municipal solid waste generation based on grey fuzzy dynamic modelling. In: 3rd IASME/WSEAS International Conference on Energy, Environment, Ecosystems and Sustainable Development, pp. 36–41. Agios Nikolaos, Greece, July 24-26. wseas.us/e-library/conferences/2007creteeeesd/papers/562-088.pdf (Accessed 23 December 2016).

Yong, J.Y., Nemet, A., Bogataj, M., Zore, Ž., Varbanov, P.S., Kravanja, Z., Klemeš, J.J., 2016. Data reconciliation for energy system flowsheets. Comput. Aided Chem. Eng. 38, 2277–2282. http://dx.doi.org/10.1016/B978-0-444-63428-3.50384-2.

Zhang, Z., Shao, Z., Jiang, P., Chen, X., Zhao, Y., Qian, J., 2010. Sequential sub-problem programming strategies for data reconciliation and parameter estimation with multiple data sets. In: 49th IEEE Conference on Decision and Control. http://dx.doi.org/10.1109/CDC.2010.5717954.

Zhao, J., Huang, L., Lee, D.-H., Peng, Q., 2016. Improved approaches to the network design problem in regional hazardous waste management systems. Transp. Res. Part E Logist. Transp. Rev. 88, 52–75. http://dx.doi.org/10.1016/j.tre.2016.02.002.

Příloha 3: Článek [A4] Review on waste generation modeling and forecasting methods

Review on waste generation modeling and forecasting methods

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Abstract

Strategic plans for waste management require as a primary data source information on the current and future waste generation. Over the years, various approaches and methods for waste generation modeling have been presented and applied. This review provides a summary of the tasks requiring information on waste generation which are most frequently handled in waste management. More than 300 publications were examined in detail, and all tracked attributes were included in the appendix. A general step-by-step guide to waste generation forecasting, comprising data preparation, pre-processing, processing, and post-processing, was proposed. The problems occurring in the individual steps were specified, and the authors' recommendations for their solution were provided. Recommendations were also made regarding the suitability of individual modeling approaches with respect to the actual application and data availability. Researchers and stakeholders can use this document as a supporting material when deciding on a suitable approach to waste generation modeling or waste management plans.

List of abbreviations:

Abbreviations	Explanation
ANN	Artificial neural networks
ANOVA	Analysis of variance
ARIMA	Autoregressive integrated moving average
ARMA	Autoregressive moving average
BIO	Separated bio-waste
CA	Correlation analysis
C&D	Construction and demolition waste
DT	Decision tree
EU	European Union
FL	Fuzzy logic
GDP	Gross domestic product
GIS	Geographical information systems
GLA	Separated glass
GLM	Generalized linear model
GM	Gray model
GR	General regression

MLR	Multiple linear regression
MAE	Mean absolute error
MAPE	Mean absolute percentage error
MMW	Mixed municipal waste
MSW	Municipal solid waste
P	Problem
PAP	Separated paper
PLA	Separated plastics
R	Recommendation
R^2	Coefficient of determination
SARIMA	Seasonal autoregressive integrated moving average
SD	System dynamics
SEP	Separated waste
SVM	Support vector machine
SWOT	Strengths, weaknesses, opportunities, and threats analysis
TSA	Time series analysis
WM	Waste Management

1. Introduction

In developing countries, the prevailing goal still is to dispose of waste, while in developed countries (e.g., the ones in the EU), there is an effort to process the waste more sustainably. The preferred ways of waste management (WM) and disposal in the EU have been stipulated in *Waste Management Hierarchy* (Directive 2008/98/EC) to make use of the waste potential. The EU member states have been implementing the necessary legislative changes, and the next step is to adapt the existing WM systems to meet the respective objectives. Strategic plans for the modernization and construction of waste collection and processing infrastructure require as a primary data source information on the generation and composition of waste, including their expected development. The aim is to create a WM system that is sustainable from both economic and environmental points of view. In response to this situation, there is a growing number of publications dealing with waste generation modeling. This review aims to summarize the available modeling approaches and discuss their suitability for different applications in WM.

1.1. Application-based targeting

WM is a very complex field in which many tasks and problems can be encountered in decision-making. Each task is unique in nature, but all stages of the process require specific input data differing mainly in time or territorial detail. The most challenging parameters are the generation rates of different types of waste and waste composition (mostly MMW or separately collected waste e.g., paper, plastic). Therefore, the tasks are divided into three logical blocks, where their characteristics are described to create models associated with the current or future waste quantities.

1.1.1. Waste management legislation and policy

Proper specification of recycling or waste prevention targets included in legislation requires reliable long-term knowledge on waste generation and treatment. Historical data can identify the links of various socio-economic and demographic factors to WM development (Gardiner and Hajek, 2020). The connections identified may reveal potential societal changes and consequently, positively affect waste generation trends and processing methods.

In the context of long-term forecasting (5-20 years), the Circular economy package of the EU is relevant because it sets recycling targets for municipal solid waste (MSW) until 2035 (Directive EU 2018/851) and landfill restrictions (Directive EU 2018/850). At the country level, data are usually aggregated annually, and as such are suitable for forecasting. The disadvantage often is the availability of only short historical data series, due to annual data records. The only reasonable alternative for forecasting is finding the trend that the data follow (Sec. 3.3.2). Ghinea et al. (2016) considered multiple functions for describing trends, of which the S-curve proved to be the most suitable for MSW. Ayeleru et al. (2018) used a linear dependence to describe the expected city-level rate of generation of MSW. Other available works dealt with very complex models which are not suitable for forecasting. A complete overview is in the Appendix A (Sec. 2.1).

Modeling waste generation makes it possible to compare mostly very ambitious legislative goals with forecasted values. The most significant shortcoming of the methods for longer-term estimation of waste generation is the failure to consider potential interventions in the waste system itself. If the forecast is not in line with the goals, then the projections are modeled. This can reveal the potential for changes in individual territorial units. Within the projections, the forecasts are modified to achieve the set target (Mena-Nieto et al., 2021).

1.1.2. Strategic decision-making on waste management infrastructure

Strategic decision-making in WM concerns the planning and implementation of long-term projects for facility construction (Tomić et al., 2017). Compared to the previous part *Waste management legislation and policy*, waste generation forecasting focuses usually on the regional level. Data at the regional level are often available on an annual basis and estimating trends from historical data is possible. However, data and trends also usually feature significant volatility, which makes forecasting more complicated and less accurate. It is good to keep in mind the conditions in the surrounding regions that may affect the planned project (Ilbahar et al., 2021). A hierarchical territorial division can ensure consistent forecasts between regions and the entire country (Pavlas et al., 2020). The definition of possible scenarios for future waste amounts takes place in strategic planning. Such scenarios arise from external interventions into the WM system, and they allow evaluating the impact on the planned projects' sustainability (Bramati, 2016).

Significantly shorter time horizon is sufficient for collection strategy planning due to the relatively short service life of collection containers and frequent legislative changes (Ghiani et al., 2012). Models for collection planning usually focus on the daily or weekly data sets. This type of data is common for cities and municipalities, where monitoring is done in greater detail and during longer time horizons.

To ensure financial and technical sustainability of a project, it is necessary to assume during its evaluation that several parameters are uncertain, including the generation rate and the waste composition (Nie et al., 2007). The current state and outlook for the area of interest are needed to site a new facility or collection infrastructure with a well-chosen capacity appropriately.

1.1.3. Operational decision-making in waste management

The last point is related to the planning of daily operations. Container-level data are needed in waste collection applications utilizing routing models (a summary of routing problems and their application was presented by Koç et al. (2016)), which may feature various targets. A typical representative is dynamic collection planning where the waste quantities at individual collection points are estimated each day. On the other hand, when creating a new collection plan, weekly or monthly data are required to properly set the collection frequency. The frequency itself depends on both waste properties and the capacities of collection points. Collection planning is closely related to the siting of collection points, which was discussed in detail in the previous sections.

1.2. Tasks encountered in waste generation modeling

When building waste generation models, it is necessary to distinguish whether an estimate of the current or the future generation rate is made. The differences in terminology regarding prediction, forecasting, and projection are provided in the following sections.

1.2.1. Prediction

Prediction of waste generation is used to describe the current or future situation. Estimating the current waste generation rate is essential to define the links in the system and develop the models for other territorial units. These links can be used to model expected future waste generation. A common application is modeling of waste generation rate depending on various socio-economic, demographic, and other factors. The pitfalls of such models were described by Rosecký et al. (2021) in more detail. The main weakness is that the links in the system can change over time. Problems may occur when the links ale modeled using all historical data without regard to their temporal variance. Consequently, this may impact the quality of future predictions of the respective models.

A common mistake also is to build models using absolute data without standardization. Then multicollinearity often is observed, which negatively impacts the obtained results. Also, the data yielded by a WM model should always include information on the uncertainty, e.g., via confidence intervals.

1.2.2. Forecasting

Forecasting, sometimes termed prognosis, concerns exclusively the estimation of future development. Most forecasts in WM involve waste generation. Other forecasting targets (waste composition, waste treatment) are rare. When making a forecast, it is necessary to remember that inferring future development based on current or historical data always is a difficult – and often largely unsolvable – task.

Forecasting models assume that the respective parameters will evolve similarly to their past development. The primary feature of a forecast is that no change in the current conditions is expected. Data from even short-term forecasts must be evaluated carefully. Longer-term forecasts are more indicative in terms of what the development of waste generation might look like if nothing changes (e.g., without any changes being made to the legislation). When it comes to waste generation, the problem is further compounded by the fact that often only data sets covering very short time ranges are available. If sociology-, economics-, or demography-related data from a "prediction" model are to be used, it is imperative that such prediction is of sufficient quality.

Forecasts also should consider the links between the waste streams, which are interrelated (higher generation of separated waste leads to lower amount of mixed municipal waste (MMW) etc.). A model should always allocate a certain number of data points at the end of the time series for verification purposes. Even in forecasting, the results should include information on uncertainty.

1.2.3. Projection

Projections also deal with the estimation of future development; however, in contrast to forecasting they assume that a change will happen in the boundary conditions (legislative, technological progress). These conditions, which affect waste generation, cannot be forecasted. Therefore, projections are often future scenarios given the specific boundary conditions chosen by the authors. Scenarios can be created with respect to the objectives of the WM, but deviations from the corresponding forecast should be as slight as possible. Due to territorial hierarchy, it is appropriate to consider the division of national targets (i.e., individual regions according to their potential for change). Monotony in terms of waste generation potential should be maintained. Possible links among waste fractions should also be taken into account.

1.3. Research questions

The underlying goal of this review is to gather supporting material for the development of a comprehensive waste generation model, especially with regard to its application (see Sec. 1.1). Before studying the available literature, research questions that are addressed in the following text are formulated.

- What are the common shortcomings of the available data, and how many data points in a time series are sufficient?

- What are the goals of individual models (prediction, forecasting, projection; see Sec. 1.2) and their weaknesses?

- Can prediction models be used to estimate future data? Under what conditions?

- What approaches and methods are suitable for certain use applications?

- How to implement changes and interventions in WM (legislative interventions, changes in data reporting methodology, introduction of new waste catalogue numbers) within mathematical models?

- Can general recommendations be formulated for other parameters such as territorial division, waste fractions, forecasting period length, etc.?

The actual review methodology is described in Sec. 2. A detailed overview of the studied publications can be found in Appendix A. The remaining sections of this paper deal with the results and conclusions of the review. Sec. 3 then summarizes the review of modeling processes (preparation, pre-processing, processing, post-processing) in the form of problems and authors' recommendations. This is the main benefit of this contribution. A SWOT analysis for individual models is provided for each method in Appendix B. A brief summary is provided in Sec. 4, including the suggestions regarding further research directions.

2. Literature review

First, attention was paid to previously published review papers on the discussed topic (see Tab. 1), with the aim being to prevent repetition.

Tab. 1: Overview of previous reviews on waste generation modeling

Reference	Time range	Number of publications	Comment

(Beigl et al., 2008)	Until 2005	45	Criteria: regional scale, MSW waste streams, independent variables, modeling methods.
(Cherian and Jacob, 2012)	Until 2011	9	Criteria: regional scale, MSW waste streams, independent variables, modeling methods, socio-economic factors.
(Kolekar et al., 2016)	2006-2014	20	Criteria: modeling methods, territorial division, amount and frequency of time-dependent data, independent variables, waste stream.
(Goel et al., 2017)	1972-2016	106	Classification into typical (multiple linear regression – MLR, time-series analysis – TSA, factor analysis) and unconventional (fuzzy methods, artificial neural networks – ANN) approaches.
(Abdallah et al., 2020)	2004-2019	85	Artificial intelligence in WM, identified six applications; described multiple models incl. hybrid ones.
(Guo et al., 2021)	2003-2020	40	Machine learning methods in organic solid waste treatment.
(Xu et al., 2021)	2010-2020	177	ANN models, categories of review scales: macroscale (mainly focused on waste generation), mesoscale (waste properties and process parameters), meso-microscale (waste process efficiencies), microscale (reaction mechanisms or microstructures).

Older reviews clearly specify the as-of-yet unresolved research gap, while the more recent works – e.g., (Abdallah et al., 2020), (Xu et al. 2021), or (Guo et al., 2021) – deal exclusively with artificial intelligence and do not consider other methods. Because the works by Cherian and Jacob (2012) and Kolekar et al. (2016) described the target periods with only a modest number of published models, a new review for that period has been conducted in the present paper. Goel et al. (2017) presented a relatively extensive review, but further applications require more elaboration in the context of waste fractions. The review by Beigl et al. (2008) is taken as the starting point, the publication is ca. 15 years old and, therefore, an update is due. The review (Beigl et al., 2008) summarizes the methods used until 2005, but there are no described new approaches that have not been addressed until then. It is therefore not necessary to study the contributions until 2006, this period has already been well covered by Beigl et al. (2008).

The following text is especially beneficial because it contains detailed modeling recommendations for specific WM applications. The criteria utilized in Beigl et al. (2008) have been kept and several new parameters (the amount of data, waste types, etc.) have been added. The main databases queried were ScienceDirect and Scopus with the keywords being: “msw prediction“, “msw forecast“, “waste prediction“, “waste forecast“, “waste generation“, “waste production“, “waste forecasting“, “municipal waste prediction“, “municipal waste forecast“. A total of 308 articles were identified for the detailed examination.

2.1. Summary of the results

This study evaluated the 308 selected publications from several points of view. A detailed overview of all monitored criteria is available in *Appendix A*, the main text contains references only to the fundamental publications that the authors have chosen for the citation in individual parts of the text. The *Appendix A* is structured as follows:

- Publication details (columns B–H): title, authors, journal, year, nationality according to the affiliation of the main author, number of citations, keywords.

- Origin of data (columns I–K): state, continent, the source of WM data.

- Data details (columns L–R): number of dependent variables, time interval, number of time intervals, territorial division, number of territories.

- Forecasting (columns S, T): forecasting (yes/no), forecasting period length.

- Waste streams (columns U–AK): MSW, MMW, bio-waste, paper, plastics, glass, etc.

- Influencing factors (columns AL–AT): influencing factors (yes/no), population size, education, age, income, gross domestic product (GDP), etc.

- Utilized methods (columns AU–BF): LR, general regression (GR), TSA, ANN, etc.

- Processing (columns BG–BH): pre-processing (yes/no), verification of assumptions for LR.

- Model quality (columns BI–BM): coefficient of determination (R^2), mean absolute error (MAE), mean absolute percentage error (MAPE), etc.

2.1.1. Data pre-processing

Pre-processing is included in 26% of the papers, but it is often introduced very briefly without a detailed description of the actual procedures used. Only 50 papers out of 308 involved pre-processing and simultaneously evaluated the quality of the developed model. About 34% of these 50 articles with pre-processing used weekly or daily data (Blázquez-Garcia et al., 2020) and about 44% of articles with pre-processing used annual data. However, the models with annual data are usually created on many territorial units, where again it was possible to use common methods such as z-score (Aggarwal et al., 2019), Grubb’s test, or Dixon’s test (De Muth, 2019). Outliers occurring in short time series often were dealt with expertly. The authors’ recommendations regarding pre-processing of short time series are provided in Sec. 3.2. It should be mentioned that pre-processing did not address changepoint detection in the studied papers although it can have a major impact on the model.

2.1.2. The detail of a dataset

The selected publications focused on different waste types as shown in Fig. 1. The most frequently modeled component was MSW at 53%. This was followed by the separately collected waste with high potential for material recovery (paper, plastics, glass, bio-waste) with a frequency of about 16%. Separated waste (SEP) was also modeled as one stream, i.e., the separately collected but not individually distinguished components of MSW. It is worth noting that a relatively small percentage of the publications (7%) focused on MMW generation (terminology is not uniform, in some publications also called residual waste). The reason might have been that this stream is quite difficult to model due to the relationship between MMW and sorted components.

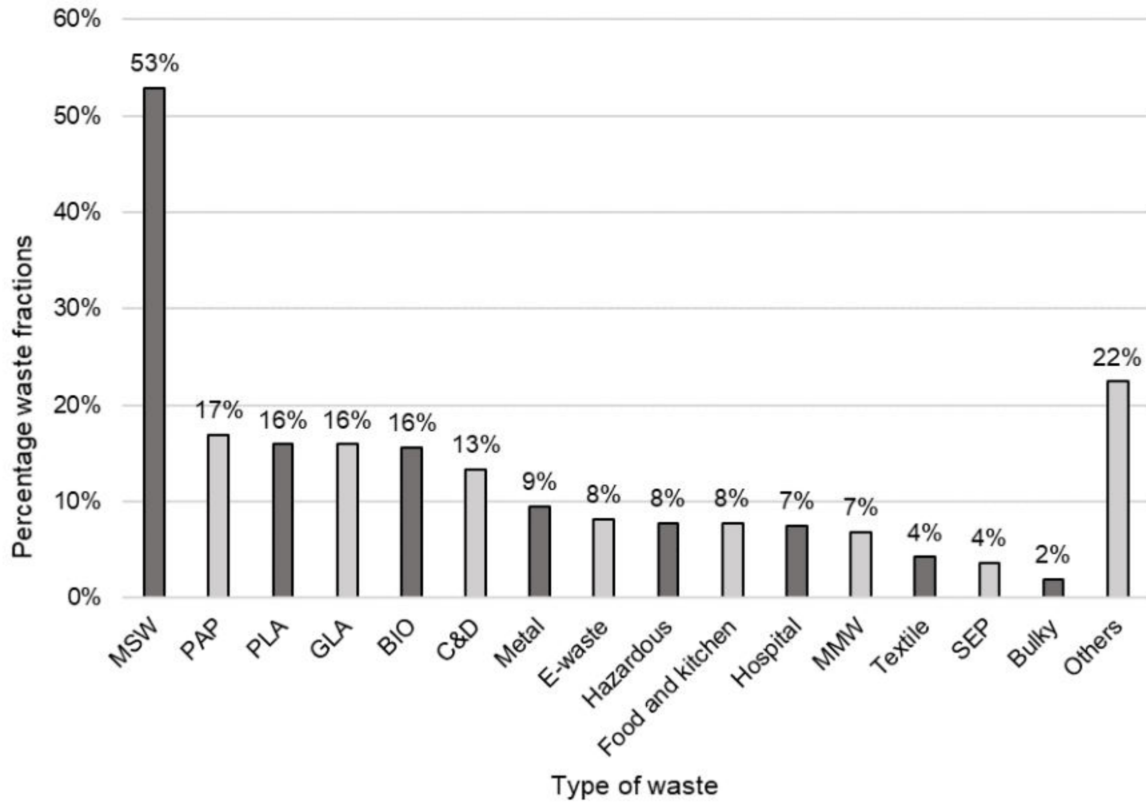

Fig. 1: Waste types studied in the evaluated publications

Legend:

MSW – municipal solid waste; PAP – paper; PLA – plastics; GLA – glass; BIO – bio-waste; C&D – construction and demolition waste; MMW – mixed municipal waste; SEP – separated waste

The following territorial divisions were monitored: state, region, municipality, household, building, hospital and "other" (which included all the remaining levels due to their infrequent occurrence). Some territorial divisions were directly related to specific waste types, e.g., building (construction and demolition waste), hospital, hotel, or aircraft. Fig. 2 shows the relationship of the territorial detail and the input data acquisition method. Regarding the household-level data (waste generation and socio-economic information), they usually were obtained via surveys, interviews, or from already existing databases (compiled during earlier similar surveys or censuses). Waste reports were mostly used as the source for collecting data for hierarchically higher levels. As already mentioned, the level of detail of the territorial division and the data source was related to data frequency. Household data were most often available on the daily basis (more than 60%). This was because they came from surveys in which the produced waste commonly was collected from a sample of households and weighed every day. National-level data, on the other hand, were available yearly in 90% of cases.

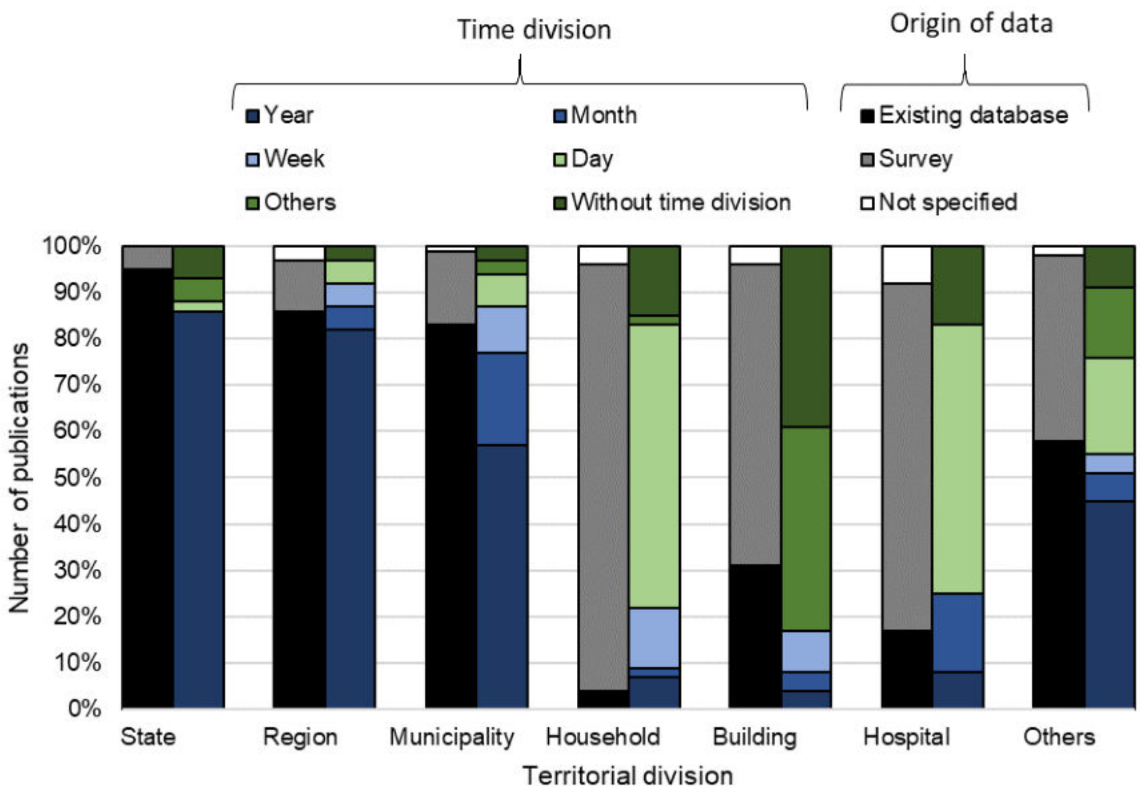

Fig. 2: The relationship between data origin and territorial division (left column in each pair), and time and territorial division (right column)

2.1.3. Approaches applied

The values indicate in Fig. 3 the shares of papers utilizing each method (please note that some articles employed multiple methods). The most common method – appearing in 32% of the studies – was MLR. In this case, the waste generation was estimated based on the available sociological, economic, demographic, and other data. ANN, which belongs to artificial intelligence methods and has become increasingly popular in recent years, was the second most used (27% approach), followed by the simple descriptive approach and GR (e.g., generalized linear model – GLM, analysis of variance – ANOVA, or nonlinear regression). Some publications also featured other methods than those listed explicitly in Fig. 3 (grouped under “Others”). These included, for instance, mass balance, the theory of planned behavior, or models based on geographical information systems (GIS). The colors in the respective composite bar chart indicate whether the models described in the evaluated papers were predictive or included forecasting as well.

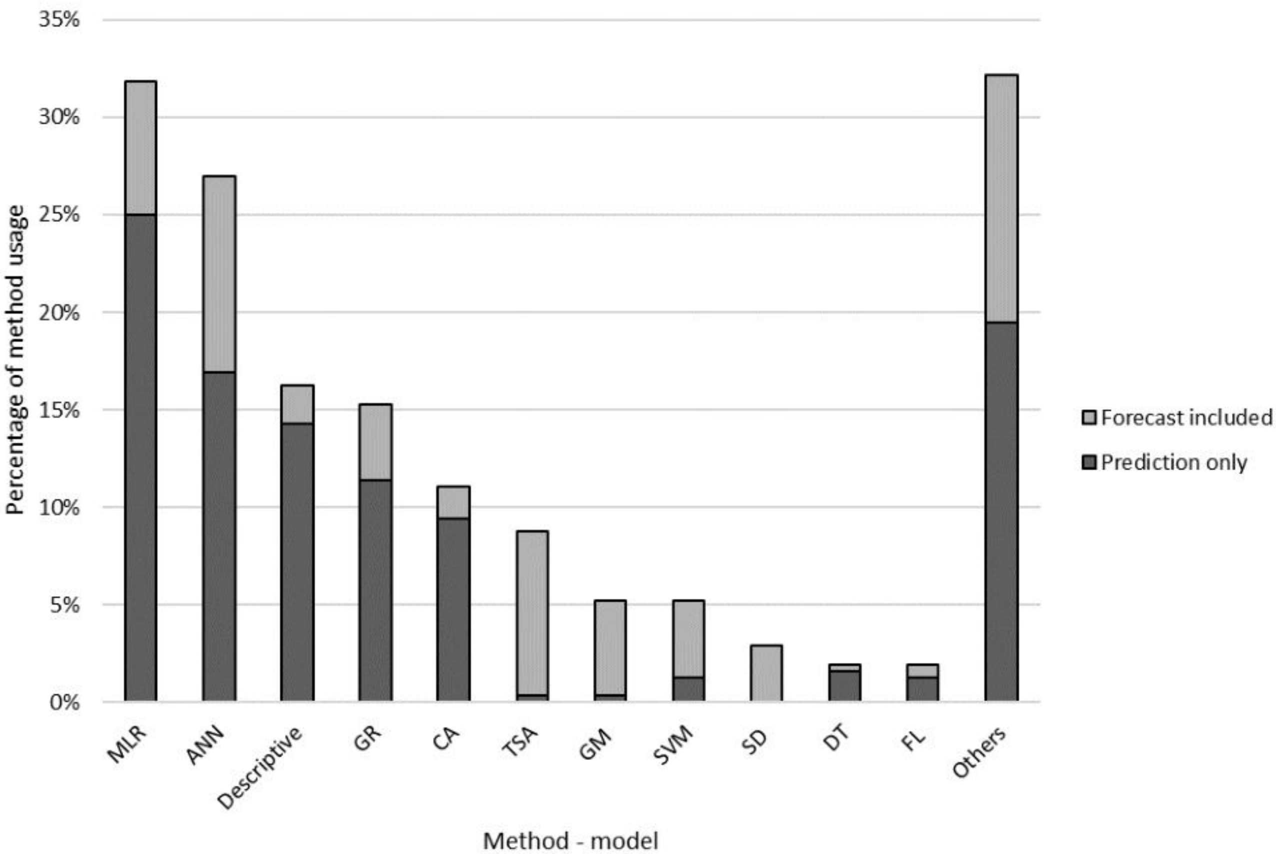

Fig. 3: Distribution of methods used in the evaluated studies

Legend:

MLR – multiple linear regression; ANN – artificial neural network; GR – general regression; CA – correlation analysis; TSA – time series analysis; GM – gray models; SVM – support vector machine; SD – system dynamics; DT – decision trees; FL – fuzzy logic

Several models were tested by Ibáñez et al. (2011), of which the most accurate results were obtained for the utilized data set using gamma regression (GLM). Karpušenkaitė et al. (2016) tested different models for a specific waste fraction (namely, medical waste), and different time series lengths. The result was that no universally applicable model exists, but GLM models provided the best results for regional-level data. Kannangara et al. (2018) compared DT and ANN and found that ANN achieved higher accuracy, while the results from DT could be interpreted more clearly. According to Xu et al. (2021), 45% of WM papers using ANN worked with at most 100 data points, but ANN have still become popular in WM. Petridis et al. (2016) compared different models for time-series and autoregressive moving average (ARMA) provided the most accurate results but Box-Jenkinson methodology (ARMA, autoregressive integrated moving average – ARIMA, and their modifications) achieves good results on long time series. Ghinea et al. (2016) presented S-curve models as the most suitable option for trend analyses depending on the data available.

A different route is followed by hybrid models which combine advantages of the individual methods used. Xu et al. (2013) showed that the combination of seasonal ARIMA (SARIMA) and grey system was robust enough to fit the seasonal and annual dynamic behavior of waste generation. The methodology proposed by Lu et al. (2016) combined the S-curve trend and ANN, where for future construction projects, the S-curve trend was linked to project characteristics via ANN forecasting of waste generation. Trend analysis, followed by correcting estimates to maintain hierarchical links in the system, was supplemented by data reconciliation in the methodology presented by Pavlas et al. (2017).

The selection of suitable methods depends mainly on the nature of the input data and objectives of the model. Evaluation of model quality presented in various studies is problematic because of different input data quality, verification of compliance with method assumptions, or model refitting risk. However, generally it holds true that higher-quality models can be obtained at higher levels of territorial division due to lower data variability.

The decision process for method selection

The selection of a suitable modeling method depends on the target application. For the applications presented in Sec. 1.1, it is advisable to use models from Tab. 2. This table shows only forecasting and projection models, which are necessary for planning of the future directions taken in WM. For *Waste management legislation and policy tasks* (Sec. 1.1), long-term forecasts at lesser territorial and temporal detail will be more advantageous. The opposite is true in the case of *Operational decision-making in waste management* (Sec. 1.1), that is, short-term forecasting, which will usually require more detail in terms of territory and time. If dynamic planning is required, then it is necessary to take into account also the computational complexity of the methods.

Among the more than 300 evaluated studies, no GLM model was found to be applied to forecasting. In the case of methods describing waste generation via influencing factors (MLR, GLM, DT, ANN), it is necessary to forecast all influencing factors in advance. This significantly limits the usability of the mentioned methods because forecasts of influencing factors are unavailable or of poor quality. As for TSA, these are mainly trend models for long-term planning. Short-term time series information, such as seasonal effects and autoregression, are essential for operational decision-making.

Tab. 2: Representative model types for individual applications

Application	Most common features	Model	Reference
Waste management legislation and policy	- long-term forecasting - smaller data frequency (e.g., years) - larger territorial units (e.g., state)	MLR	(Andersen et al., 2012) (Hřebíček et al., 2017) (Awasthi et al., 2017)
		ANN	(Chhay et al., 2018) (Yusoff et al., 2018)
		TSA	(Karpušenkaité et al., 2018) (Islam and Huda, 2019)
		Scenario models	(Cole et al., 2014) (Mena-Nieto et al., 2021)

			(Klavenieks and Blumberga, 2016)
Strategic decision-making on waste management infrastructure	- long-term forecasting - smaller data frequency (e.g., years) - different territorial levels (city, region, state)	MLR	(Lebersorger and Beigl, 2011) (Ayeleru et al., 2018) (Chen et al., 2020)
		DT	(Johnson et al. 2017)
		ANN	(Kannangara et al., 2018) (Vu et al., 2019) (Sunayana et al., 2021)
		TSA	(Denafas et al., 2014) (Ghinea et al., 2016)
		Scenario models	(Dwivedy and Mittal, 2010) (Komwit et al., 2020)
Operational decision-making in waste management	- shorter-term forecasting - greater data frequency (e.g., months, days) - smaller territorial units (e.g., municipalities)	MLR	(Gu et al., 2017) (Denafas et al., 2014)
		ANN	(Yang et al., 2021) (Song et al., 2014)
		TSA	(Rimaityté et al., 2012) (Montecinos et al., 2018)
		Scenario models	(Long et al., 2012)

A general guide to selecting an appropriate forecasting method is shown in Fig. 4. The flow chart also contains the assumptions and requirements put on the input data. The main steps in the process of forecasting are summarized below:

I. Conversion of data to unit quantity (with respect to activity rate) and data transformation

Requirement: Activity rate is a significant parameter. Typically, generation per capita is considered as unit quantity for MSW. Then the number of inhabitants represents the activity rate. If desired, the data can be transformed at this stage.

II. Data pre-processing (level A in Fig. 4)

Detection of outliers and changes in the trend.

III. Assessment of significant parameters

Requirement: Data for all territorial units of the system.

IV. Selection of the modeling method (level B in Fig. 4)

Requirement: Validity of assumptions with respect to the selected method. Sufficient time series length for TSA depends on the method used in level C. Generally, the most stringent limitations are set for cyclic and seasonal components and the Box-Jenkinson methodology. Expert estimates and average models, on the other hand, can be applied to only a few data points.

V. Forecasting via the selected method (level C in Fig. 4)

Requirement: Validity of assumptions for the respective method.

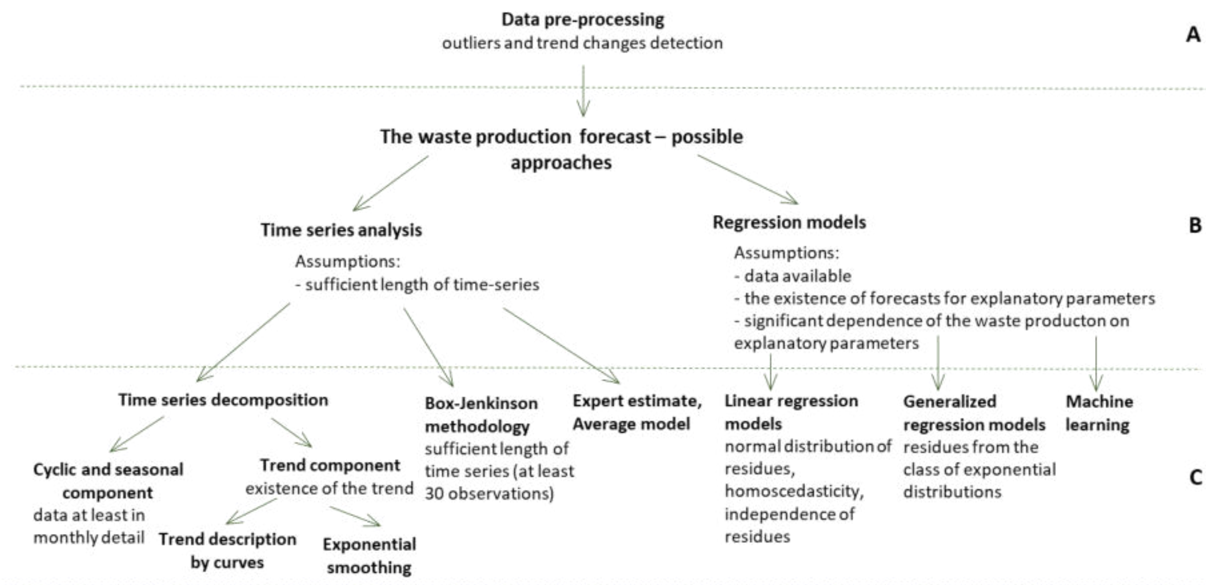

Fig. 4: Forecasting method selection procedure

The final forecast should meet the following criteria:

Compliance with balances and interactions: balance of estimates on different hierarchy levels. The hierarchical structure of territorial units and waste fractions should be maintained (Pavlas et al., 2017), see Sec. 3.3.3.

Confidence intervals: the expected uncertainty is integral to the results (Abbasi et al., 2014). In most cases, however, information on model uncertainty is missing.

Evaluation of the model quality: most models involve at least some quality assessment. Several commonly used criteria are R^2, MAPE, and prediction errors. It also is recommended to verify the quality of the forecast based on testing data. Before the forecast is made, a certain part of the data at the end of the time series is allocated for just this purpose, and then the prediction provided by the model is compared to this pre-allocated data set.

3. Problems and recommendations for waste generation forecasting

A wide range of theoretical basis for forecasting approaches is provided by Petropoulos et al. (2022) but without a link to specific applications in WM. The requirements and processes that are inherent to each waste generation estimate are explained below. Based on the studied publications, the authors of this review proposed a 13-step approach for forecasting which can be divided into four parts: data preparation, pre-processing, processing, and post-processing. Predictive models are described in detail in the previous papers and will therefore not receive much attention. It is possible to be inspired by predictive models when processing data for forecasting. The following text will formulate the problems (P) and recommendations (R) for the individual forecasting steps based on the experience of the authors and the comprehensive review of published papers. Almost every article dealing with waste-related data features some steps from Fig. 5 and, therefore, potential research gaps will also be specified for issues that have not been sufficiently addressed.

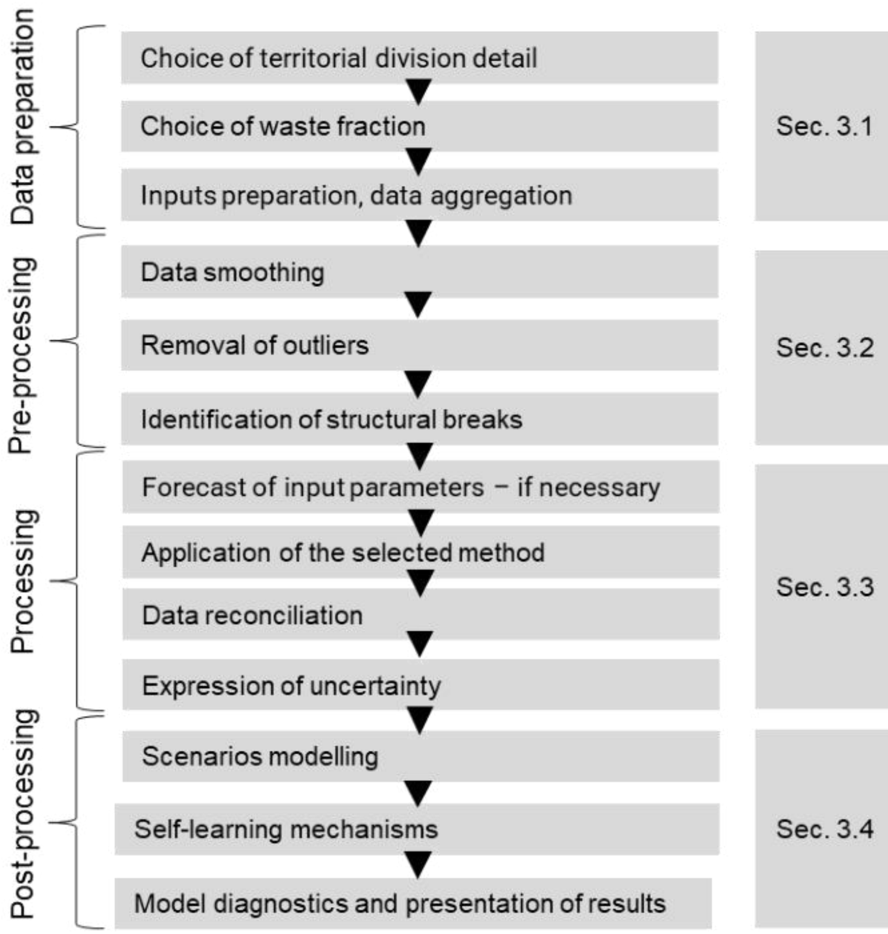

Fig. 5: Schematic representation of the waste generation modeling procedure

3.1. Data preparation

P1: The use of historical data within time series can be complicated due to a change in the methodology of monitoring and recording this data.

R1: Historical data must be collected using the same methodology. If the methodology changes, it is necessary to delete the data prior to the alteration or to modify the data accordingly. An example is the merging of some waste streams for recording. Then it is possible to merge these waste streams also in historical data before the change.

P2: The required data are not available for all variables or territorial units.

R2: The data can be aggregated to obtain the missing values for higher territorial units. Aggregation also reduces data variability that is more pronounced at lower levels. In addition, the missing data can be added using predictive models (see Sec. 1.2, Rosecký et al., 2021).

P3: It is difficult to compare regions in absolute terms due to the different sizes of producers. The analysis is therefore problematic because of extreme values.

R3: The data often needs to be normalized to check the relationships between variables (Rosecký et al., 2021). Normalization or standardization applies to both waste and socio-economic data. The most common is normalization per capita or area. The normalization can also be shifted for better interpretability (e.g., the number of stores per 1000 inhabitants). If the data are not normalized per capita, it is recommended to discard extreme values in predictive models. Such data usually originate in capital or other big cities that, due to their size, can have a considerable impact on the model behavior.

P4: Heteroskedasticity frequently occurs in the data.

R4: For some variables, it is recommended to transform the data to obtain a more even distribution of values. Logarithmic transformation is used most often. The logarithm with base 2 is recommended due to the character of data in WM. However, here the possible zero values must be treated appropriately. For zero values, the logarithmic transformation is not defined at all, values close to zero will have a disproportionately significant impact in subsequent analyses. At present, the authors do not know a suitable approach for the processing of zero values in logarithmic transformation.

P5: The data on waste generation include waste fractions which influence the generation of other fractions.

R5: Interdependent waste fractions should be modeled together. For instance, there is a significant interdependence between MMW and SEP (Šomplák et al., 2022). It may be advantageous to forecast the generation of these waste fractions as an aggregate in absolute value (e.g. MMW + SEP) and simultaneously individual fractions as a rate of total quantity (e.g. MMW/(MMW+SEP)). This will cause smoothing in the data.

3.2. Data pre-processing

P1: Historical waste management data may be influenced by unknown or complicated regressors (economic cycles).

R1: It is possible to adjust the data for changes in given parameters over time, such as economic cycles or one-off situations like the covid-19 pandemic. The adjusted (smoothed) data can then be used for modeling and forecasting.

P2: The presence of outliers negatively impacts the model.

R2: For long time series it is possible to follow common methods for the detection of outliers (see, e.g., Blázquez-García et al. (2020)). These methods, however, are problematic when it comes to short time series (typically annual data) because the methods' assumptions cannot be confirmed. Therefore, it is necessary to use a combination of approaches and supplement it with an expert view. The authors can recommend the Holt method (for trend cleaning) together with the Grubbs' test for the identification of outliers in residues.

P3: The common methods for changepoint detection are not suitable due to short time series (Blázquez-García et al., 2020).

R3: The following points are recommended for changepoint detection.

- Historical data should be normalized. This makes it possible to specify the same critical limit for each time series.
- Use data visualization if the amount of time series allows.
- Do not identify multiple changepoints in one time series if it is not long enough.
- Focus on the angles between the partial subsequences of the time series and the angles of the historical data lines with the x-axis.
- For further calculations, use the part of the time series behind the changepoint.

P4: It is difficult to detect data anomalies (outliers, changepoints) at the endpoints of the time series.

R4: It is risky to mark an anomaly endpoint as an outlier or a changepoint because no subsequent development in the data is known. It is recommended to test the model with and without the endpoint and compare the output ranges. This will verify the effect of the endpoint on the resulting model. The final decision on consideration resp. removal of endpoint due to anomaly is up to the user.

P5: A time series behaves differently than the other time series (i.e., the whole time series has an extreme generation of waste compared to other producers).

R5: If the entire time series features anomalies, it is advisable to look for influencing factors that may affect it. Another option is to test for a possible correlation between neighboring territorial units because the WM characters may be similar in nearby localities. Expert judgment is the only way to assess the results and evaluate pre-processing quality.

3.3. Data processing

3.3.1. Forecasting of input parameters

P1: Finding models which describe the waste generation based on input parameters with sufficient accuracy is not guaranteed.

R1: Clustering can be applied to territories, and then the model can be built at the cluster level (Adeleke et al., 2020). By compiling a model for each cluster separately, higher accuracy can be achieved due to local conditions. The different links can be described in specific clusters of territories and increase the model accuracy.

P2: Forecasting models require the forecasts of all their input parameters for the desired level of territorial division (Kalina et al., 2014), but for some influencing factors these are not available. Alternatively, only short-term forecasts of influencing factors are available, but they do not cover the entire waste generation forecasting horizon (Smejkalová et al., 2022). Enormous uncertainty would enter waste modeling right at the beginning (not to mention the fact that it is not desirable to proceed with flawed input data).

R2: The inclusion of influencing factors in the waste generation forecast is not suitable if the forecast of influencing factors does not cover the whole forecasting horizon or there is significant uncertainty. Then it is recommended to use the principles of TSA. Forecasts of demographic influencing factors differ from other socio-economic characteristics, and it is recommended to include demographic development to waste management forecasts (Smejkalová et al., 2022). Long-term demographic projections usually are of sufficient accuracy, but unfortunately, they may not be available for smaller regions. It must be noted that demographic models are, in fact, projections because they are created in the form of scenarios (Bleha et al., 2018).

3.3.2. Application of the selected method

P1: A specific method for TSA must be chosen concerning the data frequency detail and the length of the time series.

R1: If daily, weekly, or at most monthly data are available, then it is possible to monitor the cyclic and seasonal components, and short-term forecasting usually is possible (Denafas et al., 2014). Otherwise, when only yearly data are available for aggregated territories (region, state; i.e., most data sets commonly provided by states or government strategic planning agencies), solely the trend can be examined (Ghinea et al., 2016) by regression function. In some cases can be advantageous to use Poisson regression. In the comparison with the trend in the form of a nonlinear function, the Poisson regression has less accurate results. However, the advantage is lower computational time.

P2: The choice of the regression function for describing the trend in the data is not clear (several different functions can give similar results).

R2: It is advisable to look for a compromise between the quality of the fitting according to the chosen criteria (e.g. R^2, MAPE) and the properties of the selected functions. The authors evaluated the following properties as substantial:

• Monotony – the trend over the forecasting horizon should not change from rising to declining and vice versa, so the trend is assumed to be monotonous. Oscillations around the trend caused by the seasonal or cyclical component are not possible to describe in short time series. Requiring monotony will also reduce the risk of model overfitting. It is recommended to use the power function for trend modeling. The advantage is its wide application for both rising and declining trends (Smejkalová et al., 2022).

• Limited growth – some time series have a very significant growth in historical data (resp. decline), which may be exponential. Such a trend is usual after the system change, e.g. by collecting a new waste fraction. It cannot be expected to continue this trend over the entire forecast horizon. The more likely development is that the waste generation will slow down the growth. In such cases, it is appropriate to model the trend using an S-shaped curve (Smejkalová et al., 2022).

It is recommended to model the trend with a simple model with a constant value in the following cases, see (Smejkalová et al., 2022):

- By excluding data after pre-processing, the time series remains too short for trend estimation. The minimum number of data can be adjusted to the specific length of the time series.
- The trend model in the data using the functions described above is of poor quality. As a criterion recommends using R^2, critical limit R^2 can be customized.
- A simple model with a constant value leads to comparable results to a more complex model.

As a special case, time series containing zero generation of waste in recent years should be extrapolated as a zero value – it is not expected to start generating this waste again.

P3: Attention should be paid to possible special cases of the waste streams. For example, the legislation may change which may then cause changepoint etc. Completely new waste streams may also be introduced after the legislative intervention. Historical data then cannot be used for forecasting in the usual manner.

R3: Mentioned special cases should be detected in pre-processing if the change has already been reflected in the historical data. It is possible to consider the trend forecasting even if not all regions have already responded to the change. In other words, more advanced regions may outline the future directions for the less developed ones (Smejkalová et al., 2020). An analogous idea can be applied at the state level considering countries with differently advanced WM. Other notable special cases represent waste fractions whose quantities are directly influenced by the developments of specific external factors. A typical example is metal waste which is linked to the purchase price of raw materials. Still, the purchase price is difficult to forecast due to its cyclic behavior, leading to complicated forecasting of the metal waste fraction.

3.3.3. Data reconciliation

P1: Historical waste generation data can contain internal consistency links which form a hierarchical structure – the state comprises regions, regions comprises municipalities. These links are not always maintained after applying the selected method (Sec. 3.3.2).

R1: The authors recommend correcting waste generation models to restore the system links using, for example, a data reconciliation model (Pavlas et al., 2017). It is assumed that the amount of waste generated at a higher territorial unit is equal to the sum of the amounts in territories that belong to it (e.g., municipalities located in a particular region). The second type of internal balance assumes links between waste fractions. An example is the effect of separated waste generation on the amount of MMW (Pavlas et al., 2020).

P2: Data reconciliation model is significantly affected by the model weight settings – different importance of the results that are balanced.

R2: It is necessary to pay attention to appropriately chosen weights when balancing, weights should be considered both in terms of total waste generation (preferably in the square root) and in terms of the quality of the estimate. In the case of the balance, percentage changes must also be taken into account (Smejkalová et al., 2022).

P3: An increase in the generation of one fraction does not mean a decrease in the production of another fraction by exactly this amount – the overflow of waste amounts is not consistent.

R3: The interdependence of waste fractions must be captured in a form that corresponds to reality – the values of the transition between the fractions do not have to be equal – individual waste streams are created and disappeared (Šomplák et al., 2022).

P4: The possibilities of the chosen solver can significantly affect the success of the calculation – when the model is stated as a mathematical programming problem.

R4: The data reconciliation model can be formulated in additive or multiplicative form (Smejkalová et al., 2022). The multiplicative form has a significant advantage for wastes with high variability between individual fractions. Producers with magnitude different waste generation can occur at different levels of the territory. The additive formulation causes numerical and rounding errors. The setting of the model weights also depends on the formulation. In addition, the multiplicative form works with percentage change, which is the problem in the case of zero values (Smejkalová et al., 2022).

P5: The solver is not able to find the optimal solution due to the task size – computational complexity problems.

R5: Usually, at least a relaxed solution is available, i.e., the balances are not met exactly. This may not be a problem for some forecasts. In other cases, it is recommended to reduce the optimization task so that smaller sets of waste streams will be balanced, e.g. only for individual catalogue numbers.

3.3.4. Expression of uncertainty

P1: Each forecast should provide confidence intervals (Jiang and Liu, 2016), ideally also prediction intervals. If data reconciliation has been carried out (previous step, Sec. 3.3.3), it is not possible to use common interval constructs with a normal probability distribution around the model mean value.

R1: The authors suggest simulating the confidence and prediction intervals with the bootstrap method. It is possible to use historical data as one of the possible realizations, and then its variance to generate new data sets. A forecast is made for these generated data, which creates different realizations of the forecast. Based on the properties of forecasts for individual realizations, confidence and prediction intervals are compiled (Smejkalová et al., 2022). In the case of a limited number of possible generations within the bootstrap, the variance of forecasts for the construction interval is estimated. In this case, approximately 30 bootstraps are considered sufficient (Smejkalová et al., 2022).

3.4. Data post-processing

3.4.1. Modeling of scenarios

P1: Forecast does not include possible changes to the system as described in Sec. 1.2. Projections deviate from a basic forecast because they must obey the model constraints and predefined boundary conditions. It is essential to ensure the feasibility and consistency of a projection.

R1: Legislative interventions take place at the state level or the levels of other self-governing units. The distribution of projection changes to the micro-region is essential for determining the potential for future development. For analyses associated with the potential to increase the separation of MSW, it is necessary to have available (or at least estimate) the MMW composition, which allows estimating the potential for change. When using projections, it is recommended to consider the links between waste streams (Šomplák et al., 2022). For the projections, it is necessary to determine the potential for change. The following applies to scenario solutions:

- The scenario does not exceed the potential for change which was set for a specific territorial unit.
- All territorial units show a shift towards meeting the scenario if the potential allows it.
- The individual territories do not overtake in terms of the fulfillment of potential and are monotonous.

3.4.2. Self-learning mechanisms

P1: The results must be updated when the input data set changes. The change may occur due to the data editing in the original database or the addition of new data on waste generation from the next period.

R1: During model re-evaluation, one must carry out all the forecasting steps specified in Fig. 5. When the data are dynamic in nature, it is necessary to react quickly and develop an adequate methodology (De Weerdta et al., 2020). As an example, one might mention forecasting utilizing smart technologies such as weight or fill level sensor-equipped containers.

3.4.3. Model diagnostics and presentation of results

P1: The quality of the models must be verified.

R1: The quality of a forecast should be tested using a pre-allocated test data set. In other words, the forecast should be made using a smaller data set, and the results should then be compared with the remaining values not used as model input data. Model verification can also be done via confidence intervals.

R2: Forecasts provided by the models must be presented clearly so that their end-users (the decision-makers) can easily interpret them. Representing results visualization ways can be found in the paper (Chen et al., 2020).

4. Conclusions

Over the years, various methods used for waste generation modeling have been proposed. Prediction, forecasting, and projection must be distinguished, while the use of various approaches depends on the specific application in WM. The data set available, its territorial and temporal detail, and the prediction horizon are decisive. If influencing factors and their links to waste generation are used for modeling, influencing factors must be forecasted as well. The use of TSA is often limited by requirements on time series length. In general, a significant number of publications have been devoted to designing a suitable modeling method. However, the authors recommend paying attention to the quality of the input data, which has been minimal in reviewed papers. It is important to remember that input data are essential for every model. At the same time, the end-user of a forecast, prediction or projection must be provided with the model uncertainties in the form of confidence intervals. This is another key part of each model which was missing in the majority of the evaluated papers on WM modeling. Although many methods do not offer a direct way of expressing the model uncertainty, bootstrapping can be used to at least estimate it.

Author contributions

Radovan Šomplák: Conceptualization, Methodology; **Veronika Smejkalová**: Validation, Investigation, Writing – Original Draft; **Martin Rosecký**: Data Curation, Investigation, Formal analysis; **Lenka Szásziová**: Investigation, Visualization; **Vlastimír Nevrlý**: Investigation, Writing – Review & Editing, **Dušan Hrabec**: Investigation; **Martin Pavlas**: Supervision.

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Reference

Abbasi, M., Abduli, M.A., Omidvar, B., Baghvand, A., 2014. Results uncertainty of support vector machine and hybrid of wavelet transform-support vector machine models for solid waste generation forecasting. Environmental Progress and Sustainable Energy, 33 (1), 220-228. doi:10.1002/ep.11747.

Abdallah, M., Talib, M.A., Feroz, S., Nasir, Q., Abdalla, H., Mahfood, B., 2020. Artificial intelligence applications in solid waste management: A systematic research review. Waste Management, 109, 231-246. doi: 10.1016/j.wasman.2020.04.057.

Adeleke, O., Akinlabi, S.A., Jen, T.-C., Dunmade, I., 2020. Prediction of municipal solid waste generation: an investigation of the effect of clustering techniques and parameters on ANFIS model performance. Environmental Technology, 43 (11), 1634–1647. doi: 10.1080/09593330.2020.1845819.

Aggarwal, V., Gupta, V., Singh, P., Sharma, K., Sharma, N., 2019. Detection of spatial outlier by using improved Z-score test. Proceedings of the International Conference on Trends in Electronics and Informatics, 788-790. doi: 10.1109/icoei.2019.8862582.

Andersen, F., M., Larsen, H.V., 2012. FRIDA: A model for the generation and handling of solid waste in Denmark. Resources, Conservation and Recycling, 65, 47-56, doi:10.1016/j.resconrec.2012.04.004.

Awasthi, A.K., Cucchiella, F., D'Adamo, I., Li, J., Rosa, P., Terzi, S., Wei, G., Zeng, X., 2017. Modelling the correlations of e-waste quantity with economic increase. Science of the Total Environment, 613, 46-53. doi: 10.1016/j.scitotenv.2017.08.288.

Ayeleru, O.O, Okonta, F.N., Ntuli, F., 2018. Municipal solid waste generation and characterization in the City of Johannesburg: A pathway for the implementation of zero waste. Waste Management, 79, 87–97. doi: 10.1016/j.wasman.2018.07.026.

Beigl, P., Lebersorger, S., Salhofer, S., 2008. Modelling municipal solid waste generation: A review. Waste Management, 28(1), 200-214. https://doi.org/10.1016/j.wasman.2006.12.011.

Bleha, B., Burcin, B., Kučera, T., Šprocha, B., & Vaňo, B., 2018. The population prospects of Czechia and Slovakia until 2060. Demografie, 60(3), 219-233.

Bramati, C.M., 2016. Waste generation and regional growth of marine activities an econometric model. Marine Pollution Bulletin, 112 (1–2), 151–165. doi: 10.1016/j.marpolbul.2016.08.025.

Blázquez-García, A., Conde, A., Mori, U., Lozano, J.A., 2020. A review on outlier/anomaly detection in time series data. ArXiv, abs/2002.04236.

Chen, D.M.-C., Bodirsky, B.L., Krueger, T., Mishra, A., Popp, A., 2020. The world's growing municipal solid waste: trends and impacts. Environmental Research Letters, 15, 074021. doi: 10.6084/m9.figshare.12102510

Cherian, J., Jacob, J., 2012. Management models of municipal solid waste: A review focusing on socio economic factors. International Journal of Economics and Finance, 4(10), 131-139. https://doi.org/10.5539/ijef.v4n10p131.

Chhay, L., Reyad, M.A.H., Suy, R., Islam, M.R., Mian, M.M., 2018. Municipal solid waste generation in China: influencing factor analysis and multi-model forecasting. Journal of Material Cycles and Waste Management, 20, 1761-1770. doi: 10.1007/s10163-018-0743-4

Cole, Ch., Quddus, M., Wheatley, A., Osmani, M., Kay, K., 2014. The impact of Local Authorities' interventions on household waste collection: A case study approach using time series modelling. Waste Management, 34(2), 266-272. doi:10.1016/j.wasman.2013.10.018.

De Muth, J.E., 2019. Tests to Evaluate Potential Outliers. APS Advances in the Pharmaceutical Sciences Series, 40, 197-210. doi: 10.1007/978-3-030-33989-0_8

Denafas, G., Ruzgas, T., Martuzevičius, D., Shmarin, S., Hoffmann, M., Mykhaylenko, V., Ogorodnik, S., Romanov, M., Neguliaeva, E., Chusov, A., Turkadze, T., Bochoidze, I., Ludwig, Ch., 2014. Seasonal variation of municipal solid waste generation and composition in four East European cities. Resources, Conservation and Recycling, 89, 22-30. doi:10.1016/j.resconrec.2014.06.001.

De Weerdta, L., Sasaoc, T., Compernolleb, T., Van Passela, S., De Jaegerd, S., 2020. The effect of waste incineration taxation on industrial plastic waste generation: A panel analysis. Resources, Conservation & Recycling, 157, 104717. doi: 10.1016/j.resconrec.2020.104717.

Directive 2008/98/EC of the European Parliament and of the Council of 19 November 2008 on waste and repealing certain Directives (Text with EEA relevance)

Directive EU 2018/850 of the European Parliament and of the Council of 30 May 2018 amending Directive 1999/31/EC on the landfill of waste (Text with EEA relevance), accessed 23.06.2020.

Directive EU 2018/851 of the European Parliament and of the Council of 30 May 2018 amending Directive 2008/98/EC on waste (Text with EEA relevance), accessed 23.06.2020

Dwivedy, M., Mittal, R.K., 2010. Future trends in computer waste generation in India. Waste Management, 30 (11), 2265-2277. doi:10.1016/j.wasman.2010.06.025.

Gardiner, R., Hajek, P., 2020. Municipal waste generation, R&D intensity, and economic growth nexus – A case of EU regions. Waste Management, 114, 124-135. doi: 10.1016/j.wasman.2020.06.038.

Ghiani, G., Laganà, D., Manni, E., Triki, C., 2012. Capacitated location of collection sites in an urban waste management systém. Waste Management, 32 (7), pp. 1291-1296. doi: 10.1016/j.wasman.2012.02.009.

Ghinea, C., Drăgoi, E.N., Comăniţă, E.-D., Gavrilescu, M., Câmpean, T., Curteanu, S., Gavrilescu, M., 2016. Forecasting municipal solid waste generation using prognostic tools and regression analysis. Journal of Environmental Management. 182, 80-93. doi:10.1016/j.jenvman.2016.07.026.

Goel, S., Ranjan, V.P., Bardhan, B., Hazra, T., 2017. Forecasting solid waste generation rates. Modelling Trends in Solid and Hazardous Waste Management, 20, 35-64. https://doi.org/ 10.1007/978-981-10-2410-8_3.

Gu, B., Fujiwara, T., Jia, R., Duan, R., Gu, A., 2017. Methodological aspects of modeling household solid waste generation in japan: Evidence from Okayama and Otsu cities. Waste Management & Research, 35(12), 1237-1246. doi: 10.1177/0734242X17738338.

Guo, H.-N., Wu, S.-B., Tian, Y.-J., Zhang, J., Liu, H.-T., 2021. Application of machine learning methods for the prediction of organic solid waste treatment and recycling processes: A review. Bioresource Technology, 319, 124114. doi: 10.1016/j.biortech.2020.124114.

Hřebíček, J., Kalina, J., Soukopová, J., Horáková, E., Prášek, J., Valta, J., 2017. Modelling and forecasting waste generation – DECWASTE information systém. IFIP Advances in Information and Communication Technology, 433-445. doi: 10.1007/978-3-319-89935-0_36

Ibáñez, M. V., Prades, M., Simó, A., 2011. Modelling municipal waste separation rates using generalized linear models and beta regression. Resources, Conservation and Recycling, 55(12), 1129-1138. doi:10.1016/j.resconrec.2011.07.002.

Ilbahar, E., Kahraman, C., Cebi, S., 2021. Location selection for waste-to-energy plants by using fuzzy linear programming. Energy, 234, 121189. doi: 10.1016/j.energy.2021.121189.

Islam, M.T., Huda, N., 2019. E-waste in Australia: Generation estimation and untapped material recovery and revenue potential. Journal of Cleaner Generation, 237, 117787. doi: 10.1016/j.jclepro.2019.117787.

Jiang, P., Liu, X., 2016. Hidden Markov model for municipal waste generation forecasting under uncertainties. European Journal of Operational Research, 250(2). 639-651. doi:10.1016/j.ejor.2015.09.018.

Johnson, N.E., Ianiuk, O., Cazap, D., Liu, L., Starobin, D., Dobler, G., Ghandehari, M., 2017. Patterns of waste generation: A gradient boosting model for short-term waste prediction in New York City. Waste Management, 62, 3-11. doi:10.1016/j.wasman.2017.01.037.

Kalina, J., Hřebíček, J., Bulková, G., 2014. Case study: Prognostic model of Czech municipal waste generation and treatment. Proceedings - 7th International Congress on Environmental Modelling and Software: Bold Visions for Environmental Modeling, iEMSs 2014, 2, 932-939.

Kannangara, M., Dua, T., Ahmadi, L., Bensebaa, F., 2018. Modeling and prediction of regional municipal solid waste generation and diversion in Canada using machine learning approaches. Waste Management, 74, 3-15. doi:10.1016/j.wasman.2017.11.057.

Karak, T., Bhagat, R.M., Bhattacharyya, P., 2012. Municipal solid waste generation, composition and management: The world scenario. Critical Reviews in Environmental Science and Technology, 42, 1509-1630. https://doi.org/10.1080/10643389.2011.569871.

Karpušenkaitė, A., Ruzgas, T., Denafas, G., 2016. Forecasting medical waste generation using short and extra short datasets: Case study of Lithuania. Waste Management & Research, 34(4), 378–387. doi:10.1177/0734242X16628977.

Karpušenkaitė, A., Ruzgas, T., Denafas, G., 2018. Time-series-based hybrid mathematical modelling method adapted to forecast automotive and medical waste generation: Case study of Lithuania. Waste Management & Research, 36(5), 454-462. doi: 10.1177/0734242X18767308.

Klavenieks, K., Blumberga, D., 2016. Forecast of Waste Generation Dynamics in Latvia. Energy Procedia, 95, 200-207. doi: 10.1016/j.egypro.2016.09.049.

Koç, C., Bektaş, T., Jabali, O., Laporte, G., 2016. Thirty years of heterogeneous vehicle routing. European Journal of Operational Research, 249 (1), 1-21. doi: 10.1016/j.ejor.2015.07.020.

Kolekar, K.A., Hazra, T., Chakrabarty, S.N., 2016. A review on prediction of municipal solid waste generation models. Procedia Environmental Sciences, 35, 238-244. https://doi.org/10.1016/j.proenv.2016.07.087.

Komwit S., Chompoonuh K. Permpoonwiwat, 2020. Effects of area characteristics and municipal waste collection fees on household waste generation. Journal of Material Cycles and Waste Management. 22, 89-96. doi: 10.1007/s10163-019-00917-2

Lebersorger, S., Beigl, P., 2011. Municipal solid waste generation in municipalities: Quantifying impacts of household structure, commercial waste and domestic fuel. Waste Management, 31(9–10), 1907-1915. doi:10.1016/j.wasman.2011.05.016.

Long, F., Song, B., Wang, Q., Xia, X., Xue, L., 2012. Scenarios simulation on municipal plastic waste generation of different functional areas of Beijing. Journal of Material Cycles and Waste Management, 14, 250-258. doi: 10.1007/s10163-012-0066-9.

Lu, W., Peng, Y., Chen, X., Skitmore, M., Zhang, X., 2016. The S-curve for forecasting waste generation in construction projects. Waste Management, 56, 23-34. doi:10.1016/j.wasman.2016.07.039.

Mena-Nieto, A., Estay-Ossandon, C., dos Santos, S.P., 2021. Will the Balearics and the Canary Islands meet the European Uniontargets for municipal waste? A comparative study from 2000 to 2035. Science ot the Total Environment, 783, 147081. doi: 10.1016/j.scitotenv.2021.147081.

Montecinos, J., Ouhimmou, M., Chauhan, S., Paquet, M, 2018. Forecasting multiple waste collecting sites for the agro-food industry. Journal of Cleaner Generation, 187, 932-939. doi: 10.1016/j.jclepro.2018.03.127

Nie, X.H., Huang, G.H., Li, Y.P., Liu, L., 2007. IFRP: A hybrid interval-parameter fuzzy robust programming approach for waste management planning under uncertainty, Journal of Environmental Management, 84 (1), 1-11. doi: 10.1016/j.jenvman.2006.04.006.

Pavlas, M., Šomplák, R., Smejkalová, V., Nevrlý, V., Zavíralová, L., Kůdela, J., Popela, P., 2017. Spatially distributed generation data for supply chain models - Forecasting with hazardous waste. Journal of Cleaner Generation, 161, 1317-1328. doi: 10.1016/j.jclepro.2017.06.107.

Pavlas, M., Šomplák, R., Smejkalová, V., Stehlík, P., 2020. Municipal Solid Waste Fractions and Their Source Separation: Forecasting for Large Geographical Area and Its Subregions. Waste and Biomass Valorization, 11 (2), 725-742. doi: 10.1007/s12649-019-00764-0.

Petridis, N.E., Stiakakis, E., Petridis, K., Dey, P., 2016. Estimation of computer waste quantities using forecasting techniques. Journal of Cleaner Generation, 112(4), 3072-3085. doi:10.1016/j.jclepro.2015.09.119.

Petropoulos, F., et al. 2022. Forecasting: theory and practice. International Journal of Forecasting. doi:10.1016/j.ijforecast.2021.11.001.

Rimaitytė, I., Ruzgas, T., Denafas, G., 2012. Waste Management & Research, 30 (1), 89–98. doi: 10.1177/0734242X10396754.

Rosecký, M., Šomplák, R., Slavík, J., Kalina, J., Bulková, G., Bednář, J., 2021. Predictive modelling as a tool for effective municipal waste management policy at different territorial levels. Journal of Environmental Management, 291, 112584. doi: 10.1016/j.jenvman.2021.112584

Smejkalová, V., Šomplák, R., Nevrlý, V., Burcin, B., Kučera, T., 2020. Trend forecasting for waste generation with structural break. Journal of Cleaner Generation, 266, 121814. DOI: 10.1016/j.jclepro.2020.121814.

Smejkalová, V., Šomplák, R., Pluskal, J., Rybová, K., 2022. Hierarchical optimisation model for waste management forecasting in EU. Optimization and Engineering. Under review.

Song, J., He, J., Zhu, M., Tan, D., Zhang, Y., Ye, S., Shen, D., Zou, P., 2014. Simulated annealing based hybrid forecast for improving daily municipal solid waste generation prediction. The Scinetific World Journal. doi: 10.1155/2014/834357

Sunayana, Kumar, S., Kumar, R., 2021. Forecasting of municipal solid waste generation using nonlinear autoregressive (NAR) neural models. Waste Management, 121, 206-214. doi: 10.1016/j.wasman.2020.12.011

Šomplák, R., Smejkalová, V., Kůdela, J., 2022. Mixed-integer quadratic optimization for waste flow quantification. Optimization and Engineering. Under review.

Tomić, T., Dominković, D.F., Pfeifer, A., Schneider, D.R., Pedersen, A.S., Duić, N., 2017. Waste to energy plant operation under the influence of market and legislation conditioned changes. Energy, 137, 1119-1129. doi: 10.1016/j.energy.2017.04.080.

Vu, H.L., Ng, K.T.W., Bolingbroke, D., 2019. Time-lagged effects of weekly climatic and socio-economic factors on ANN municipal yard waste prediction models. Waste Management, 84, 129-140. doi: 10.1016/j.wasman.2018.11.038

Xu, A., Chang, H., Xu, Y., Li, R., Li, X., Zhao, Y., 2021. Applying artificial neural networks (ANNs) to solve solid waste-related issues: A critical review. Waste Management, 124, 385-402.

doi: 10.1016/j.wasman.2021.02.029.

Xu, L., Gao, P., Cui, S., Liu, Ch., 2013. A hybrid procedure for MSW generation forecasting at multiple time scales in Xiamen City, China. Waste Management. 33(6), 1324-1331. doi:10.1016/j.wasman.2013.02.012.

Yang, Y., Yuan, G., Cai, J., Wei, S., 2021. Forecasting of disassembly waste generation under uncertainties using digital twinning-based hidden markov model. Sustainability 13(10), 5391. doi: 10.3390/su13105391

Yusoff, S.H., Din, U.N.K.A., Mansor, H., Midi, N.S., Zaini, S.A., 2018. Neural network prediction for efficient waste management in Malaysia. Indonesian Journal of Electrical Engineering and Computer Science, 12(2), 738-747. doi: 10.11591/ijeecs.v12.i2.pp738-747.

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ORIGINAL PAPER

Municipal Solid Waste Fractions and Their Source Separation: Forecasting for Large Geographical Area and Its Subregions

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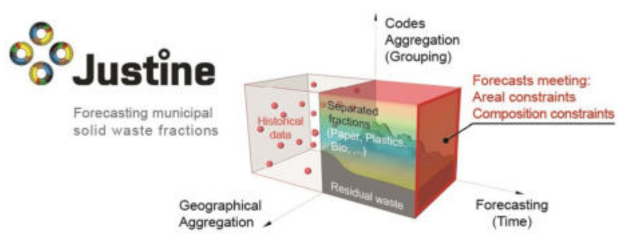
Abstract

This paper introduces an approach toward forecasting municipal solid waste and its fractions in a large geographical area divided into subregions. A multi-commodity system, where components overlap between streams of residual waste and separately collected recyclables, is developed to predict composition, future amounts and separation efficiencies. The approach combines a reconciliation-based balancing model with regression analysis and time series analysis. Regression analysis provides models which are later used to get complete information for all nodes of tree-like structure describing the geographical area of interest. Time series analysis proposes initial models on future amounts for all fractions. The balancing model with newly formulated composition constraints corrects initial estimates, which is a key issue especially for short-time series where precise extrapolation models can hardly be secured. The developed approach contributes to analysing rational recovery targets by reflecting the current situation in individual (micro) regions and, at the same time, it exploits examples of good practice from regions with high recovery rates. Here the analogy with rigorous regression models (historical data from one region can serve as one scenario for another region) is utilised. The algorithm is demonstrated through a case study inspired by an extensive project for the Ministry of the Environment of the Czech Republic.

Graphic Abstract



Keywords Municipal solid waste · Circular economy · Separation efficiency · Separation rate · Network flow model · Paper separation · Plastic separation · Forecasting

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Abbreviations

ARIMA	Auto-regressive integrated moving average
ARMA	Auto-regressive moving average
BAU	Business-as-usual scenario
BIO	Bio-waste
CA	Correlation analysis
CE	Circular economy
CEP	Circular economy package
CZE	Czech Republic
GLA	Glass
GLM	Generalised linear model
MSW	Municipal solid waste
NN	Neural networks
PAP	Paper
PLA	Plastics
RA	Regression analysis
RES	Residual solid waste
RES_{PAP}	Paper in residual waste
RES_{PLA}	Plastics in residual waste
RES_{GLA}	Glass in residual waste
RES_{OTH}	Other fractions in residual waste
SE	Separation efficiency
SEP	Waste collected as separated
SEP_{BIO}	Bio-waste collected as separated
SEP_{PAP}	Paper collected as separated
SEP_{PLA}	Plastics collected as separated
SEP_{GLA}	Glass collected as separated
$TOTAL_{SEP}$	Total amount of waste collected as separated
TSA	Time series analysis
$k \in K$	Set of micro-regions
$j \in J$	Set of regions
$t \in T$	Set of time periods
x_k	Waste production in micro-region k
f_k	Prediction model for micro-region k
F_j	Prediction model for region j
m_k^*	Prediction model for micro-region k in specific time period
M_j^*	Prediction model for region j in specific time period
t_r	Specific time period
m_k	Corrected value of prediction model for micro-region k
ε_k^m	Correction for micro-region k
M_j	Corrected value of prediction model for region j
ε_j^M	Correction for region j
$\delta_{i,opt}$	Defines the sum of least square errors
Q	Quality of extrapolation model criterion
a, b, c	Regression parameters
N	Number of years
T_1, T_2	First and last point of time series
$d_{i,t}$	Historical data of time series i in the year t
e	Euler's number

Statement of Novelty

This paper introduces an approach toward forecasting municipal solid waste and its fractions in a large geographical area divided into subregions. Recyclables as paper, plastics, glass and their contents in residual waste is modelled in a new way. In addition, current and future residual waste composition and separation efficiencies are predicted. The approach combines several techniques of statistics and optimization. Additional constraints are newly proposed for a tree-like structure, which secures that amount of waste produced in all subregions is equal to amounts produced in a region consisting of these subregions. The developed approach contributes to analysing rational recovery targets and, at the same time, it exploits examples of good practice from regions with high recovery rates. The case study is solved.

Introduction

Whereas developing countries face increasing production of waste and are in the process of establishing organised waste treatment systems, in the EU and in other developed countries the so-called circular economy (CE) is widely discussed as a concept with minimised waste production and maximum secondary sources utilisation. The initiative is implemented into legislative by so-called circular economy package (CEP). Within the framework of CEP, the amended Directive [1] introduces ambitious goals in municipal solid waste (MSW) recycling. Whereas meeting the goals will be monitored on the country level, measures have to be implemented at the micro-regional and municipal level. Similarly, current separation efficiency and its future progress have to be monitored on this level of detail, too. It is believed that CE will change needs on infrastructure that processes gathered waste streams and produces desired semi and final recycling products.

Regardless of the geographical area in question, be it a developing country or an EU Member State, the basic assumption for qualified and efficient decisions and consequently also policy settings in waste management is the availability of quality forecasts. Estimates of the amount of MSW serve as a basis for infrastructure plans (landfill, waste-to-energy, advanced sorting lines and recycling systems and their combinations) and provide inputs for advanced modelling tools. Inaccurate forecasts can lead to an increase in construction costs or operating costs (waste collection and processing).

The paper is focused on simultaneous forecasting on MSW amounts in fragments of a large geographical area. The outcomes of the methodology proposed can be beneficial for (i) analysis on future waste management concepts of a particular region; (ii) complex modelling of waste flows between producers and processing plants within one or more regions. Therefore, a brief review on state-of-the-art in reverse models is provided first highlighting poor pre-processing of quantitative data on production. Since the problem relates to forecasting in waste management in general, recent works published in this field are provided first. Limitations of frequent approaches are highlighted. Finally, based on a research gap identified, the contribution of this paper is introduced at the end of this section.

Reverse Models—Tools for Waste Management Improvements

Reverse models, which are a special case of supply chain models, focus on the pathway of used products back from customers, as described by Ghiani et al. [2]. Reverse models are promising and often used tools for optimisation of networks in waste management as highlighted by [3]. There have been several works published on this issue. Since they involve analysis of a network comprising 10^2 to 10^3 nodes, we focus on how waste quantities are addressed here. Rudi et al. [4] presented a case study application of a biomass value chain design for the tri-national Upper Rhine Region. The task was based on mixed integer linear programming. It took into account household waste (incl. a fossil fraction). Even though, future scenario 2030 is modelled, the allocated quantities related to 36 locations are not provided. Zis et al. [5] focused on municipal solid waste generated in remote areas and examined alternative options for its treatment. The research focused on 13 small Greek islands. It is claimed, that a regression estimate model was constructed (as it provided the best fit) to predict waste generation until the year 2040. No details on waste quantities are provided. Saif et al. [6] focused on optimisation of system with transfer stations handling organic MSW operated in 5 locations of the central west part of Mexico. The available waste amounts are mentioned for each of the locations without providing any details. Galan et al. [7] oriented on construction and demolition waste. The aim of the paper was to identify the locations and capacity of the transfer stations and processing plants and the corresponding distribution network. Fifty-one municipalities of the Cantabria region in Spain were included. The waste quantities were simply considered proportional to the population, based on an average annual amount produced in the whole region.

Gathering waste production data and its reprocessing into a suitable form are crucial steps leading to the practical application of any optimisation tool for modelling future improvements in waste management. Regarding network flows modelling generally, the situation is complicated due to:

- Forecasting is inevitable since the calculation focuses on future state modelling.
- Waste quantities have to be known for all nodes of the investigated region.
- There are interactions between streams. MSW consists of several sub-streams and fractions, such as paper, plastics, bio-waste, mineral, etc. Some of them are recyclables, and these are collected separately within various collection systems (containers, bring-in systems, kerb-side or a combination thereof). Efficiencies in the systems may differ; however, they are supposed to increase over time, resulting in higher rates of recyclables and a lower amount remaining in residual solid waste (RES).

Approaches Towards Forecasting MSW

There have been several works published on the topic of MSW quantities modelling and forecasting. They come from different countries and regions and employ different statistical techniques. Regression analysis (RA) or time series analysis (TSA) are often employed, and sometimes both are combined. A comprehensive review on this topic was published by Beigl et al. [8] in 2008.

The RA implemented in a large number of models explain variations in production among producers. A wide range of independent (explaining) parameters is tested to find those with the most significant impact. These often include gross domestic product, income, share of different types of housing, type of heating, tourism rate, container distance, etc. The correlation analysis (CA) is often performed for the choice of regressors.

CA and RA have been frequently practised. Both were applied recently in the study undertaken to evaluate the quantity and composition of household solid waste to identify opportunities for waste recycling in Can Tho city, the capital of the Mekong Delta region in southern Vietnam [9]. Similarly, Lebersorger and Beigl [10] identified and quantified differences in MSW production and collection on the municipal level in Province Styria, Austria. Socio-economic indicators were involved. A large set of 116 indicators from 542 municipalities in Austria was investigated. Li et al. [11] introduced a model, based on the interrelationships of expenditures on consumer goods, time distribution, daily activities, residents' groups and waste generation, to estimate MSW generation by different activities and resident groups in Beijing. Geographically weighted regression was applied to predict MSW production in Turkey [12].

Regarding forecasting, knowledge of explanatory parameters opens new opportunities for an indirect change of future course of the production. Initiatives for encouraging desired trends of explanatory parameters may be discussed. Alternatively, the explanatory parameters may be forecasted and results may be introduced into the regression models to forecast waste production.

RA, if employed correctly from a mathematical point of view, requires that strict conditions are met before RA may be applied. Among others, the residues were supposed to be of the normal distribution, see Ruckstuhl [13] for nonlinear regression. These conditions may be relaxed by more generalised ones resulting in the generalised linear model (GLM) [14]. GLM can solve problems other than just the normal distribution of residues, for example, the problem of residues heteroscedasticity, multicollinearity and distribution of residues. Guisan et al. [15] collected information about GLM and discussed utilisation of several new approaches, such as GLM in a regression tree. GLM can also be successfully applied in nonlinear models, as Lane [16] showed. Zhang et al. [17] summarised the possibilities of neural networks (NN) as an alternative forecasting approach, Abbasi and Hanandeh [18] dealt with other artificial intelligence algorithms. Azadi and Karimi-Jahni [19] verified NN and multiple linear regression (MLR) predictive models by four performance measures. NN model showed higher accuracy in the sense of mentioned measures for the chosen case study. The classical methods are sometimes combined, grey model together with TSA was successfully implemented for estimation of waste production in Xiamen City, China [20]. The consideration of variables such as demographics and socio-economic factors is not needed.

The above-discussed methods (RA, GLM, NN) require independent variables. In addition, independent variables should be available from all the regions. Since the socio-economic data are very often available only on the state level or for large regions, this situation discards RA involving this kind of variables from any investigations with micro-regions and small territorial units. TSA employs time as the sole explanatory parameter. Waste amounts in previous years are investigated to develop a model which describes the variation over time. Forecasts are then derived by extrapolating historical data.

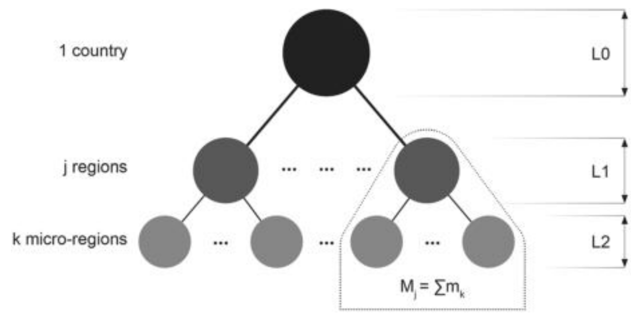

Fig. 1 Investigated geographical area represented by hierarchical tree-like structure (simplified after [29])

Some articles dealt with waste production forecasts for detailed time steps ([21] in time steps of 1 week). A shorter time interval is inevitable when waste collection systems are optimised. Extensive data processing to predict waste production in Finland was described by Korhonen and Kaila [22]. Socio-economic factors can significantly affect the amount of generated waste. For example, the influence of tourism on the production of waste was discussed by Arbulú et al. [23]. Mwenda et al. [24] analysed, compared and selected the best time series model for forecasting the amount of solid waste generated in the city, Arusha (Tanzania) by using ARMA (auto-regressive moving average)/ARIMA (auto-regressive integrated moving average) and exponential smoothing models. Here only tens of samples were available for forecasting. Monthly production between 2008 and 2013 was analysed.

The work presented by Ghinea et al. [25] used a small dataset prognostic tool [26] combining RA and TSA for forecasting MSW generation in Iasi (Romania) in 2023 with the use of data from the period 2001 to 2013. This study also focused on predicting the number of solid waste fractions (paper, plastic, metal, glass, biodegradable and other waste). A different methodology was chosen by Intharathirat et al. [27] who presented an analysis of possibilities for determining the prediction interval for MSW production. This analysis was conducted over a long-term period, and it used optimised multivariate grey models. However, only 13 samples were available here.

From a mathematical point of view, accuracy is secured only for series with a large number of values. Concerning strategic decision-making, which this paper focuses on, the time series method for waste production (which are reported on an annual basis) are often too short because older data are not available. Any attempt at a rigorous TSA of such data results in a heavily skewed estimate of the real underlying trend, and hence, is of limited use. There is also the practical impossibility of stage-wise identically independent probability distributions of random errors or homoscedastic random errors as it is required by ARMA models [28].

As a consequence, a precise data analysis is nearly impossible, and the only component which can be observed is the trend one. Therefore, this technique is preferred to model large data, that is data gathered within a shorter period (daily, hourly, etc.) to support tactical and operational decisions.

Contribution of this Paper

In this contribution, an approach towards forecasting of MSW streams and their parameters is introduced.

From the previously mentioned points, we may assume that strict assumptions limit RA applications. Regarding TSA, one has to cope with short time series. From a statistical point of view, the accuracy of extrapolation models is rarely guaranteed with a high level of confidence if the series consists only of few points. Despite this setback, these models do provide important information about the trend. Therefore, they are acceptable from an engineering point of view as no other models are available, and they offer an improvement to existing approaches.

In comparison to previously published works, this is done for a large geographical area consisting of up to hundreds of points, where waste is generated (see L2 for micro-regions in Fig. 1). The division of the region has been inspired by the official European NUTS (Nomenclature of Units for Territorial Statistics) and LAU (Local Administrative Units) system. The level L0 corresponds to NUTS 1 which represents the national level. Next level, L1 signifies the NUTS 3. But the most detailed structure relevant for this paper is L2, which is the organisational structure of the Czech Republic. It does not have the equivalent in the European NUTS and LAU system. The problem is not decomposed. Instead, it is solved simultaneously for all nodes and desired parameters. Simultaneous forecasting of MSW and its components seems to be inevitable for the following reasons:

- It is a multi-component system where components interact.
- Regression models are limited by unavailable socio-economic data from micro-regions.
- Short time-series hinder formulation of reliable extrapolation models.
- Simultaneous forecasting, if done in the tree-like structure, can be used effectively to overcome poor extrapolation quality, for details see Pavlas et al. [29].

To our best knowledge, such an approach has not been published before, and therefore it may be considered novel. The approach extends the idea of application of reconciliation technique based tool presented by Pavlas et al. [29], see Section "Reconciliation Technique Based Tool". Whereas uncertainty related to poor extrapolation models was introduced and discussed by Pavlas et al. [29], the extension of the algorithm presented in this contribution is done in terms of handling:

- The multicommodity problem (see Section "Waste Composition and Composition Constraint") and proposal of composition constraints.
- Incomplete data by two-level methodology (see Section "Regression Models to Get Complete Information").
- National targets are cascaded down to regions and micro-regions. Specific local aspects of these subparts are considered. On the other hand, the realistic performance of individual regions is used to define rational national targets.

The proposed approach can be applied for investigations of a particular area. However, it can also support reverse logistics model. Simultaneous forecasting of the waste amounts for the large geographical area, and its subregion can serve as inputs for reverse logistics models.

Materials and Methods

A balancing tool based on a reconciliation technique is introduced first in this section. Then its extension towards a system enabled handling of several fractions within the interconnected system is discussed next. Finally, the most crucial steps of the algorithm are pointed out in more detail.

Reconciliation Technique Based Tool

Pavlas et al. [29] discussed the varying quality of extrapolation models, especially the varying quality caused by the short time series. The paper focused on hazardous waste. However, similar issues are concerned with other waste streams, including MSW and its fractions. The original problem was denoted "uncertainty of forecasted values" since it meant a challenge to make any projection by using TSA [29]. The problem was linked to the extreme variability of historical data and the effects of random components. Also, outliers must be identified and handled.

The uncertainty was reported quantitatively, and it was demonstrated that the quality of forecast increases with the level of data aggregation. Data on hazardous waste production available for the Czech Republic (CZE) and its organisational units (see L0, L1, L2 in Fig. 1) was analysed.

Extensive investigation of this dataset also revealed a violation of mass-balances in a tree-like hierarchical structure which describes the organisational arrangement of the investigated region. In other words, the following basic

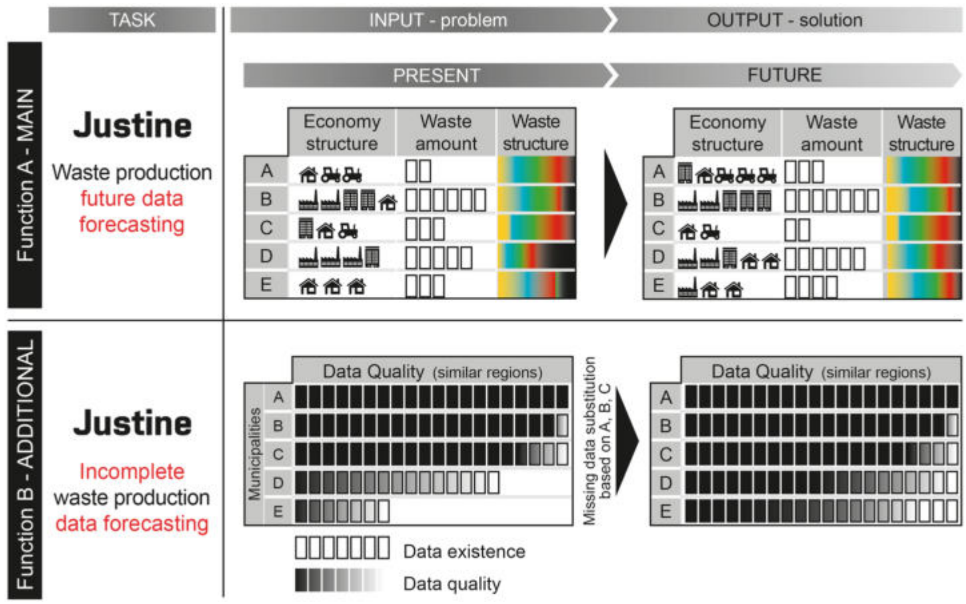

Fig. 2 Basic idea and two functions of system for forecasting waste amounts of MSW

assumption was violated if extrapolated values were treated: The sum of forecasted values for all lower organisational units in the region must be equal to the result of the forecast performed on the aggregated data of the region. Further investigation revealed that the achievement of a full consistency is not guaranteed even from a mathematical point of view. Nonlinear extrapolation models do not generally meet the rule Eq. (1), that is m_k^* is not equal to M_j^* (Eq. (2)):

$$\sum_{k \in K} f_k(t, x_k) = F_j\left(t, \sum_{k \in K} x_k\right), \forall t \in T, \tag{1}$$

$$m_k^* = f_k(t_r, x_k), \forall k \in K; M_j^* = F_j\left(t_r, \sum_{k \in K} x_k\right), \forall j \in J, \tag{2}$$

$$m_k = m_k^* + \varepsilon_k^m, \forall k \in K; M_j = M_j^* + \varepsilon_j^M, \forall j \in J. \tag{3}$$

The parameters x_k indicate productions; the functions f_k and F_j determine prediction models for micro-regions (L2) k and for superior territory j (L1 and L0), respectively; parameter t specifies the time. Based on Eq. (2), m_k^* and M_j^* denote the prediction model in a specific time period t_r for micro-region k and region j, respectively. To ensure the validity of Eq. (1), the values m_k^* and M_j^* are corrected by ε_k^m and ε_j^M in Eq. (3). This adjustment maintains the validity of relationships in the hierarchical structure, as Fig. 1 shows.

Reported uncertainty at a lower level (quality of extrapolation models was often low) was reduced by newly proposed areal constraints. It guarantees mass conservation in a tree-like structure. Additional information from areal constraints is positively utilised to produce more reliable forecasts. Deviations are realised by a data reconciliation-based tool.

Extension Towards Modelling A Multi-Component System

In this paper, the original algorithm, also called Justine, is adjusted to handle so-called multi-commodity system, where components overlap between observed streams. MSW represents a good example as it consists of several fractions (see section "Waste Composition and Composition Constraint"). For simplicity, let us considered only the following fractions: paper (PAP), plastics (PLA), glass (GLA) and bio-waste (BIO). Generally, these fractions may be either gathered as separately collected recyclables (SEP, for example by kerbside collection systems) or they may contribute to residual waste quantities – RES. RES comprises paper (RES_{PAP}), plastics (RES_{PLA}), glass (RES_{GLA}) and others (RES_{OTH}). Whereas SEP streams are candidates to subsequent refining through sorting processes to prepare recyclables, the latter residual stream is subject to limited material recovery possibilities. RES stream is preferred to energy recovery. Each of the fractions can be further composed of other elements. For example, PLA consists of foils, 3D-hollows, PET of different colours, etc. This fractioning was not considered for demonstration reasons in this paper.

In this respect, the algorithm was extended by the following:

- RA is providing models, which are later on used to get complete information for all nodes, including nodes

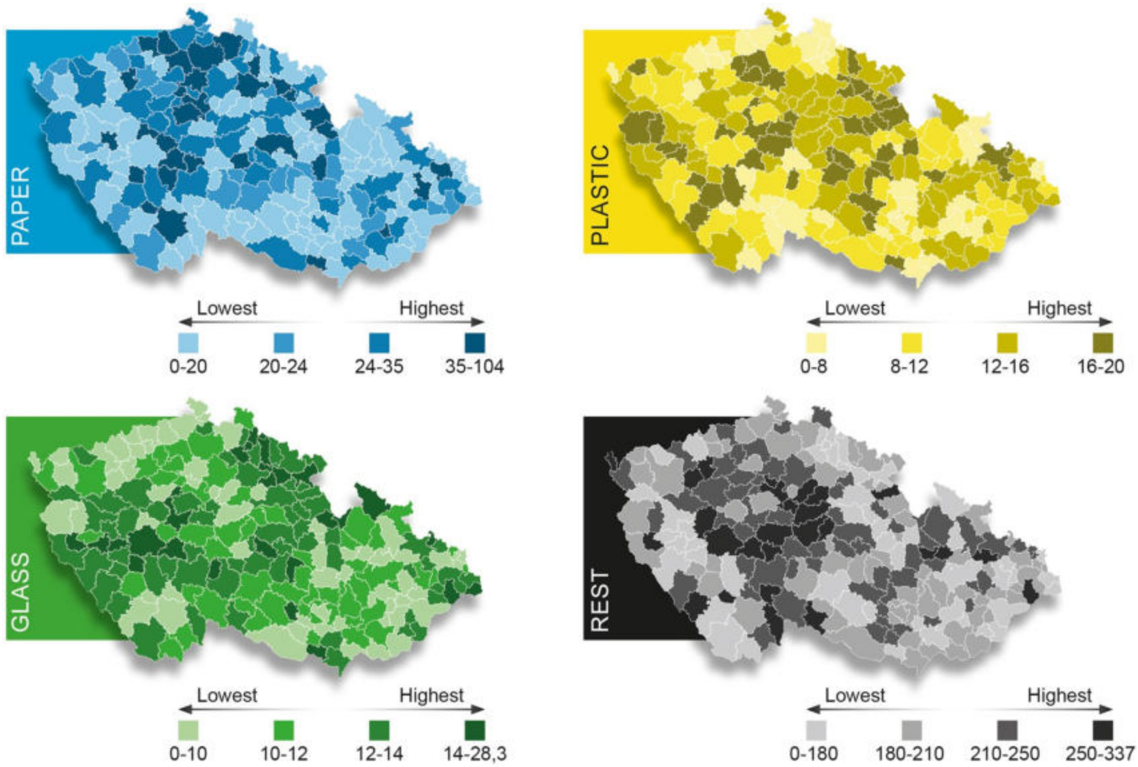

Fig. 3 MSW fractions rates distributed in investigated region of CZE [kg/(cap·y)], L2 detail, data 2014

where input data is missing (see Function B in Fig. 2 and section "Regression Models to Get Complete Information").

- Extrapolation techniques for data on various levels of detail (see Function B in Fig. 2 and section "Trend Series Analysis—Initial Models Generation").
- Specification of newly formulated composition constraints (see Eq. (4) through Eq. (11) and section "Waste Composition and Composition Constraint").
- Modification of reconciliation-based balancing model (see section "Balancing and Corrections of Initial Estimates").

At this point, the main aim of Justine concerning practical application on MSW is mentioned. It is illustrated in Fig. 2 as the main function A in the upper part of the figure. The aim is to forecast future waste amounts and composition (SEP, RES and its fractions) in various locations (see A, B, C, D, E) while taking into account current specific features of the localities (housing, economic and population changes, etc.) and their expected future development. The analysis is covered by prediction models (TSA or RA).

However, the forecasting can only be performed if all current input data is known. In this case, we talk about the complete dataset. Oppositely, the incomplete dataset means that some information is missing and not all information from all locations is available. Particular information is available only from a few geographical units. And here, the auxiliary function of the approach (see the lower part of the Fig. 2) is appreciated. The incomplete dataset is transformed into complete information by assessing missing data. The assessment is done by RA, and this step is described in more detail in section "Regression Models to Get Complete Information". This function is considered as an initial phase which precedes the forecasting. However, in some applications, it acts as a standalone analysis. For instance, see [30], where it was applied to predict current metal, and glass content in RES collected from several micro-regions. The result was then compared with bottom ash investigations from waste-to-energy facilities.

Input Data

Yield and Production Data

First, let us review the input data. Essential inputs for a particular case addressing household waste are as follows:

- separated paper yield (all points, all levels (L0 to L2), several years),
- separated plastic yield (all points, all levels (L0 to L2), several years),

- separated glass yield (all points, all levels (L0 to L2, several years),
- separated bio-waste yield (all points, all levels (L0 to L2), several years) and
- residual waste amount (all points, all levels (L0 to L2), several years).

The L2 level is considered as a base level in this paper. Following the tree diagram (see Fig. 1), the historical base data may be aggregated to generate productions on higher levels. The aggregation is highlighted by the sum in Fig. 1. This summation was labelled as "areal aggregation" in [29]. This areal aggregation corresponds to the administrative division where data for higher organisational levels (regions, country, see L1 and L0 level in Fig. 1, respectively) is reported as sums of production in all subordinate nodes. It also secures that mass is conserved in the system around the particular node and its descendants, as required by Eq. (1).

An example of spatially-distributed data for the CZE, the year 2014 and level of detail L2 (micro-regions) is illustrated in Fig. 3. The production is expressed as specific per capita and year [kg/(cap·y)].

The current collection rates can be summarized as follows: PAP 17.5–30.0 kg/(cap·y); PLA 10.1–14.5 kg/(cap·y); GLA 10.2–13.3 kg/(cap·y); BIO 19.9–58.9 kg/(cap·y). The lower and upper values are represented by 25 percentile and 75 percentile, respectively.

The time series exists for each territorial unit (L0, L1, L2) and also for each waste type RES, PAP, PLA, GLA, BIO. Each of the L2 regions commonly makes provision of such data. Therefore this data is denoted as "complete". In our case, the task encompasses 206 time series at L2. Considering an organisational structure, additional aggregated time series were generated: 14 on L1 and one on L0 level.

Data fluctuation varies from region to region, which is essential for the forecasting step. This topic is covered in section "Trend Series Analysis—Initial Models Generation" in more detail. Therefore, the quantity of data is "complete" and "uncertain".

Additional and very valuable input information is on residual waste composition.

Waste Composition and Composition Constraint

Often, this type of data is available only from a few points, since the complex waste composition analysis is labour and time-consuming. Also, the result is only relevant to the specific period and a particular location. Therefore, this data is denoted as INCOMPLETE and also UNCERTAIN. Uniform methodology on composition analysis is often missing. For instance, it is standardised by ÖNORM Serie S 2123 in Austria. The analyses often have different objectives, and results are not easily comparable. However, every composition analysis provides useful information, which can positively contribute to more precise models if integrated into the complex system as presented in this paper.

There is a strong difference in the composition of waste produced in cities and villages. The cases were studied in many papers, such as [31]. Key aspects are the overall MSW production and current level of primary sorting by producers. Whereas developing regions report high bio-waste shares, developed regions and related consumerism increase the production of packaging materials like paper and plastics. The production (sum of RES plus SEP) is proportional to the economic power of the specific territory, Bandara et al. [32] shows. The economic power can be measured with the gross domestic product on the country level or similar parameters for smaller geographical areas, for example, average income, living standards etc. The correlation of waste amounts with economic power may be shortly disturbed by the rise of public awareness of waste reduction and similar educative actions. On the other hand, the distribution between SEP and RES is highly locally dependent, and it is subject to the adopted collection scheme, taxation and other economic incentives (for example, Pay-as-you-throw mechanism). Public awareness and environmental thinking play an important role, too.

Information about RES composition forms another set of equations. There are approximately eight extra equations originating from mass balances of fractions:

$$PAP = SEP_{PAP} + RES_{PAP} \tag{4}$$

$$PLA = SEP_{PLA} + RES_{PLA} \tag{5}$$

$$GLA = SEP_{GLA} + RES_{GLA} \tag{6}$$

$$MSW^{*} = SEP_{PAP} + SEP_{PLA} + SEP_{GLA} + RES \tag{7}$$

$$TOTAL_{SEP} = PAP + PLA + GLA \tag{8}$$

$$SEP = SEP_{PAP} + SEP_{PLA} + SEP_{GLA} \tag{9}$$

$$RES_{SEP} = RES_{PAP} + RES_{PLA} + RES_{GLA} \tag{10}$$

$$RES = RES_{PAP} + RES_{PLA} + RES_{GLA} + RES_{OTH} \tag{11}$$

All of them were applied for all locations and all levels (L0–L2). They are called "composition constraints".

Separation Efficiency

Separation efficiency is highly monitored characteristics which evaluate the performance of any collection system in place. Many studies focus on measures to enhance separation efficiency of individual fractions and the system as a whole [33]. Separation efficiency (SE) is defined as:

$$SE_{*} = \frac{SEP_{*}}{TOTAL_{*}}. \tag{12}$$

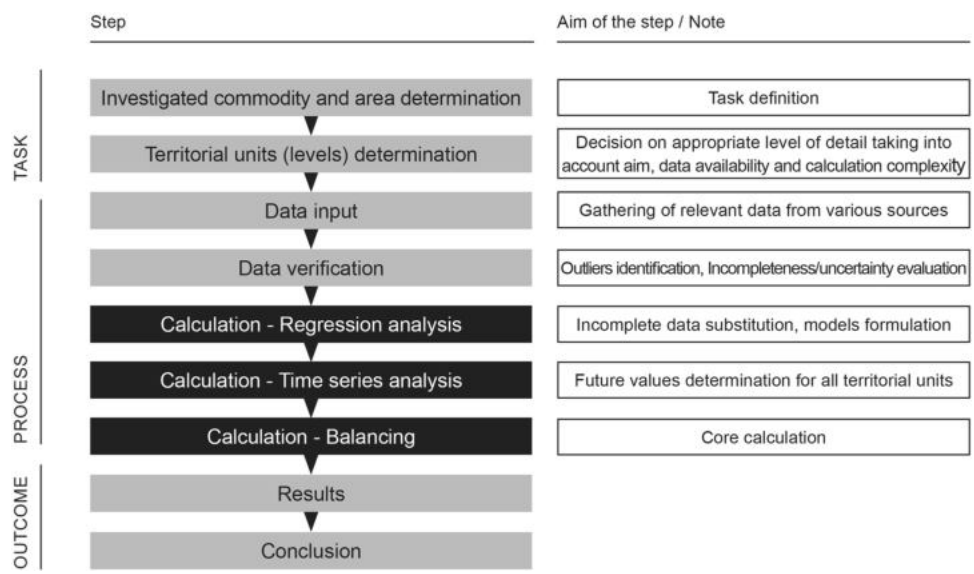

Fig. 4 Schematic representation of overall methodology with highlighted steps relevant to this paper

The symbol * indicates the fraction of MSW (e.g. PAP, PLA, GLA). SE will be further evaluated in section "Future Amounts Modelling". SE can also form constraints, which is demonstrated in scenario 4.

Steps in the Algorithm

The overall methodology consists of several steps which are listed in Fig. 4. In this paper, we focus on three crucial steps which are labelled as "Calculation" in Fig. 4.

Regression Models to Get Complete Information

After introducing steps processing all inputs, data is gathered and verified. As mentioned above, some historical data is "incomplete". Typically, this incompleteness concerns composition. Therefore, the calculation starts with a detailed analysis to get complete information in all nodes. Where input data is missing, it is substituted by models. Also, the models are used to identify outliers.

Detailed RA is performed. The goal is to develop models which help explain variation in parameters within the investigated area. In the case of household waste, it was:

- Model on PAP, PLA, GLA yields as separated (SEP) and its residual values (RES) as a function of the housing structure.
- Model on the composition of residual waste as a function of the housing structure.

A correlation between RES and other MSW fractions (e.g. metals, BIO) has not been revealed by CA and RA and

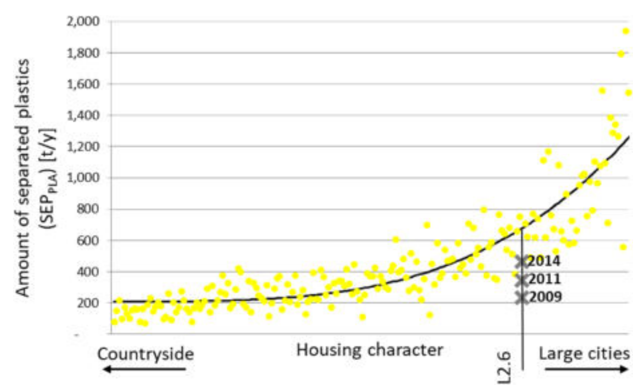

Fig. 5 Regression model of SEP_{PLA} as function of housing character in 2009

L2 data. It is assumed that the increase in the amount of these fractions is not compensated by RES reduction. Minor fractions such as textile are excluded as well.

The housing structure represents an important socio-economic aspect with significant influence on the results. The influence was confirmed by several studies [31]. Three categories of buildings were considered in our case of the CZE. They differ with inhabitants' density, which is a count of inhabitants living in one building. They were single houses (up to 8 inhabitants) and small apartments houses or multi-dwelling units (up to 30 inhabitants) and blocks of flats or apartments houses (more than 30 inhabitants). Considering that there are 10.5 million Czech citizens living in the CZE, half of these lives in individual houses. The other half lives in blocks of flats.

These three types of housing entered RA. Other socio-economic variables, such as age, income, education etc., were identified as insignificant.

Table 1 Average values of Q achieved for various territorial units (–)

MSW fraction	L0	L1	L2
RES	2183.5	2528.7	593.1
SEP_{PAP}	1483.4	247.9	100.0
SEP_{PLA}	4452.2	652.3	176.4
SEP_{GLA}	1127.7	697.6	149.7
SEP_{BIO}	59.5	33.6	19.7

The meaning of Q can be found in [29]

In general, RA represents the behaviour of an average producer. The disadvantage is that such an average model can hardly be applied equally to describe the future trend in all particular micro-regions. There are often local specifics which influence previous and future performance. On the other hand, RA provides information about distribution around this average. So, producers performing below, around and above the average may be identified. In this respect, results may be used as benchmarks, and future targets can be specified.

This is demonstrated in Fig. 5, where the benefit of RA models, if applied on a long-term basis, is shown. A model on SEP_{PLA} as a function of housing structure compares separation yields in similar micro-regions. Whereas it seems that highlighted node L2.6 is an outlier, according to 2009 data, it improves significantly with time, and in 2014 it is much closer to an average model. Another discovery is that the average increases with time, which is not visible directly from Fig. 5 since only 2009 data is displayed.

These findings have been exploited to forecast RES fractions. Continuing with L2.6 as an example and considering similar plastics generation in similar regions (other parameters are not important as revealed by CA), the Fig. 5 indirectly says that the waste that has not been separated must remain part of the RES. If separation is increased in the coming years, the amount of RES is adequately reduced.

By using RA in a similar way for all the fractions of SEP (SEP_{PAP}, SEP_{PLA}, SEP_{GLA}) and RES (RES_{PAP}, RES_{PLA}, RES_{GLA}), it is possible to estimate the total production of individual fractions.

Trend Series Analysis—Initial Models Generation

As far as all information in the nodes is complete, the second part of the methodology starts. It establishes the future values of desired parameters. TSA is performed for data on all hierarchical levels (that is L0, L1, L2) and models on future production in all micro-regions, all regions and the whole country are formulated. Not only the input time series SEP_{PAP}, SEP_{PLA}, SEP_{GLA} and RES_{OTH} are extrapolated, but also series newly derived by function B in Fig. 2 are treated in the same way (RES_{PAP}, RES_{PLA}, RES_{GLA} and RES_{OTH}). In other words, the composition of RES is extrapolated, too.

Regarding the involved models, the model used (function f or F depending on the level, see Eq. (1)) is generally defined as [29]:

$$m^* = a + bt^c \tag{13}$$

where t is an independent variable whose values are the year(s) of waste production, m^* is the dependent variable giving the amount of produced waste in year t and a, b, c are regression parameters to be estimated. Additionally, $m^* \geq 0$ is valid. The correlation between independent variable t and waste production m^* differs for individual time series. The Pearson correlation for MMW on L0 level is

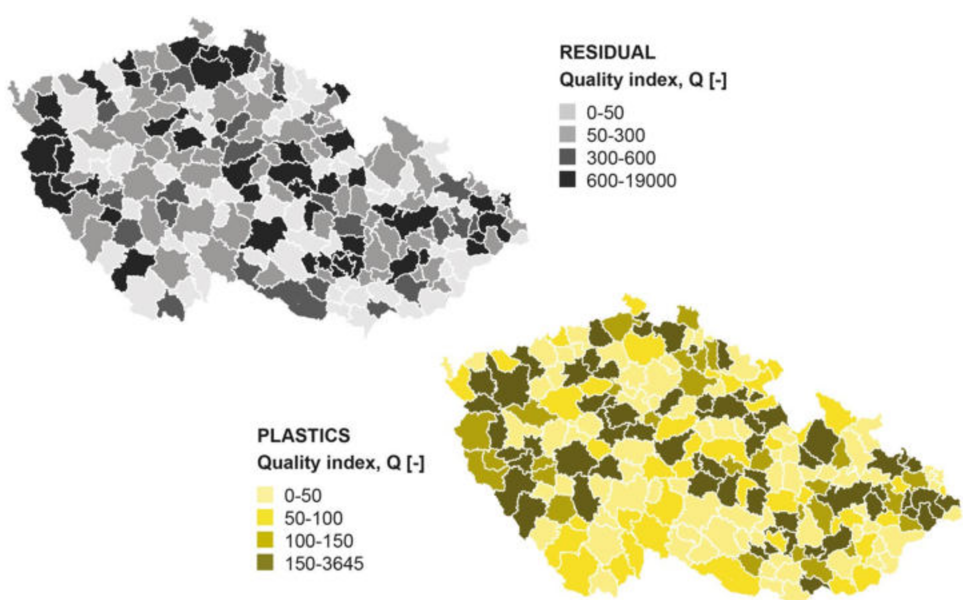

Fig. 6 Quality of extrapolation model expressed as Q and its spatial variation among micro-regions (L2) for RES and SEP_{PLA}

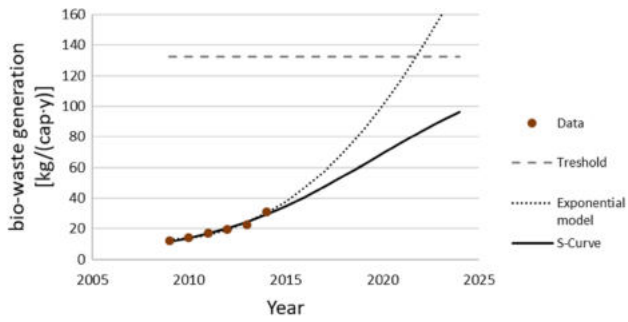

Fig. 7 Increased SEP_{BIO} as reported for CZE (L0 level) and its extrapolation models

$r_{MMW,L0} = -0.904$. The separated fractions are described by $r_{PLA,L0} = 0.995$, both $r_{PAP,L0}$ and $r_{GLA,L0}$ are almost equal to 0.9. For the next territorial units L1, L2 the correlation is lower due to higher data variability.

To measure the quality of the extrapolation model in case of short-time series, where traditional metrics fail, a parameter Q was proposed by Pavlas et al. [29]. This Q was evaluated for all time series as a part of a study presented in section "Results". The analysis confirmed the statement presented by Pavlas et al. [29] that with deeper aggregation, the quality of extrapolation models is increased. Whereas the original work of [29] was focused on hazardous waste, here we present the results for MSW and its fractions. The details on how parameter Q is calculated can be found in [29].

The Table 1 summarizes average values of criterion Q_i for various territorial units. Q variation for RES and SEP_{PLA} among micro-regions is visualised in Fig. 6.

The higher value of the criterion Q_i leads to better quality of the extrapolation model. As Table 1 shows, the better model fit is achieved for higher territorial units. With the only exception when in case of RES, L1 exceeds L0. The small difference proves that this data of RES has comparable quality on levels L0 and L1. It is caused by significantly larger amounts of this type of waste than others.

Low-quality indexes open a discussion on suitable models [Eq. (13)]. There are a variety of potential models. Their testing on the L2 level for the same dataset was performed in [34]. To keep the processing time reasonable (1442 time series, seven fractions, 3665 models), a special approach based on cluster analysis was proposed. The outcomes pointed out that the quality of the forecast is subjected to MSW fractions. RES was forecasted with high preciseness. The situation is much complicated for SEP fractions, where the Q is much lower, especially on micro-regional level L2.

Because of this principle, outcomes from TSA describe so-called "Baseline scenario" or "business-as-usual scenario (BAU)", where no significant changes in the course are expected. In some cases, extrapolation provides unrealistic models, which leads to overestimation or underestimation. As an example, the model on future amounts of SEP_{BIO} for CZE L0 is presented in Fig. 7.

There is no expectation that the production will follow the exponential model on a long-term basis. The sharp increase reported by latest data, as a response on new legislation introduced in 2014, will be exhausted within a couple of years as soon as a waste management system in the majority of municipalities will be adjusted. Therefore, an additional corrective model specifying realistic future target respecting the character of the area is needed.

A logistic function (Sigmoid) could be a good candidate for these cases Eq. (14):

$$m^* = \frac{1}{1 + e^{-(a+bt)}}, \tag{14}$$

where m^* is the amount, e is Euler's number, a and b are constants and t represents time. Logistic function (Sigmoid) reaches values within the range 0 and 1. Therefore data on production have to undergo a transformation. For this reason, a threshold has to be determined. In the case of SEP_{BIO}, it is the maximum fraction rate which can be potentially achieved in the studied area. This value, in case of SEP_{BIO}, is subject of the housing structure, as confirmed by several previous works (e.g. [35].). Karkanias et al. [36] focused on the home composting scheme in Northern Greece and the effect of this programme on the citizens' behaviour. The following threshold per capita is assumed for two types of urban areas:

- Blocks of flats: 60 kg/(cap·y).
- Single-family houses: 200 kg/(cap·y).

Whereas the production of 60 kg/(cap·y) of kitchen waste is assumed in both residential types, an additional 140 kg/(cap·y) of yard waste is expected in case of individual buildings. The building structure of the CZE mentioned in section "Regression Models to Get Complete Information" expects an average SEP_{BIO} of approximately 132 kg/(cap·y) (see a threshold in Fig. 7) and absolute amount of 1400 kt/y.

Balancing and Corrections of Initial Estimates

The computational system processes a variety of spatially distributed forecasts (initial models) on production and composition at every point obtained by the RA or TSA above. In the next step, these initial models are treated by reconciliation-technique based algorithm [29]. Applying areal and composition constraints, the initial forecasts are corrected to get a solution with the overall lowest distances between initial models and the result. Such a solution is denoted "final forecasts".

Table 2 Average composition of RES in 2014 (L0–country level)

Fraction	Amount (%)
PAP	8.11
PLA	9.25
GLA	4.37
BIO	28.21
Other	47.41

From a mathematical point of view, the procedure follows the principle of least squares method as a proposed in [29]. Least square method, in its traditional applications, results in a description where square distances between each of the input data and the description (model) are minimised. Following the visualisation in [29] input data from TA and RA is horizontally fragmented forming vertical groups of points. Each of the groups is associated with one unknown parameter, which in our case is the amount of RES and all SEP fractions. Input point estimates may differ and even frequently provide contradictory information. Balancing performs corrections where distances between resulting values (an unknown parameter) and all available forecasts are minimised, taking into account each of the locations, all territorial units and all fractions. The task cannot be decomposed due to the additional constraints and reasons mentioned above (section "Waste Composition and Composition Constraint").

Results

Several examples of a comprehensive analysis done for the area of the CZE are presented in this section. The simultaneous calculations for 206 micro-regions, 14 regions and the country were performed. Data on residual waste amounts and the yield of separately collected fractions for the years 2009 to 2014 were available. Residual waste analysis coming from a few micro-regions represented additional input.

The investigated system involved several fractions. RES and amount of SEP for three fractions, namely PAP, PLA, GLA were considered as one interacting system. Regression models on the composition of RES and amount of SEP for these fractions were generated. RA also revealed that there is no correlation between amounts of BIO and amount of RES. Considering increased BIO generation (see Fig. 7), lower amounts of RES were expected. Unfortunately, this was not confirmed by the analysis of L2. Amount of BIO dominantly consists of garden waste and the only little amount is kitchen waste diverted from RES. Therefore, BIO was forecasted as an independent stream with no interaction with RES. The same applies to metals which were also considered as an individual stream. RES_{OTH} fractions were forecasted in the second step, and this stream contains fractions with no link to RES production. RES_{OTH} is composed of BIO, metal, textile, etc.

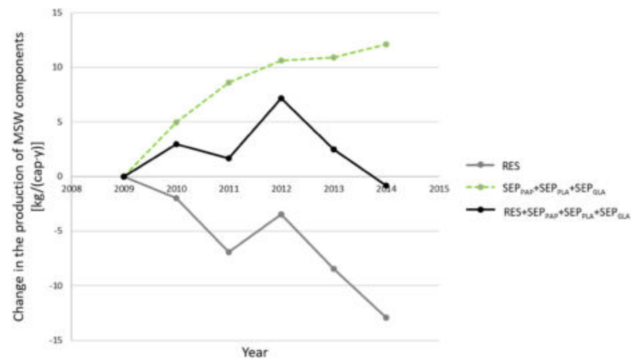

Fig. 8 Trend in MSW fractions generation

Average Composition and Overall Trends on L0

First, results for apex L0 are presented. It is worth mentioning that these results represent a bottom-up approach. They were formulated by an analysis on lower levels, that is on L2 and L1. In other words, trends on L0 are corrected taking into account trends on lower hierarchical units L1 and L2.

Current (2014) generation of MSW in the CZE is 5324 kt/y (506.3 kg/(cap·y)). 34.8% of this amount is supposed to be materially recovered [37]. Amount of waste considered in the analysis is 2661 kt (253 kg/(cap·y)), which is 50% of the overall production of MSW. Excluded was 2663 kt of RES_{OTH}, because it forms a completely new waste stream. There is no link between SEP and RES.

Composition of RES

Average composition of RES was estimated involving available inputs and models. The methodology itself is based on RA. It includes several explaining parameters including housing structure which was identified as the most significant variable. The methodology is described in more detail in [30].

The sum of PAP, PLA, GLA counts approximately 23.8% of RES. This amount represents approximately 9.5% of the total MSW. In the case of achieving absolute sorting efficiency (SE for all fractions is equal to 100%), the rate of material recovery of MSW will increase to 44.3%. For comparison, targets implemented by CEP are 60% in 2025 and 65% in 2030.

Table 3 Maximum feasible SE for fractions as proposed for CZE (%)

Fractions	Housing structure		
	Rural area (%)	Combined (%)	City (%)
PAP	93	86	70
PLA	73	64	52
GLA	90	89	73
$SEP/TOTAL_{SEP}$ Eqs. (9)–(8)	86	72	59

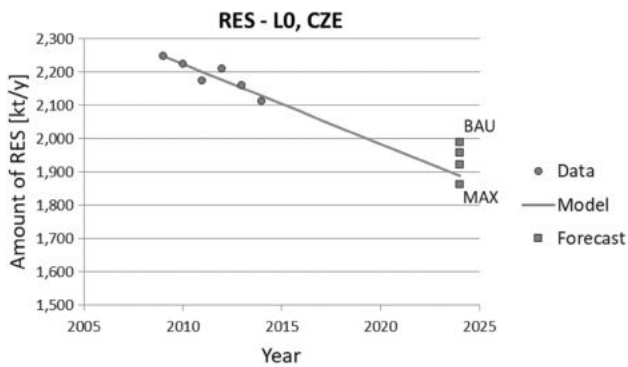

Fig. 9 Forecasted amount of RES for various scenarios, L0, CZE

As Table 2 summarises, the other fractions occupy a significant part of RES. Nevertheless, they are not part of the analysis.

Reported Trends

Overall production of RES is approx. 200 kg/(cap·y) plus 53 kg/(cap·y) was collected as separated SEP_{PAP}, SEP_{PLA} and SEP_{GLA}. This production is stable in the investigated time interval 2009 through 2014. A drop in 2015 compared to 2009 was approximately 0.5% (see Fig. 8), which is a negligible change. However, a significant reduction in RES is observed and is accompanied by an increase in SEP. In other words, considering the constant generated amount, fractions were transformed from RES to SEP, which is the desired trend.

Future Amounts Modelling

Time series from 2009 to 2014 (both input and developed by RA) were extrapolated using the methodology described in sections "Trend Series Analysis—Initial Models Generation" and "Balancing and Corrections of Initial Estimates". The year of interest was 2024, which is an important future milestone in the waste management of the CZE. As given by [38], landfilling of untreated residual MSW, recyclable fractions and fractions suitable for further recovery is to be

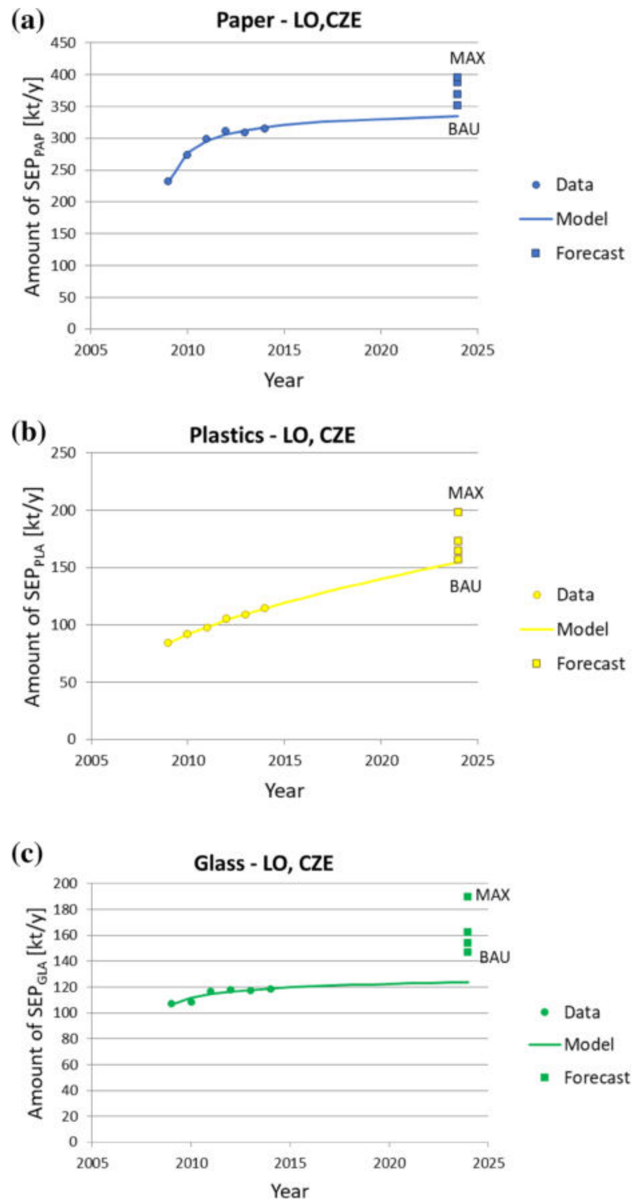

Fig. 10 Forecasted amount of SEP fractions for various scenarios, L0, CZE. **a** Paper, **b** Plastics, **c** Glass

banned since 2024. This change requires the improvement of existing infrastructure.

Following the mass conservation equations Eqs. (4) to (6), it is assumed that higher SE decreases fraction content in RES. The following four scenarios were modelled:

- Scenario 1–A basic scenario which reflects recent trends in the development of waste management in the CZE. Forecasts are based on TSA. No significant corrections of observed trends are expected. This scenario can also be denoted as a business-as-usual scenario (BAU).

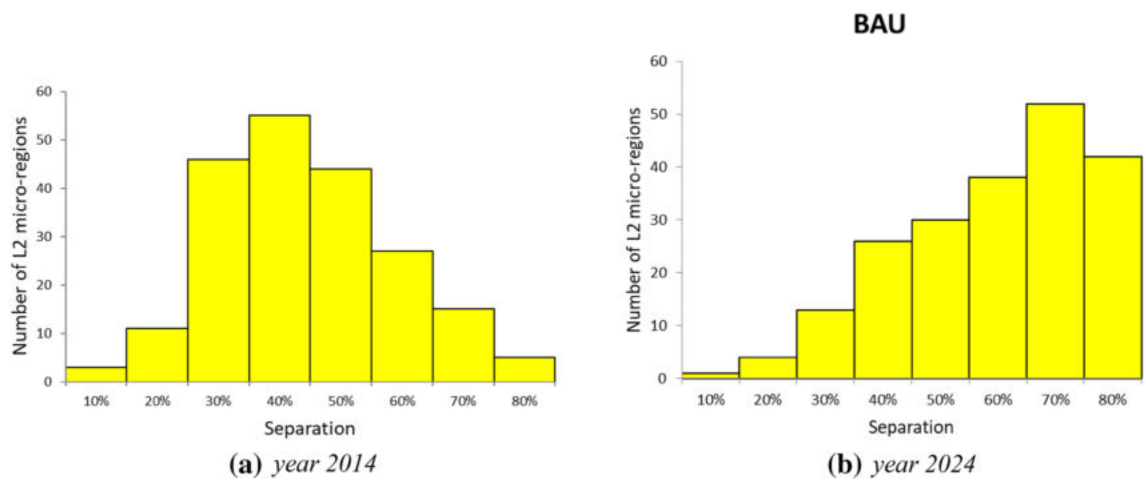

Fig. 11 Frequency diagram of plastics separation efficiency [%] for 206 CZE micro-regions in 2014 and 2024

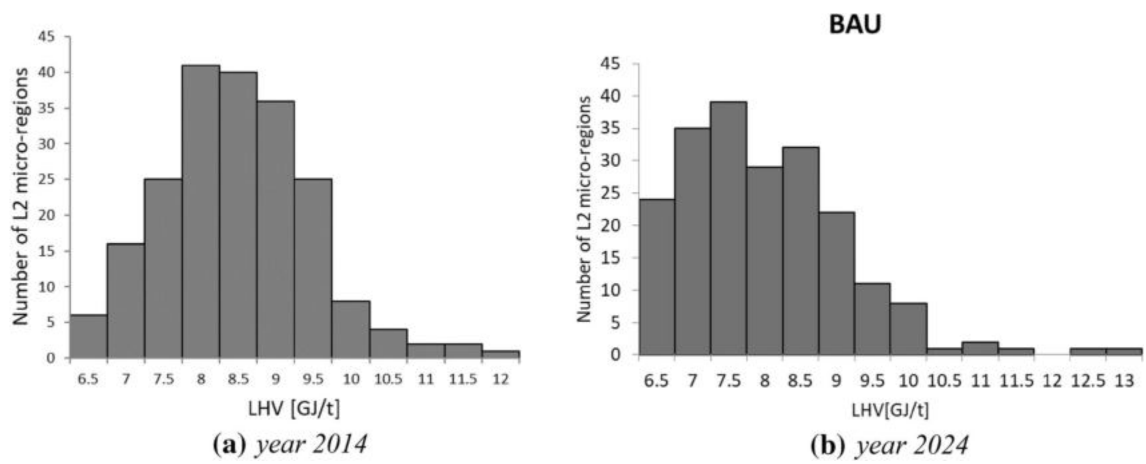

Fig. 12 Frequency diagram of lower heating value [GJ/t] of RES for 206 CZE micro-regions in 2014 and 2024

- Scenario 2–The second scenario extends the previous one. Increase in SE of 5% is assumed for all investigated fractions on an annual basis.
- Scenario 3–The second scenario extends the previous one. Increase in SE of 10% is assumed for all investigated fractions on an annual basis.
- Scenario 4 (MAX)–This scenario introduces challenging separation targets. Following the cooperation between our team with experts from Germany, the experience of waste management development in Germany was exploited and the maximum feasible SE were proposed individually for fractions. Here, the housing structure was considered an influential parameter. The limiting SE forming additional constraints for balancing the results are summarised in Table 3.

Representative outcomes from the complex analysis are displayed in the following figures.

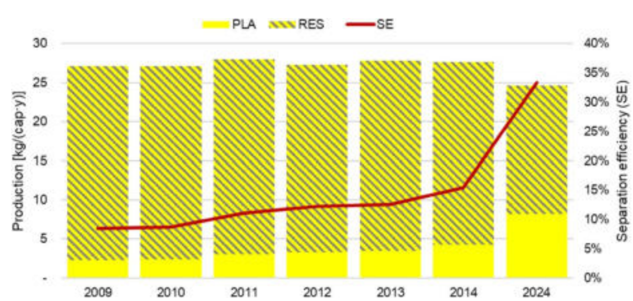

Fig. 13 Production and separation efficiency of plastics in selected micro-region

First, the development of RES is forecasted in Fig. 9. Afore-mentioned four scenarios are distinguished. The outcome confirms the recent trend, where the production of RES is constantly reduced. Solid line denoted as “Model” describes an extrapolation model obtained by applying

Table 4 Summarization of data reconciliation results on the L0 and L1 levels in the year 2024

Fractions	L0 value—model (kt/y)	L0 value balanced scenario BAU (kt/y)	L0 correction (%)	L1 (14 nodes) average correction (%)	L1 min correction (%)	L1 max correction (%)
RES	1887.8	1989.3	5.4	4.9	0.7	13.9
PAP	334.1	351.1	5.1	6.1	0.002	13.5
PLA	154.4	156.5	1.3	14.2	3.4	37.0
GLA	123.5	146.6	18.5	14.3	1.4	48.5
Total	2500.1	2643.5	5.7	1.4	0.3	2.5

Table 5 Results of scenario modelling on L0 level in the year 2024—Separation efficiency (%)

	Scenario 1 (BAU)	Scenario 2	Scenario 3	Scenario 4 (MAX)
PAP separation rate	70.6	74.1	77.8	79.4
PLA separation rate	49.2	51.7	54.3	62.3
GLA separation rate	62.3	65.4	68.9	80.5
Separation rate of recyclables	62.3	65.4	68.7	74.5

Eq. (13). Function value for this model for argument 2024 represents an "initial" estimate. This value is corrected to get the final estimate according to section "Balancing and Corrections of Initial Estimates".

More detailed analysis of paper, plastics and glass fractions is provided in Fig. 10, where amounts of SEP_{PAP}, SEP_{PLA} and SEP_{GLA} are in an opposite relation with RES. The expected increase in three fractions leads to the elimination of these fractions in RES. The resulting amount of RES decreases, too.

The following increase in separation of fractions is expected for scenario BAU:

- Paper separation increased from 65.4% in 2014 to 70.6% in 2024. The rest of the paper is present in RES.
- Plastics separation increased from 35.2% in 2014 to 49.2% in 2024. The rest of the plastics is present in RES.
- Glass separation increased from 50.5% in 2014 to 62.3% in 2024. The rest of the glass is present in RES.

Detailed Analysis at L2

The trends on country level L0 presented in the previous section stem from the situation in regions and micro-regions, which is the basic principle of the proposed approach. In other words, contributions of micro-regions to achieving national targets in separation have been investigated, too. SE forecasts on all 206 L2 units were determined. These are displayed in Fig. 11 for plastics in 2014 and BAU scenario 2024. Comparison of both frequency diagrams clearly shows development towards more effective waste management, where the mode in 2024 reaches 70%, while it was 40% in 2014. The positive trend in increased separation of calorific fractions (not only of plastics but also of paper) results in a decrease in lower heating value (compare diagram for 2014 and 2024 in Fig. 12).

Particular Region L2

Figure 13 demonstrates one particular result for a selected L2 micro-region and fraction plastic. It shows the constant production of plastic waste between 2009 and 2014 and a slight decrease to 2024. It also stresses an ineffective plastic separation, since only 15% of its production was separated in 2014. This very low value is highlighted concerning Fig. 11a. The micro-regions belong to less-performing micro-regions of the CZE. A future increase in yield is expected, resulting in lower amounts of plastics in residual waste and significantly increased efficiency. Similar outcomes were obtained for all territorial units but are not mentioned to keep the contribution of reasonable length.

Discussion

The presented approach combines trend analysis in historical data followed by data reconciliation (see section "Steps in the Algorithm"). The plain trend in the data is corrected in a particular year to address additional constraints. The model takes into account the links in the territorial structure (as Fig. 1 shows) as well as the relations between the waste fractions [Eqs. (4)–(11)]. The effect of data reconciliation is summarised in Table 4. First, initial guesses denoted as L0 value-Model, which can be considered as a traditional way of treating the extrapolation, is provided. Then, balanced result and extent of corrections in percentage are evaluated for L0. Finally, corrections at the L1 level are elaborated. In the case of L1 level, the average value of corrections, as well as the ranges, are shown. It can be observed that to gain balanced scenario BAU, the model value has to be corrected meaningfully in some cases. Especially GLA required significant correction both at L0 and L1 level, which is caused by higher variability in historical data.

Currently, waste management is facing some changes, and legislative interventions affect waste production. EU member states are obliged to meet targets on minimum waste separation in the coming years as a result of efforts to material or energy waste recovery.

The approach presented can also be used successfully for scenario modelling. Scenarios defined in the section "Future Amounts Modelling" will be considered. Scenario 1 (BAU) denotes the same development to future as was established in the historical data (Table 5). Scenarios 2 and 3 consider 5% resp. 10% increase of SE on the L0 level. The results specify, how much the lower territorial unit would improve their separation to reach the required SE on L0 level. The last scenario MAX shows the highest possible SE on L0 level.

The Czech Republic is committed to separate 50% of MSW by 2020 with a 5% increase each five years up to 2035. There are four methods introduced to evaluate current rates of preparation for reuse and recycling in [39]. In this paper, the calculation method no. 1 has been applied. The results are presented at the bottom of Table 5. CZE meets the target for 2020 (50%) and 2030 (60%) even for Scenario 1 (BAU), which exceeds 62% of considered recyclables separation rate (PAP + PLA + GLA).

Conclusion

In this contribution, an approach towards simultaneous forecasting of waste amounts and waste parameters at different territorial units, which has been first introduced in [29], is further developed. In general, the approach can be applied to any task where forecasts are performed based on spatially distributed data from previous years. This data is supposed to be incomplete (data for locality is missing), sometimes even uncertain.

In this paper, the original algorithm is adjusted to handle a so-called multi-commodity system where components overlap between observed streams. MSW represents a good example as it consists of several fractions, such as paper, plastics, glass, metals and bio-waste. These fractions may be gathered either as separately collected recyclables (for example, by kerbside collection systems) or they may contribute to residual waste quantities with limited material recovery possibilities. The algorithm was extended by the following: (1) regression analysis providing models which are later used to get complete information for all nodes, including nodes where input data is missing; (2) extrapolation techniques for data on various levels of detail; (3) specification of newly formulated composition constraints; (4) modification of reconciliation-based balancing model. The complications related to short-time series, which are very frequent in the waste management field, was highlighted. From a mathematical point of view, preciseness is secured only for series with a large number of values. Any attempt at a rigorous time series analysis of short-time series is going to result in a heavily skewed estimate of the real underlying trend, and hence, is of limited practical use. Therefore, extrapolation models provided by such an analysis are considered as initial estimates, which are further corrected by the balancing model to meet areal and composition constraint. Such simultaneous forecasting done in the tree-like structure is an effective measure to overcome poor extrapolation quality.

The algorithm is demonstrated through a case study inspired by an extensive project for the Ministry of the Environment of the Czech Republic. Future amounts of residual waste and recyclable fractions, such as paper, plastic, glass and kitchen bio-waste produced in one country as well as in its 14 regions and 206 micro-regions, are forecasted. The source-separation efficiency in all of the 206 micro-regions is analysed for four different future scenarios. The basic scenario called "BAU—Business as usual scenario" reported the following increase in separation on the country level: Paper separation will increase from 65.4% in 2014 to 70.6% in 2024; plastics separation will increase from 35.2% in 2014 to 49.2% in 2024; glass separation will increase from 50.5% in 2014 to 62.3% in 2024. The rest of the paper, plastics and glass is present in the residual solid waste. Amount of bio-waste comes dominantly from garden waste, and an only little amount is from kitchen waste diverted from residual waste. Therefore, bio-waste was forecasted as an independent stream with no interaction with residual waste. Its amount is expected to rise from 40 kg/(cap·y) in 2014 to 130 kg/(cap·y) in future.

Similar results were derived for all of the territorial units of the investigated area. Some examples for micro-regional level were presented including investigation of the lower heating value of residual waste. While the current average value is 8.5 GJ/t, it is expected to decrease to 7.8 GJ/t by 2024 in response to increased source separation of calorific fractions.

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References

1. European Parliament legislative resolution of 18 April 2018 on the proposal for a directive of the European Parliament and of the Council amending Directive 2008/98/EC on waste (COM(2015)0595–C8-0382/2015–2015/0275(COD)). https://www.europarl.europa.eu/sides/getDoc.do?pubRef=-//EP//NONSGML+TA+P8-TA-2018-0114+0+DOC+PDF+V0//EN. Accessed 6 Sept 2018
2. Ghiani, G., Lagan, D., Manni, E., Musmanno, R., Vigo, D.: Operations research in solid waste management: a survey of strategic and tactical issues. Comput. Oper. **44**, 22–32 (2014)
3. Bing, X., Bloemhof, J.M., Ramos, T.R.P., Barbosa-Povoa, A.P., Wong, ChY, van der Vorst, J.G.A.J.: Research challenges in municipal solid waste logistics management. Waste Manage. **48**, 584–592 (2016)
4. Rudi, A., Müller, A.K., Fröhling, M., Schultmann, F.: Biomass value chain design: a case study of the upper Rhine region. Waste Biomass Valoriz. **8**, 2313–2327 (2017)
5. Zis, T., Bell, G.H., Tolis, A., Aravossis, K.: Economic evaluation of alternative options for municipal solid waste management in remote locations. Waste Biomass Valoriz. **4**, 287–296 (2013)
6. Saif, Y., Rizwan, M., Almansoori, A., Elkamel, A.: Municipality solid waste supply chain optimization to power production under uncertainty. Comput. Chem. Eng. **121**, 338–353 (2018)
7. Galan, B., Dosal, E., Andrés, A., Viguri, J.: Optimisation of the construction and demolition waste management facilities location in Cantabria (Spain) under economical and environmental criteria. Waste Biomass Valoriz. **4**, 797–808 (2013)
8. Beigl, P., Lebersorger, S., Salhofer, S.: Modelling municipal solid waste generation: a review. Waste Manage. **28**, 200–2014 (2008)
9. Thanh, N.P., Matsui, Y., Fujiwara, T.: Household solid waste generation and characteristic in a Mekong Delta city, Vietnam: note II. Proc. Environ. Sci. **35**, 238–244 (2016)
10. Lebersorger, S., Beigl, P.: Municipal solid waste generation in municipalities: quantifying impacts of household structure, commercial waste and domestic fuel. Waste Manage. **31**, 1907–1915 (2016)
11. Li, Z., Fu, H., Qu, X.: Estimating municipal solid waste generation by different activities and various resident groups: a case study of Beijing. Sci. Total Environ. **409**, 4406–4414 (2011)
12. Keser, S., Duzgun, S., Aksoy, A.: Application of spatial and non-spatial data analysis in determination of the factors that impact municipal solid waste generation rates in Turkey. Waste Manage. **32**, 359–371 (2012)
13. Ruckstuhl, A.: Introduction to Nonlinear Regression. ZHAW Zürcher Hochschule für Angewandte Wissenschaften, Winterthur, Switzerland (2010)
14. Ibázez, M.V., Prades, M., Simé, A.: Modelling municipal waste separation rates using generalized linear models and beta regression. Resour. Conserv. Recycl. **55**, 1129–1138 (2011)
15. Guisan, A., Edwards, T.C., Hastie, T.: Generalized linear and generalized additive models in studies of species distributions: setting the scene. Ecol. Model. **157**, 89–100 (2002)
16. Lane, P.W.: Generalized nonlinear models. In: Albert, P. (ed.) COMPSTAT, pp. 331–336. Physica-Verlag HD, Heidelberg (1996)
17. Zhang, G., Patuwo, B.E., Hu, M.Y.: Forecasting with artificial neural networks. Int. J. Forecast. **14**, 35–62 (1998)
18. Abbasi, M., Hanandeh, A.E.: Forecasting municipal solid waste generation using artificial intelligence modelling approaches. Waste Manage. **56**, 13–22 (2016)
19. Azadi, S., Karimi-Jashni, A.: Verifying the performance of artificial neural network and multiple linear regression in predicting the mean seasonal municipal solid waste generation rate: a case study of Fars province, Iran. Waste Manage. **48**, 14–23 (2015)
20. Lilai, X., Peiqing, G., Shenghui, C., Chun, L.: A hybrid procedure for MSW generation forecasting at multiple time scales in Xiamen City, China. Waste Manage. **33**, 1324–1331 (2013)
21. Noori, R., Abdoli, M.A., Ameri Ghasrodashti, A., Jalili Ghazizade, M.: Prediction of municipal solid waste generation with combination of support vector machine and principal component analysis: a case study of Mashhad. Environ. Progress Sustain. Energy **28**, 249–258 (2008)
22. Korhonen, P., Kaila, J.: Waste container weighing data processing to create reliable information of household waste generation. Waste Manage. **39**, 15–25 (2015)
23. Arbulú, I., Lozano, J., Rey-Maquieira, J.: Tourism and solid waste generation in Europe: a panel data assessment of the Environmental Kuznets Curve. Waste Manage. **46**, 628–636 (2015)
24. Mwenda, A., Kuznetsov, D., Mirau, S.: Time series forecasting of solid waste generation in Arusha City—Tanzania. Math. Theory Model. **4**, 29–39 (2014)
25. Ghinea, C., Dragoi, E.N., Comanita, E.D., Gavrilescu, M., Campean, T., Curteanu, S., Gavrilescu, M.: Forecasting municipal solid waste generation using prognostic tools and regression analysis. J. Environ. Manage. **182**, 80–93 (2016)
26. Den Boer, E.: Waste Management Planning and Optimisation: Handbook for Municipal Waste Prognosis and Sustainability Assessment of Waste Management Systems. Ibidem Verlag, Stuttgart (2005)
27. Intharathirat, R., Salam, P.A., Kumar, S., Untong, A.: Forecasting of municipal solid waste quantity in a developing country using multivariate grey models. Waste Manage. **39**, 3–14 (2015)
28. Box, G.E.P., Jenkins, G.M., Reinsel, G.C., Ljung, G.M.: Time Series Analysis: Forecasting and Control, 5th edn. Wiley, New York (2015)
29. Pavlas, M., Šomplák, R., Smejkalová, V., Nevrlý, V., Zavíralová, L., Kůdela, J., Popela, P.: Spatially distributed production data for supply chain models—forecasting with hazardous waste. J. Clean. Prod. **161**, 1317–1328 (2017)
30. Šyc, M., Krausová, A., Kameníková, P., Šomplák, R., Pavlas, M., Zach, B., Pohořelý, M., Svoboda, K., Punčochář, M.: Material analysis of bottom ash from waste-to-energy plants. Waste Manage. **73**, 360–366 (2018)
31. Ciuta, S., Apostol, T.: Urban and rural MSW stream characterization for separate collection improvement. Sustainability **7**, 916–931 (2015)
32. Bandara, N.J.G.J., Hettiaratchi, J.P.A., Wirasinghe, S.C., Pilapiiya, S.: Relation of waste generation and composition to socio-economic factors: a case study. Environ. Monit. Assess. **135**, 31–39 (2007)
33. Vassanadumrongdee, S., Kittipongvises, S.: Factors influencing source separation intention and willingness to pay for improving waste management in Bangkok, Thailand. Sustain. Environ. Res. **28**, 90–99 (2018)
34. Smejkalová, V., Šomplák, R., Nevrlý, V., Pavlas, M.: Heuristic methodology for forecasting of quantities in waste management. Mendel J. Ser. **1**, 185–192 (2017)
35. Eurostat, Generation and Treatment of Municipal Waste, by Country, Year and Treatment Type (Recycling, composting, incineration, landfill), in kg per inhabitant. https://ec.europa.eu/eurostat/web/waste/transboundary-waste-shipments/key-waste-streams/municipal-waste. Accessed 18 Apr 2016
36. Karkanias, C., Perkoulidis, G., Moussiopoulos, N.: Sustainable management of household biodegradable waste: lessons from home composting programmes. Waste Biomass Valoriz. **7**, 659–665 (2016)

37. Ministry of the Environment of the Czech Republic. Public Waste Management Information System. https://isoh.mzp.cz/VISOH/Main/ZpravyZp
38. Act No. 229/2014 Coll. on Wastes Which Amends Act No. 185/2001 Coll. on waste, in Czech. https://ftp.aspi.cz/opispdf/2014/096-2014.pdf. Accessed 9 Aug 2018
39. 2011/753/EU: Commission Decision of 18 November 2011 establishing rules and calculation methods for verifying compliance with the targets set in Article 11(2) of Directive 2008/98/EC of the European Parliament and of the Council (notified under document C(2011) 8165). Official J. Eur. Union, **L310**, 11–16 (2011)

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Trend forecasting for waste generation with structural break

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ABSTRACT

For waste management planning, the adequate estimation of future waste production is crucial. Within waste production forecasting it is necessary to tackle with several challenges. The waste production data often consists of annual short time-series, but prediction horizon considers long-term estimation. Trend analysis seems to be a suitable approach for modelling waste production and its extrapolation. A methodology for forecasting waste generation based on historical data with a structural break is presented. To apply the approach, it is necessary to determine the estimation of separation potential. The principle is based on the idea of credibility theory where information from all territories is combined. Experience from other territories, which are more advanced in separation development, is used for forecasting. Finally, the population projection is taken into account to obtain information on absolute waste production. The case study is devoted to the forecasting of bio-waste production at the micro-regional level in the Czech Republic. There has been revealed an essential impact when population forecasting was included in the model. The increase in the average bio-waste production for micro-regions is expected. It will grow from 67 kg/cap/year in 2017 to 156 kg/cap/year in 2030. In 2030, most micro-regions would reach their potential based on this forecasting.

1. Introduction

Current society is facing a rapid increase in waste production as a response to the demographic changes, technological developments, growing wealth and consumption (Zaman, 2016). Even, waste generation rates are expected to be more than double over the next twenty years in lower-income countries (Hoornweg and Bhada-Tata, 2012). This fact necessitates intervention in existing waste management (WM). WM is the service which local governments provide to their inhabitants. Moreover, the level of WM varies greatly across countries. Decisive is the maturity and economic strength of the country (Khatib, 2011). Access to waste management can be crucial for other municipal or state activities. It is, therefore, necessary to modernize the WM system, which will be economically, ecologically and socially sustainable.

WM system includes complete waste handling issues from waste collection, through transportation to processing. Just waste processing is a major issue in terms of sustainability. The current trend in the developed countries is the transition from the classical linear economy to the circular economy (Prieto-Sandoval et al., 2018). Within EU, the preferred WM methods are given by *Waste hierarchy* (Directive (EU) 2008/98). This document appeals to waste production prevention and prioritises recycling, material or energy utilisation. The least desirable waste treatment method is landfilling. The effort is to save limited primary resources and the environment (Yi et al., 2018). For assessment of the *Waste hierarchy* fulfilment, it is essential to evaluate the current situation of waste production and treatment (Šomplák et al., 2019). To create a sustainable WM system, it is necessary to come out from requisite plans. The high-quality models of waste production are the essential assumption to make future plans in WM. The waste production models are valuable in many ways, such as:

- The estimation of current waste production – Current waste production models can identify the links between waste production and various factors.

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- The waste production forecasts – The future waste production estimation is modelled if the existing conditions and inhabitants' behaviour will be maintained. This development is expected to most likely. The current trend is unlikely to change significantly in the near future.
- The waste production projection – Evaluation of waste production in response to external interventions in the form of scenario modelling. The projection arises under predetermined conditions.
- The dimensioning of treatment facilities – Modification of handling infrastructure can take several years. Inaccurate waste production prediction may cause insufficient capacity or, on the contrary, oversizing the waste treatment facility.

The expected development based on current conditions was an impulse for the creation of new rules included in some EU Directives. The aim is the fluent change in waste treatment and supports *Waste hierarchy*. The essential for municipal solid waste (MSW) are following directives. (Directive (EU) 2018/850) prohibits landfilling more than 10% of recyclables materials to the year 2035. (Directive (EU) 2018/851) gives the minimal municipal solid waste recycling efficiency or reuse from 2025 to 55% and next 5% each five years up to 2035. These EU directions are implied to states legislative. In order to keep these aims, it is necessary to react in advance. The building of adequate handling infrastructure is necessary for keeping mentioned milestones. From the perspective of system sustainability, it is appropriate to take into account the rules of green development. Green development is a system influencing the social, economic and natural environment. In the context of rapid economic and social development, governments make strategic decisions in accordance with green development (Li et al., 2019a). The study (Li et al., 2019b) proposes a theoretical framework to explain the green development system in China and its mechanism using mathematical modelling approaches. In order to propose achievable WM plans, high-quality prognostic tools considering the available timeframe and waste composition have to be used.

Waste management is a very complex area that involves a wide range of tasks – waste prevention, production, collection, transportation, recycling, treatment and many others. The problem is usually solved according to basic criteria: economic, environmental, social and ecological. In some cases, these aspects are combined. The methods presented are often based on operational research, namely mathematical programming. Specifically, the most often encountered tasks are location problem (Farahani et al., 2012), allocation problem (Ganesh et al., 2015), network flow models (Engeland et al., 2018), supply chain models (Barbosa-Póvoa et al., 2018).

Solely waste management models were reviewed by Adriyanti et al. (2018) in a total of 26 publications. The waste management models include collection path planning, determination of points for recycling, location of collection depots and others. Many models use Geographic Information System (GIS) technology as a support tool. The tools available within GIS can be used in the forecasting, or also in the visualisation results (Wu et al., 2016).

Operational research occurs at various stages of waste production and treatment. Design of representative models in the field of waste management is of interest to many authors. It is necessary to have adequate input data to obtain the required quality outputs from models. The use of inappropriate data may invalidate the model's use. It is, therefore, highly advisable to pay close attention to high-quality input data. For decision-making in waste management, it is essential to analyse the current situation (Haas et al., 2015). However, waste management planning often has to be based on information about the expected waste production in future. Waste production forecasts have been addressed in several publications before. The literature review is provided in sec. 1.1. This paper presents an approach for forecasting waste production based on historical data that exhibits special characteristic – short time-series with structural break due to external intervention.

1.1. Literature review – waste production modelling

Waste production is currently a very discussed topic, as the number of publications testifies. Several works reviewed publications on the topic "waste production modelling". The contributions presented up to the year 2005 were discussed by Beigl et al. (2008). The estimation of the current or future MSW production was studied using 45 modelling approaches. The input parameters include various factors. The solved tasks were often very similar in the presented case studies, but the approaches differed a lot. Those 45 approaches were classified according to four criteria: territorial division, waste streams, independent variable, methods. The most commonly used methods were found principles based on regression and correlation analysis, time-series analysis and other classical methods.

The extensive study was presented by (Goel et al., 2017), where MSW production was explored in more than 100 publications from the years 1972–2016. Within this long-term period, the significant growth of the number of contributions can be observed. This review divides the methods into traditional and unconventional approaches. A lack of MSW production data is often pointed out (Goel et al., 2017).

The existing approaches used different methods categorised into two basic directions – data correlation and time-series analysis.

1.1.1. Data correlation

Data correlation utilises both classical methods and machine learning methods. WM is a complex area which reflects many factors and social behaviour. Waste production can be therefore described by the socio-economic, demographic and other independent variables. Table 1 summarises applied methods mentioned by reviews (Beigl et al., 2008) and (Goel et al., 2017). Goel et al. (2017) also considers machine learning methods. They are usually models describing the current generation of waste. However, most models can also be applied to the forecast, but it is necessary to have a prognosis of influential factors.

The quality of the models varies considerably. In addition, the assumptions of linear regression are often not evaluated. Decisive for the quality of linear regression models is the level of spatial distribution. The reason is that aggregated data are able to inhibit deflection on the municipal level. Case studies from the Czech Republic can prove this fact. Linear regression model presented by Rybová et al. (2018) on municipality level considered 12 factors to

Table 1
Modelling method describing relationships between data.

Modelling method	Number of models	
	Beigl et al. (2008)	Goel et al. (2017)
Sample survey method	16	12
Input-output analysis	5	–
Linear regression	15	13
Econometric forecasting method	–	4
System dynamic method	2	15
Factor models	–	9
Artificial neural network	–	16
Fuzzy logic	–	9
Support vector machine	–	3

model MSW production in Czech municipalities. Eight characteristics were identified as significant, but they were able to explain only 5.1% of waste generation variability. By comparison with study (Kováčová et al., 2011) where it was possible to create a model for the regional level with $R^2 = 0{,}86$. Higher accuracy compared to the result of work (Rybová et al., 2018) is probably due to higher territorial detail (regions). The approach based on linear regression is objectionable for forecasting if it is not possible to quality predict significant factors. Forecasts of significant factors are often very limited in time and do not cover the entire needed forecast horizon. For example, economics is a very dynamically developing area, so forecasts are usually made only months in advance. If forecasts are long-term, their quality is usually poor. On the other hand, demographics were found to be a well-predictable area. It is possible to include demography in waste production models successfully.

1.1.2. Time-series analysis

Time-series analysis study the development of the monitored variable in time. The representation of time-series analysis in the mentioned reviews is in Table 2.

Table 3 summarises waste generation models based on time-series analysis principles. A sufficiently long time-series is required for the application of the Box-Jenkins methodology, which applies autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA) and in the case of seasonal components sARMA and sARIMA. Data of sufficient length are usually not available in annual detail. However, in short time-series on annual detail, it is possible to model the trend in data. Mostly the trend in historical data is modelled through curves or exponential smoothing (ES).

The time-series models for MSW generation forecasting were compared by Mwenda et al. (2014) for Tanzania city. Long time-series cannot be achieved for annual data, so it usually works with monthly data. For annual data, only trend component can be observed and could be relatively successfully modelled in those cases as Ghinea et al. (2016) presented.

The trend analysis seems to be a useful tool for annual waste generation prediction. Under the assumption, that waste production exhibits a steady trend in long term series of historical data, can be expected similar development henceforward (Pavlas et al., 2017). The form of regression function for relationship description depends on the particular dataset (Smejkalová et al., 2017). Even if the data show high variability without apparent trend, it could be profitable to model it by a simple average or naïve method. The trend modelling face with several obstacles such is: short time-series, data quality, limited representativeness of the data, nonlinearity – possible local solution, bounds settings, etc. None of the above-mentioned studies in Table 3 modelled future waste production based on data with a structural break.

Nevertheless, waste production can be once affected by an external intervention which can cause a structural break. When changing the system, it is advisable to analyse the new situation and adapt the necessary infrastructure, including transport and collection points (Palomar et al., 2019). The ability to change suddenly and at the same time dramatically waste production has several origins such as the principal change of:

Table 2
Number of models based on time-series analysis.

Modelling method	Number of models	
	Beigl et al. (2008)	Goel et al. (2017)
Time-series analysis	9	5

- legislation (eg. separation targets),
- system of waste collection (e.g. bag collection),
- technology development (e.g. new packaging materials),
- new fraction separation (e.g. obligation to separate bio-waste since 2014 in the Czech Republic).

Ghinea et al. (2016) presented a trend model with 16 points of historical data. The S-curve was found as the most suitable model for MSW prediction. S-curve modelling is typical for spreading systemic changes. S-curve in the form of logistic function needs the upper bound setting, and this value is not easy to estimate. The S-curve trend is suitable waste production modelling when the time-series begin by gradual growth. Subsequently, the development slows down and converges to its potential. The problem is that if the historical data currently did not reflect the structural break yet, it will be likely observable in future. A simple trend model is unable to capture this fact. The new presented methodology should consider expected change which is not currently observable in historical data for some territories. In such cases, the trend is corrected on the basis of the experience of territories that are at a more advanced stage in separation.

1.2. The novelty of the contribution

The quality of waste production forecasts is crucial for the creation of sustainable WM system. Based on the literature review (sec. 1.1), two main approaches for waste production forecasting were identified. Methods using links between waste production and influenced factors often face with the weak explanatory power of models. Besides, forecasting of socio-economic data can be problematic in some cases for the reason of high data variability and character of some datasets. The second class of frequently using methods includes time-series analysis, which comes from historical development. The trend in historical data can be successfully observed also in the short time-series (Pavlas et al., 2017) under the assumption that the historical data maintain the same trend all the time.

However, WM is a rapidly developing area, where frequent legislative, technological and infrastructure modifications can cause a sudden change in waste production. This feature makes it difficult to predict waste production using historical data because data before the intervention lose their credibility. The usually used methods, mentioned in sec. 1.1, are not able to cope with a structural break in data and the forecast could be distorted.

The research intends to develop an approach for forecasting waste production if the input information is in the form of short time-series of historical data. Moreover, data contain a breakpoint in the trend due to legislative, technology or other changes. A short time-series is in itself complicated for forecasting, and in addition, a structural break reduces the predictive value of the data before the change. The main idea of the presented forecasting approach is that experience in other territories will also be used to forecast waste production in a given territory. The novel methodology is based on credibility approach, which combines information from individual territories. As sec. b) shows, the individual territories are not able to react to the intervention (legislative, technological, etc.) immediately and simultaneously because innovation is spreading gradually. The critical step is to recognise the phase of production development if the change has done. The main idea of the presented procedure is to utilise experiences of others which have already passed the change to predict more preciously the expected change of remaining territories. Important assumptions for the presented approach are that the intervention in the system was carried out in the past, and some territories have already responded to it. The assumption that regions which have not yet started to

Table 3
Time-series analysis — used approaches.

Reference	Time-series analysis approach	Detail data	Number of data points
Ayeleru et al. (2018)	linear trend	year	20
Cole et al. (2014)	ARIMA	month	84
Denafas et al. (2014)	seasonal ES, winters additive	month	24
Ghinea et al. (2016)	trend analysis	year	16
Innocent et al. (2016)	ARIMA	month	144
Intharathirat et al. (2015)	trend analysis, naïve, grey models	year	13
Jiang et al. (2016)	ARIMA, ES	year	32
Marandi et al. (2016)	ARIMA	month	82
Mwenda et al. (2014)	ARMA, ARIMA	month	66
Owusu-Sekyere et al. (2013)	ARIMA	month	72
Pavlas et al. (2020)	trend analysis, data reconciliation	year	6
Petridis et al. (2016)	trend analysis, ARMA, ES	year	27
Rimaitytė et al. (2012)	ARIMA	week	416
Song et al. (2014)	sARIMA	day	1001
Xu et al. (2013)	sARIMA	month	132
Younes et al. (2014)	ARIMA	month	72

separate waste will be followed by historical increases in already successfully deployed systems represents enormous progress in modelling the development of waste production.

The following text presents the theoretical basis of the theory of credibility, the idea behind the modelling approach (see sec. 2.1), followed by its modification for waste production forecasting (sec. 2.2). The procedure is presented using bio-waste production data in the Czech Republic on the micro-regional level without affecting the generality of the task. The database consists of 206 territories and time-series from 2009 to 2017. First, the current data analysis is presented, and the setting of separation potential is provided (sec. 3). Finally, the results of the bio-waste generation forecast in the Czech Republic are presented (sec. 4).

2. Modelling approach for waste forecasting with a structural break

2.1. Credibility theory

Support measures leading to an increase or decrease in waste separation and generation cannot be identified based on historical data. Such changes in trend will not be comprised when estimating future waste production. However, the change observed in somehow similar subjects can be projected. The behaviour of waste producers can be similar but with certain time delay. The approach used for the combination of individual and overall information for predicting future development is called credibility theory (Mahler and Dean, 2001), originally used in the insurance industry. The credibility is built on the principle of weighting together two estimates, the basic formula for credibility estimation of parameter e is given by Eq (1):

$$e = \lambda x + (1 - \lambda)y, \tag{1}$$

$$0 \le \lambda \le 1, \tag{2}$$

where λ is the credibility factor with the value between 0 and 1, Eq (2). Value x denotes the individual data and y average of the overall dataset. The credibility λ is closer to 1 if the dataset is large and not likely to vary much from one period to another. The credibility theory formulates several special types, e.g. Bühlmann credibility model (Bühlman, 1967), which works with variance across the dataset.

2.2. Credibility model for waste forecasting with a structural break

The mathematical approach of individual and collective data combination from sec. 2.1 can be applied in the waste management sector. The forecasted value is given by the difference between production from the S-curve model in the present and the previous year. However, all territories did not respond to such a change with the same efficiency, as the schematic Fig. 1a) shows for individual territories. The vertical axis indicates the percentage fulfilment of the separation potential. The change of conditions in waste management occurred in the year 2014, which is reflected in the picture. In general, the reaction to a change in trend is also related to Fig. 1b), which shows the difference in territorials' behaviour. The two particular developments of the waste fraction that has undergone a systematic change are figured — low and high separation. However, the main idea is that the territories will approach average behaviour in the future.

The new approach was designed for trend-based data modelling. The methodology includes the ideas of trend analysis and credibility theory. The complete approach is presented in six steps in the following algorithm, and it is made iteratively for individual territories.

2.2.1. The notification

$j, \bar{j} \in J$ set of producers (territories)
$i \in I$ set of years with available data (from year $i = 1$ to $i = t - 1$)
$t, \tau \in T$ set of years within forecasting period
$s_{j,t}$ S-curve model of separation potential fulfilling in the territory j and year t [%]
$m_{j,t}$ difference based on the S-curve model in the territory j and year t — individual information [%]
$n_{j,t}^{\bar{j}}$ the difference of producers shifted in time according to producer $j, \bar{j} \neq j$ [%]
$\overline{m}_{j,t}$ average $n_{j,t}^{\bar{j}}$ for the territory j and year t — collective information [%]
$d_{j,t}$ the corrected trend in the data using credibility model [%]
w_j normalisation parameter - modifying collective information taking into account type of housing [-]
$\lambda_{j,t}$ credibility factor given by separation potential fulfilling [%]
o_j percentage of rural housing [%].
$\overline{o}$ average of percentage of rural housing [%]
P_j separation potential [kg/cap/year]

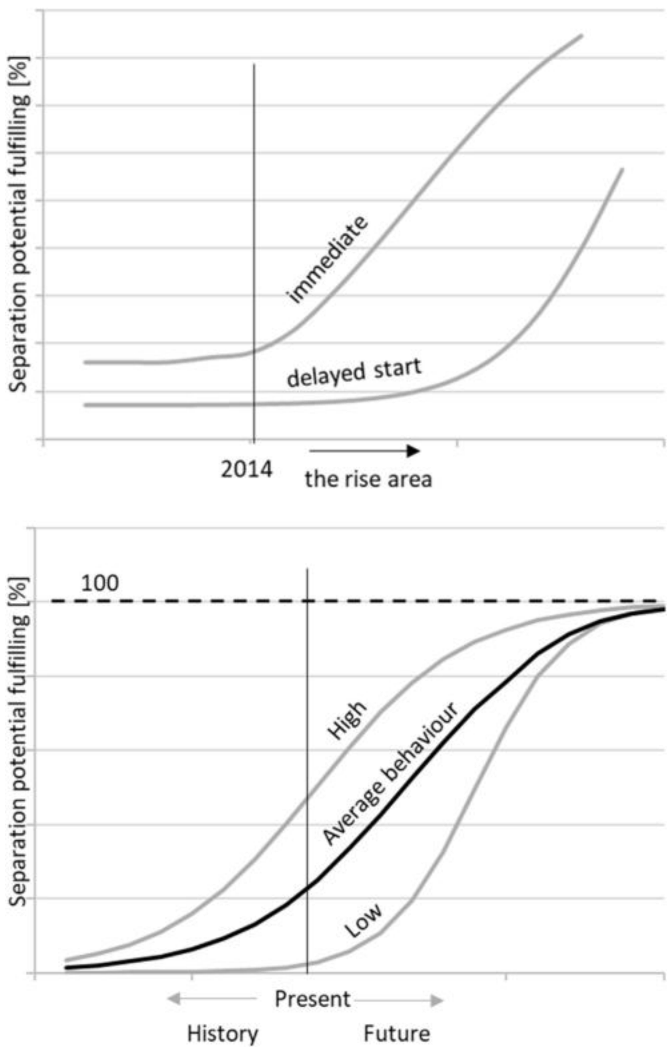

Fig. 1. The schematic representation of possible waste production development with systematic change.

$p_{j,t}$ model of waste production in the territory j and year t [kg/cap/year]
t_0, j_0 parameters for iteration counting [-]

2.2.2. Algorithm

The algorithm is performed in repeated iterations. The procedure is described in Fig. 2 by flowchart. Individual steps 1–6 (blue colour in Fig. 2) are discussed in more detail below.

The calculation is structured in the cycle gradually for each predicted year t from the set T. For each year, element $t\in T$, is defined procedure consisted of six operations:

1. S-curve trend $s_{j,t}$ is modelled using data given by set I and trend is extrapolated to cover the entire set T. Indispensable information is separation potential P_j which can be generally different for individual areas. The separation potential is discussed in sec. 3.1. Separation potential is the limit value for S-curve. Waste production data is normalised by separation potential before modelling. Simultaneously, this step makes it possible to compare areas with different waste production. Thanks to normalisation, expected separation potential fulfilling in the particular year from $T$is given by S-curve trend $s_{j,t}$.

Next loop through all elements $j\in J$ begins after S-curve trend calculation for each area $j\in J$. The trend in historical data given in part 1 is used.

2. Because of the requirement for monotony trend, the difference was chosen as the considered parameter. The difference $m_{j,t}$ is defined as Eq (3):

$$m_{j,t} = s_{j,t} - s_{j,t-1}. \tag{3}$$

3. The determining of overall information differs from classical credibility theory in the two characteristics.

2.2.3. Producers selection

The credibility theory usually considers all subjects ($\forall j\in J$) to gain overall information. However, the presented methodology works in a different way, and the overall information is set considering only chosen producers. The principle of producers selection for collective information is figured in Fig. 3a). The individual production $m_{j,t}$ is corrected by producers $\bar{j}\in J$ who report more advanced separation. Fig. 3a) illustrates four producers, $j = 1, 2, 3, 4$. In the case of production forecasting for $j = 2$ and year t, the individual information is $m_{2,t}$ and overall information is average of $n^3_{2,t}$ and $n^4_{2,t}$. The producer $j = 1$ is not considered, because in comparison with $j = 2$ it has delayed reaction. Briefly, the inspiration from others is given only by producers who are in front of the forecasted producer j in the meaning of separation potential fulfilling.

2.2.4. Timeshift

The parameter $n^{\bar{j}}_{j,t}$ is a difference in the S-curve model but in the year τ, not t. Year τ is generally different for each $\bar{j}\in J$ and it determines the year with the same separation potential fulfilling as the producer j in the year t has. The situation is illustrated in Fig. 3b). The producer $j = 2$ is forecasting and the information from producer $\bar{j} = 3$ is needed. Point marked by letter A is found as the S-curve model of production in the year t, $s_{2,t}$. In the previous year $t - 1$, the S-curve model production is marked by letter B, $s_{2,t-1}$. Individual information $m_{2,t} = s_{2,t} - s_{2,t-1}$. The overall information is given by all producers who have a higher separation potential fulfilling. One of them is the producer $\bar{j} = 3$. First, the year τ for $\bar{j} = 3$ is found, it corresponds with the same separation potential fulfilling as producer $j = 2$ in the year t has. This point is marked by letter C in Fig. 3b). In reality, the available data are in the annual detail, so they are not continuous. The year τ is chosen as the year with the closest value of separation potential fulfilling. Value $n^3_{2,t}$ is then determined by S-curve model difference between years τ and $\tau - 1$ (points C and D in Fig. 3b)). Difference $n^{\bar{j}}_{2,t}$ is identified in the same way for each $\bar{j}\in J$, which has higher separation potential fulfilling than $j = 2$.

This reasoning can be interpreted in such a way that the territory j will be inspired by the production of other territories, but at a time when they were at the same separation potential fulfilling.

4. Collective information $\overline{m}_{j,\,t}$is determined as the average value of other territories differences $n^{\bar{j}}_{j,\,t}$. Therefore, the parameter $\overline{m}_{j,\,t}$ retains both indices j and t, because for each territory j and each modelled year t the collective information is given differently.
5. The production difference for next year will be given by a linear combination of the difference in a particular territory and collective difference. They are both calculated prior to the computation of credibility model from the S-curve regression. As a result, the territories with currently low fulfilling of

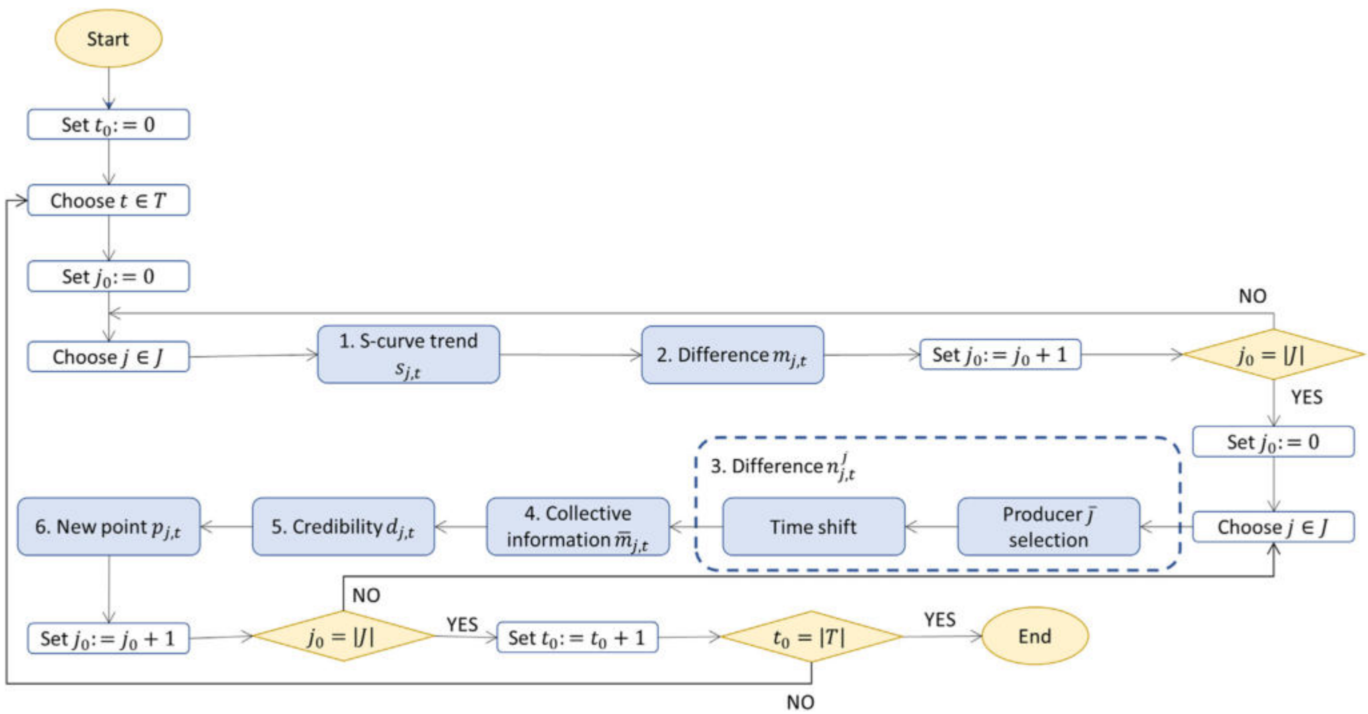

Fig. 2. Flowchart of the algorithm.

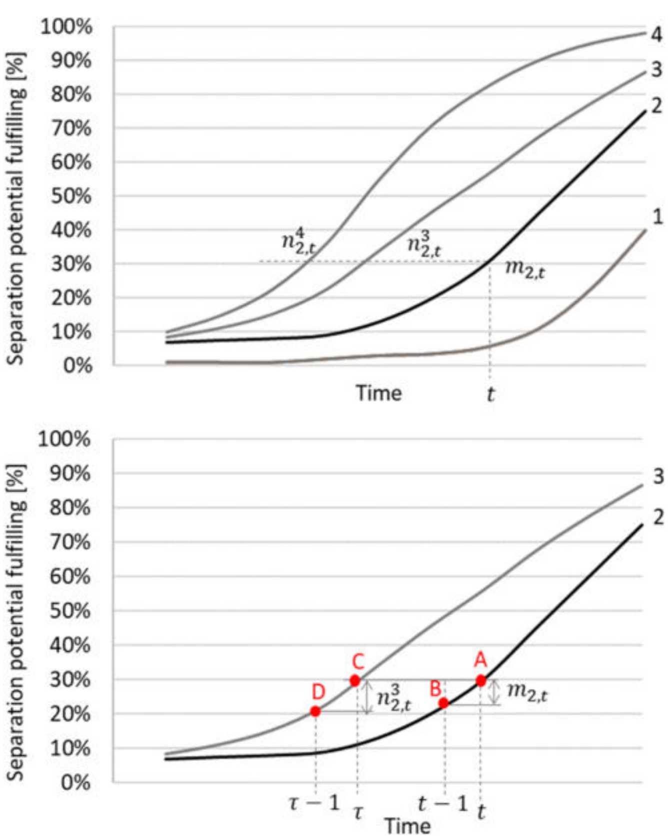

Fig. 3. The principle of obtaining collective information.

separation potential will accelerate the growth in the next year, and at the same time, the high growth ones will slow down. Simultaneously, the changes are based on other experiences, so the unreal separation growth is not expected within the long-term prognosis.

The expected bio-waste production difference $d_{j,t}$ is estimated, and the change in production from the year $t-1$ to t is set by Eq (4):

$$d_{j,t} = w_j(1-\lambda_{j,t})\overline{m}_{j,t} + \lambda_{j,t} m_{j,t}, \tag{4}$$

$$w_j = 1 + \frac{o_j - \overline{o}}{\overline{o}}, \tag{5}$$

where $m_{j,t}$ is the difference within the S-curve production model in the particular territory j and year i. Using the weight $\lambda_{j,t}$ the linear combination of $m_{j,t}$ and average $\overline{m}_{j,t}$ is given with adjustment that average $\overline{m}_{j,t}$ is multiplied by w_j (normalisation parameter) in Eq (4). The $\lambda_{j,t}$ sets up the credibility of own data and it corresponds with fulfilling of separation potential from the previous year, $\lambda_{j,t} = p_{j,t-1}/P_j$. The reason is that the low separated territory will copy the behaviour of territories which are more advanced in the bio-waste separation process, and they can provide the inspiration in production behaviour. The parameter w_j normalizes the territories and moves the average $\overline{m}_{j,t}$ based on rural/urban region, so for rural regions, it increases and decreases for urban regions due to significantly higher separation potential in rural regions. Specific setting of separation potential is described in sec. 3.1. w_j is given by Eq (5), where o_j means the percentage representation of rural buildings in territory j and $\overline{o}$ is the average rural building considering o_j for all $j \in J$.

6. The production estimation $p_{j,t}$ in the territory j and year t is then given by Eq (6):

$$p_{j,t} = p_{j,t-1} + P_j d_{j,t}, \tag{6}$$

where P_j is potential separation considered in kg/cap/year and $d_{j,t}$ is percentage separation potential fulfilling. The value $p_{j,t}$ gives the new point of time-series considered as input data. Actually, the set I is expanded.

The procedure continues iteratively, and so the production based on the S-curve model is modified by credibility approach for each territory $j \in J$ in each year $t \in T$. The model presented here is based on the approach presented in the paper (Smejkalová et al., 2019). However, it was expanded in this contribution, especially in the meaning of the producer selection and time shift. Consequently, the waste generation forecast takes into account demographic trends, see section 2.3. The approach presented here gives better models compared to the usual trend analysis, which was partially tested in the paper (Smejkalová et al., 2019).

2.3. Population forecasting

The presented forecasting model considers waste production $p_{j,t}$ per capita. The main reason for using the relative unit is to make a possible comparison of waste production in territories of different population size. Use of results for infrastructure modification and processing capacity assurance, the absolute amount of waste produced is major information. The forecast of the waste production overall volume taking into the forecast of unit production has to be necessarily based in corresponding population forecast results estimating future development of the given population size.

Population forecasts designed by the co-authors of this study (Burcin et al., 2019) were used for the purpose of this study to illustrate the use of the proposed methodology. These regional forecasts were produced within a pilot project on re-introducing of the system of mutually interconnected population forecasts on national, regional and micro-regional levels of the Czech Republic administrative division. The micro-regional level is here represented by the administrative districts of municipalities with extended powers (206), in particular, 15 of them located on the territory of Hradec Králové Region.

The forecasts making process followed proven and internationally accepted approaches and procedures for population forecasting at regional level (Kučera, 1998). The classical cohort-component method was applied to produce the necessary population forecasts. Its principle consists in dividing the overall process of population reproduction into four relatively autonomous subprocesses – the components of reproduction: fertility, mortality, immigration and emigration, and in their separate forecasting. The results of the analysis of each component at different levels of territorial division (country, region, micro-regions) and other similar territorial units led to the formulation of partial forecasting assumptions. These were transformed into the expected values of the cohort-component projection model parameters. In the following forecasting step, the final results of population development forecast were obtained by repeated use of the projection model.

The micro-regions' forecasts are based on data of official demographic statistics provided by the Czech Statistical Office and covering individual years of the period 2000–2017. Referring to its analysis results, the general, aggregate and detailed assumptions of the future development of individual reproduction processes in the given territorial frameworks were formulated, see (Burcin et al., 2019).

Each resulting population forecast consists of three variants of future development: medium, high and low. The medium variant represents the most likely trajectory, while the high and low variant merely defines realistic frameworks of future development with respect to the degree of uncertainty of the results given by the medium variant. These frameworks are relatively unlikely to be exceeded. Occasional assessments of the reliability of the author's comparable forecasts show that the field between low and high variants of the total population forecast covers more than three-quarters of cases at the level of smaller regional units such as the micro-regions.

The population forecast results used in the derived forecasts of MSW production and separation show an apparent future total population decline in all micro-regions of Hradec Králové Region, with some minor temporary exceptions (Fig. 4). In the following figures is the metropolitan micro-region divided to the regional centre with a higher total population and the remaining, substantially less populated part of the administrative district. It means that even this micro-region will likely face the decrease of total population closer to the forecast horizon. The expected population development in the entire Hradec Králové Region will be primarily the result of the relatively old age structure of the population and its continuing ageing, and in several cases also expected migration deficit.

3. Bio-waste production

The bio-waste is defined as follows*: biodegradable garden and park waste, food and kitchen waste from households, restaurants, caterers and retail premises and comparable waste from food processing plants* (Directive, 2008/98/EC). By definition, two basic sources can be included in bio-waste, kitchen and garden waste. Cooking oils are appropriate to be collected separately. They can be successfully used to produce biodiesel (Hajjari et al., 2017).

Separated bio-waste currently accounts for a significant proportion of MSW. For example, in the Czech Republic, bio-waste is 15% of the MSW in the year 2017, and its production is a rising trend. Nevertheless, a significant part of bio-waste is still not separated and remains in mixed municipal waste (MMW), as Fig. 5 shows. These are analyses of the MMW composition from different European countries. Some studies are not entirely up to date, but the overall picture creates an idea on the amount of bio-waste in the MMW. The average based on 13 considered studies is close to 33% of bio-waste in the MMW. According to the development of waste management, the Czech Republic ranks approximately to the average countries also for waste separation efficiency and production, see (Eurostat, 2019).

It can be assumed that bio-waste in MMW is almost exclusively kitchen waste. Apart from minor exceptions, garden waste is either separated or processed in domestic composts. This is confirmed by the study (Lebersorger and Schneider, 2011), where the mean value of food waste in MMW in Austria is estimated at 25.1%. Bio-waste in MMW is represented by 20.5% (Vogel et al., 2009). That means that it cannot be assumed that there is a significant amount of garden waste in the MMW.

The bio-waste production (both kitchen and garden) is significantly affected by geographical location and the associated climatic conditions. Therefore, the estimate of bio-waste production needs to be adapted to local conditions. Shi et al. (2013) estimated that the potential of garden waste is from 5.60 t/ha/year to 7.67 t/ha/year, depending on a particular part of China. The application of these estimates to garden waste production in the Czech Republic is about 112–153 kg/cap/year when considered 210,060 ha of gardens and orchards and 10,578,820 inhabitants. On the lower bound of China's estimate is situated Danish current garden waste production. The garden waste from households in Denmark in the year 2006 is 110 kg/cap/year. However, it is merely an assessment of the current status and information about expected future developments is not included. The potential is certainly higher. On the other hand, some studies are concerned with estimating the overall bio-waste separation potential. Three studies of bio-waste production in EU are summarised in Table 4. The estimations are set up

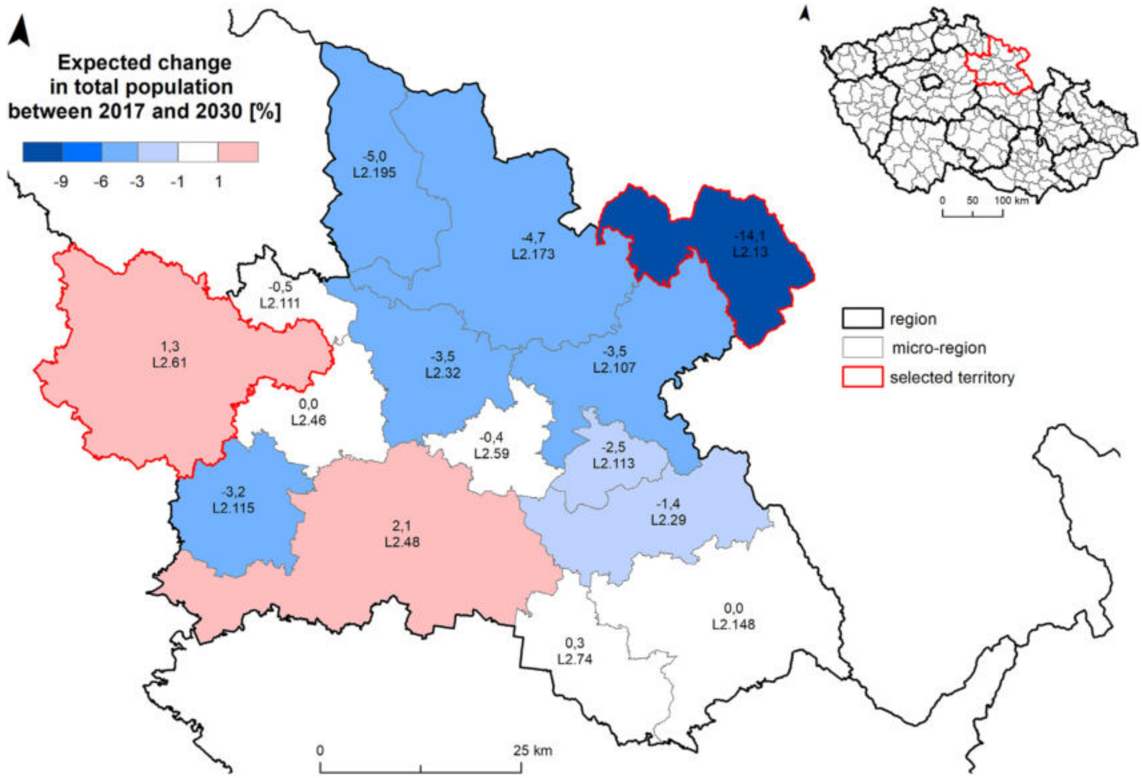

Fig. 4. Expected change in total population between 2017 and 2030 (as on Dec. 31), micro-regions, Hradec Králové Region, a medium variant of the forecast.

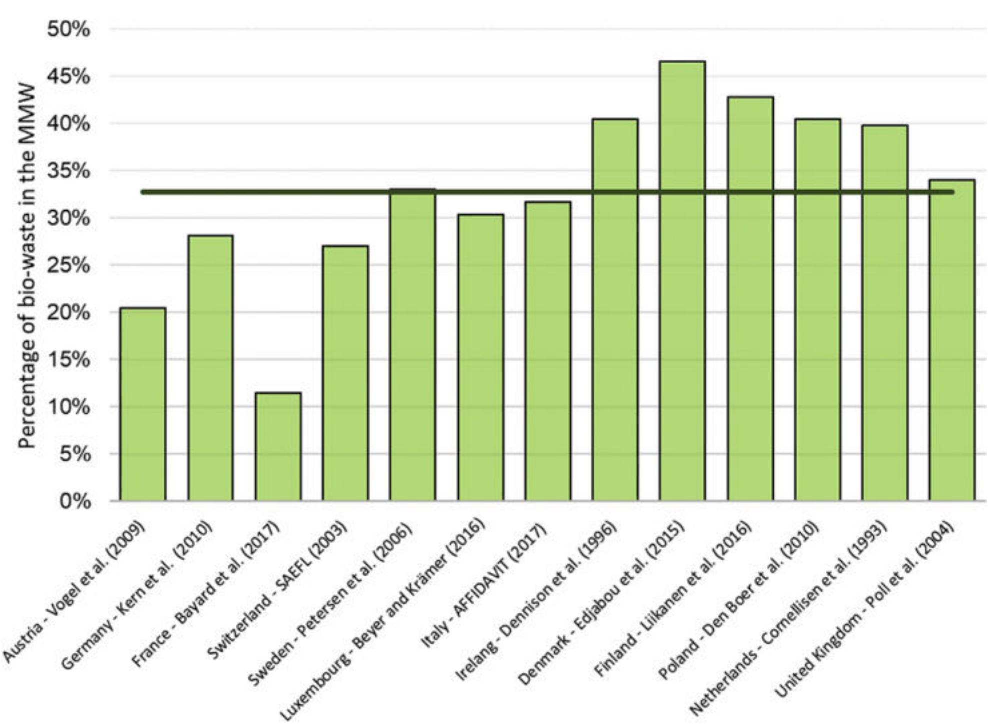

Fig. 5. Amount of bio-waste in the MMW in Europe. References: Vogel et al. (2009), Kern et al. (2010), Bayard et al. (2017), SAEFL (2003), Petersen et al. (2006), Beyer and Krämer (2016), AFFIDAVIT (2017), Dennison et al. (1996), Edjabou et al. (2015), Liikanen et al. (2016), Den Boer et al. (2010), Cornellisen et al. (1993), Poll et al. (2004)

Table 4
Bio-waste separation potential – literature review.

	Location	Garden waste [kg/cap/year]	Total bio-waste [kg/cap/year]	Remark
(Razza et al., 2018)	EU	–	150	Realistic potential
(Eunomia, 2010)	EU	–	190	High recycling and prevention scenario (60% separation of food waste and 90% separation of garden waste)
(Orbit association, 2008)	EU	–	158	The full potential of bio-waste and green waste
(Boldrin et al., 2010)	Denmark	110	–	In the year 2006
(Shi et al., 2013)	China	112–153	–	Depends on the particular area (climate conditions)

between 150 and 190 kg/cap/year considering both kitchen and garden waste.

3.1. Bio-waste production and separation potential in the Czech Republic

The bio-waste is a type of waste that has recently undergone a major change due to legislation in the Czech Republic. Since 2014, municipalities are obliged to allow citizens to separate bio-waste (Amendment to the Waste Management Law 229/2014). The result is a sudden increase in the production of this type of waste. The same behaviour is obvious also in the real data for micro-regional bio-waste production, see Fig. 6. Fig. 6 shows the trend in the bio-waste production per capita in the Czech Republic for the available time period (2009–2017) for 206 micro-regions, except the outliers - upper and lower deciles were removed for clearer representation. In the period under review, the growing trend of bio-waste production is evident (Fig. 6). This characteristic appears to be reflected in the average production (dashed line). In 2014, the beginning of a trend change due to legislative intervention can be observed. The scale of production across micro-regions in 2009 (*a*) and 2017 (*b*) indicates that there is a significant difference between micro-regions and their response to system change. It is therefore not reliable to forecast waste production based solely on historical data if there has been an intervention that causes a change in trend.

Waste fractions show different behaviour. If, for example, paper separation is increased, this type of waste is moved from MMW to separate collection. Other commonly collected components, plastic and glass, exhibit the same behaviour (Pavlas et al., 2017). The waste produced is thus only transferred to another waste fraction. Though, increasing bio-waste production does not mean a decrease of MMW, as Fig. 7 illustrates on the micro-regional level in the Czech Republic for the year 2017. The Spearman correlation coefficient is only 0.15 for bio-waste and MMW production. Therefore, no links were found between production these two waste fractions. This finding provides information on the existence of a new waste stream, which appears in MSW, respectively bio-waste. Linear regression model of MMW production based on independent variable – bio-waste production – shows very low reliability. It is able to describe only 1.3% of data variability.

Separate bio-waste production grows (see Fig. 6), but there is no MMW loss (see Fig. 7). If the higher production of the separated bio-waste is not caused by the loss in the MMW, there must be a new waste stream. It is the amount of waste that has not yet been reflected in the MSW. As was mentioned in sec. 1.2 the bio-waste separated from MMW is almost exclusively food waste. So, kitchen waste is not yet effectively separated in the Czech Republic, and it is in MMW. The new waste stream is probably bio-waste that was previously composted or burned at gardens (see Fig. 8).

The sudden historical increase of bio-waste production will not be maintained in future because of limited separation potential. The indicated trend in historical data can be successfully modelled by so-called S-curve (Smejkalová et al., 2017). Modelling of the trend by S-curve and also new presented methodology utilise the information about bio-waste production potential.

3.1.1. Bio-waste separation potential

The division of bio-waste into the kitchen and garden is

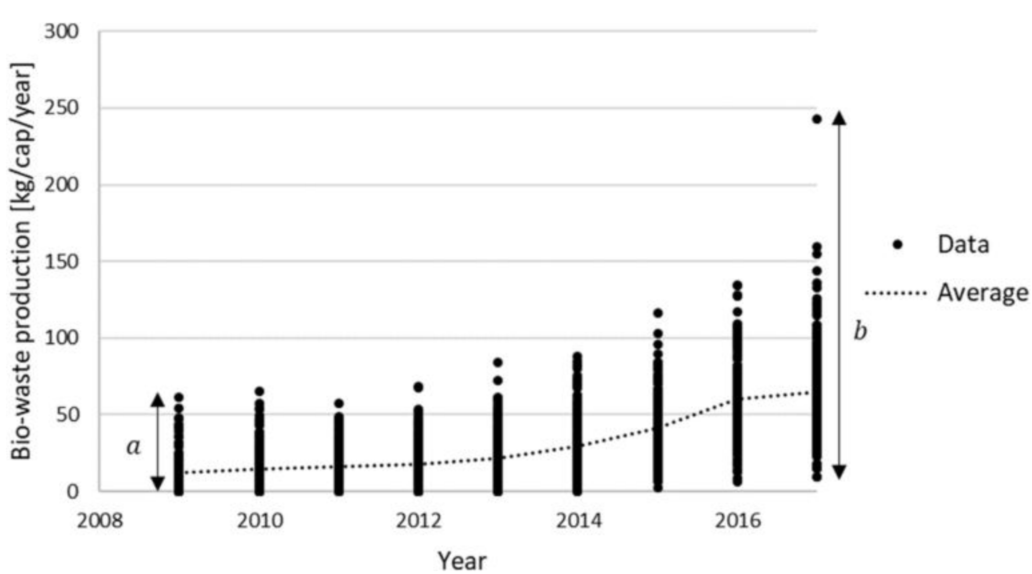

Fig. 6. The bio-waste production in the Czech Republic – historical data.

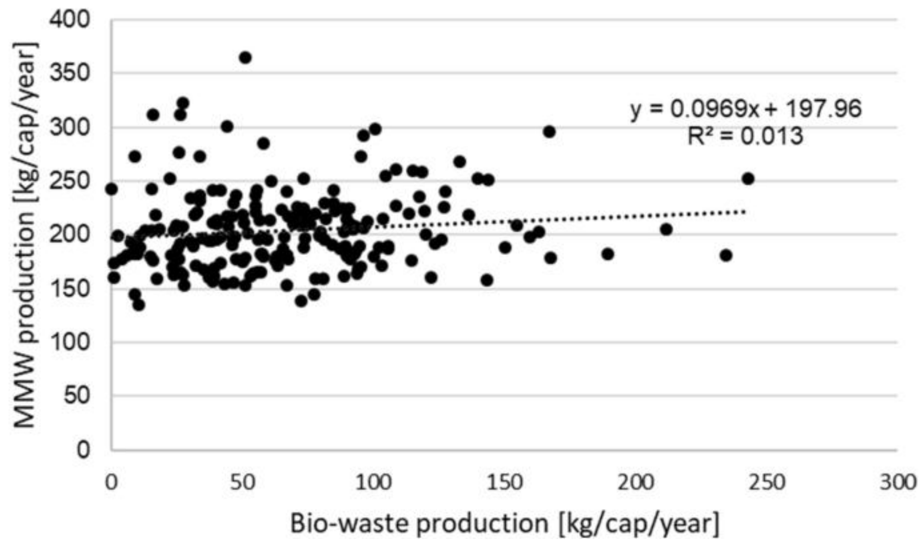

Fig. 7. The relationship between bio-waste separation and MMW production.

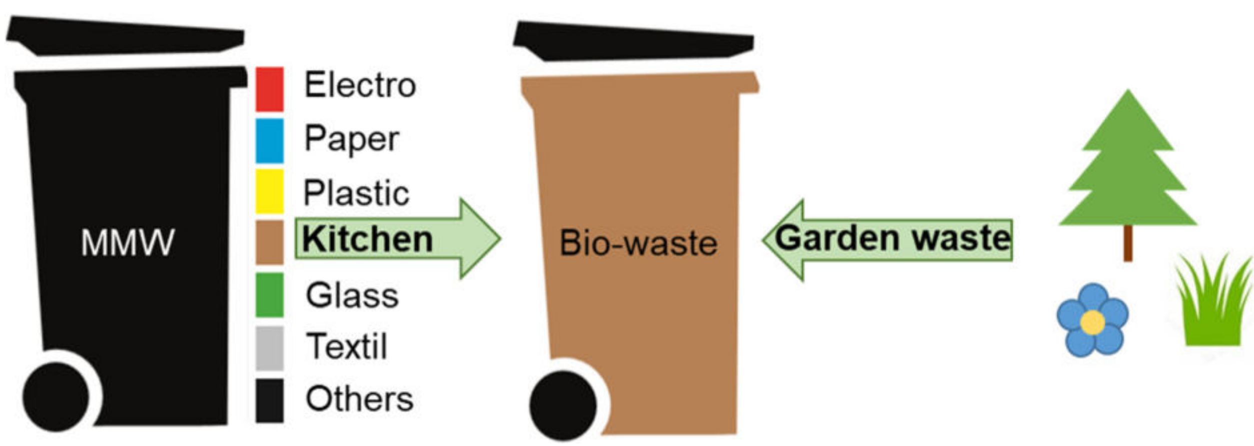

Fig. 8. Waste streams of bio-waste.

preserved, as was defined in sec. 1.2. The setting of bio-waste separation potential comes from the literature review, and it is adapted to the type of building considering the urban and rural area. Potential of kitchen waste separation is based on the assumption, that this fraction is separated from MMW. In the year 2017, bio-waste filled about 30% of MMW, which corresponds with 60 kg/cap/year. The potential of kitchen waste estimate is 60 kg/cap/year for both urban and rural area if all kitchen waste is separated from MMW.

The garden waste production is expected only in rural buildings, and it is estimated at 140 kg/cap/year. The garden waste potential is set to correspond with studies (Razza et al., 2018) and (Orbit association, 2008) from Table 4. (Eunomia, 2010) is not included in this issue, because it assumes waste prevention and this task is not part of the model. The estimation of 140 kg/cap/year is in the link with other studies. It lies within the bounds of the study (Shi et al., 2013) from China and expects an increase over (Boldrin et al., 2010) in Denmark.

The separation potential considers the type of building in specific areas, and it is given by the number of inhabitants per one house number. More than eight people living in one house number is specified as an urban building, and up to eight people, it is a rural building. Each micro-region's separation potential comes out of a number of urban and rural buildings, see Table 5. The average bio-waste separation potential in Czech micro-regions is close to 150 kg/cap/year.

Bio-waste potential separation is determined at 60 kg/cap/year for the urban population and 200 kg/cap/year for the rural population. The overall separation potential for 206 micro-regions in the Czech Republic is given by the number of inhabitants living in the specific type of building (urban and rural).

3.1.2. *Verification of model applicability*

Data from micro-regions in the Czech Republic were analysed (206 micro-regions) to verify the suitability of the method application. The aim is to show whether it is possible to transfer information on waste production across micro-regions. The development of datasets of similar parameters shifted over time was monitored. Specifically, micro-regions that separated a certain part of the maximum potential in 2013 were selected (group 2013). Then other micro-regions of the same parameters but shifted in time 2015 were marked as group 2015. Subsequently, the change in production for the 2013 group recorded by the micro-regions in 2015 was compared. Similarly, for the 2015 group, the change in 2017 (over two years) was monitored. The same analysis was carried out for the micro-region in three stages of increasing bio-waste

Table 5
Bio-waste separation potential in the Czech Republic.

	Urban building >8 inhabitants/house number	Rural building 1–8 inhabitants/house number
Population	5,083,333	5,432,684
Kitchen waste	60 kg/cap/year	60 kg/cap/year
Garden waste	–	140 kg/cap/year
Bio-waste potential	**60 kg/cap/year**	**200 kg/cap/year**
Absolute amount of bio-waste potential	**304 kt/year/**	**1,087 kt/year**

Table 6
Results of analysis of method assumptions verification on real data.

	Spearman correlation coefficient	
	Group 2013	Group 2015
Separated 5–15%	0.841	0.844
Separated 15–25%	0.866	0.825
Separated 25–35%	0.822	0.880
Average (5–15%)	14.95%	16.31%
Median (5–15%)	10.74%	9.95%
Average (15–25%)	12.40%	14.65%
Median (15–25%)	10.55%	12.78%
Average (25–35%)	8.87%	17.65%
Median (25–35%)	9.72%	18.28%

separation, namely: 5–15% of the separated potential, 15–25% and 25–35%, in 2013 (respectively 2015).

The main result is the same character of development in individual micro-regions from the monotonic point of view (calculated using the Spearman correlation coefficient). This result suggests that micro-regions increase separation regularly, avoiding "overtaking". That is, a micro-region that has separated little does not have a better result in two years than a micro-region that has separated more bio-waste. It is possible to use the value of a micro-region with a higher separation for the forecast of a micro-region where little separation has yet taken place. The results are supplemented by the average and median change between selected years, see Table 6. It is appropriate to point out the considerable differences in Table 6 between 2013 and 2015 for average and median for data with potential fulfillment of 25–35% in selected years. This is due to the occurrence of a negative separation change in the 2013 group for five micro-regions. Looking more closely, this is a remote observation in the overall time series. Thus, this aspect is not significant from the perspective of the overall analysis that verified the validity of the assumption on real data.

4. Results

The methodology is presented on bio-waste production in the Czech Republic on the micro-regional level. The available dataset consists of annual data from 2009 to 2017. The forecast goal is in the years 2020, 2025 and 2030. The bio-waste separation potential was set in Table 5. The following Table 7 shows the average separation potential fulfilling for the regions. By 2030, the separation potential fulfilling in most regions is expected to be met, or at least significantly closer to that potential. The exception is the Capital city of Prague, which also has the worst starting position in the year 2017.

The classification of regions within the territory of the Czech Republic is numbered in Fig. 9.

The separation potential fulfilling in 2017 is geographically illustrated in Fig. 10. Regions are divided into micro-regions and labelled with marks. Some micro-regions already crossed their estimated limit. For further investigation, two specific micro-regions were selected. Based on the results, up to 2030, most of the micro-regions will achieve their separation potential.

Table 7
Average separation potential fulfilling for regions in the Czech Republic.

Region	Average separation potential fulfilling			
	2017	2020	2025	2030
Karlovy Vary Region	29%	50%	83%	97%
Ústí nad Labem Region	37%	61%	88%	98%
Plzeň Region	33%	61%	92%	99%
Liberec Region	20%	47%	88%	99%
Capital city of Prague	19%	29%	50%	73%
Central Bohemian Region	58%	83%	99%	100%
South Bohemian Region	49%	74%	95%	100%
Hradec Králové Region	40%	69%	95%	100%
Pardubice Region	37%	63%	91%	100%
Vysočina Region	67%	90%	100%	100%
South Moravian region	41%	72%	95%	100%
Olomouc region	65%	87%	100%	100%
Zlín Region	34%	60%	93%	100%
Moravian-Silesian region	45%	68%	92%	100%

Fig. 11 shows the shift of separation potential fulfilling from the current situation in the year 2017–2030.. The micro-regions are situated in the Hradec Králové Region (number 8 in Fig. 9). It can be observed that also micro-regions, which do not show a clear increasing trend currently, were inspired by other territories for the trend change. For example, it is the situation of the micro-region L2.61. On the other hand, micro-region L2.13 has different development. The separation potential was fulfilled in the year 2017 more than the median, and the subsequent increasing was already slower than L2.61.

On the basis of the forecast, the average bio-waste production is expected to be 116 kg/cap/year in 2020 and 147 kg/cap/year in 2025 in micro-regions of the Czech Republic (not accounting the population distribution). Some European countries with advanced waste management are already reaching these levels. Some of these can be mentioned for the most recent available year (2018), e.g. Germany – 110 kg/cap/year, Denmark – 128 kg/cap/year, Austria – 187 kg/cap/year (source Eurostat, 2019), compared to the estimated average in 2018 of 92 kg/cap/year in the Czech Republic. According to the forecast, bio-waste production in the Czech Republic will be closer to countries with more advanced waste management. The estimated development of separation is depicted in Fig. 12a) and b). Micro-regions of the Czech Republic will reach 80–100% by 2025, except Capital city of Prague. As can be seen, Central Bohemian (number 2 in Fig. 9) and Vysočina Region (number 10 Fig. 9) are the most promising areas followed by the Olomouc Region (number 12 in Fig. 9).

As it is desirable to estimate the absolute value of separated bio-waste, it is necessary to use the demographic forecasts (sec. 2.3 for population forecasting). The expected bio-waste production with regards to population forecast is illustrated in Fig. 13. The modelled bio-waste forecasting per capita was completed by population forecast, Fig. 13 shows only the middle scenario for clarity. The micro-region L2.61 does not expect significant population changes, as Fig. 13a) shows. Compared to that, L2.13 micro-region should face a population decline. As a result, the overall production of bio-

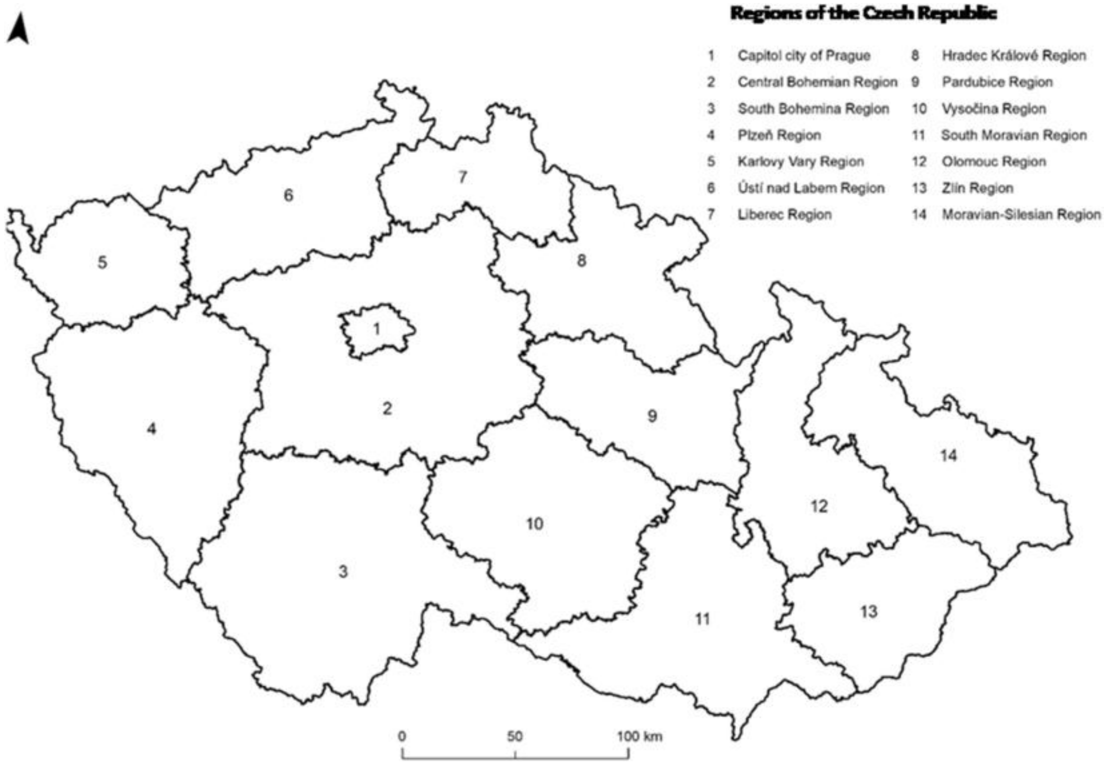

Fig. 9. Regions of the Czech Republic.

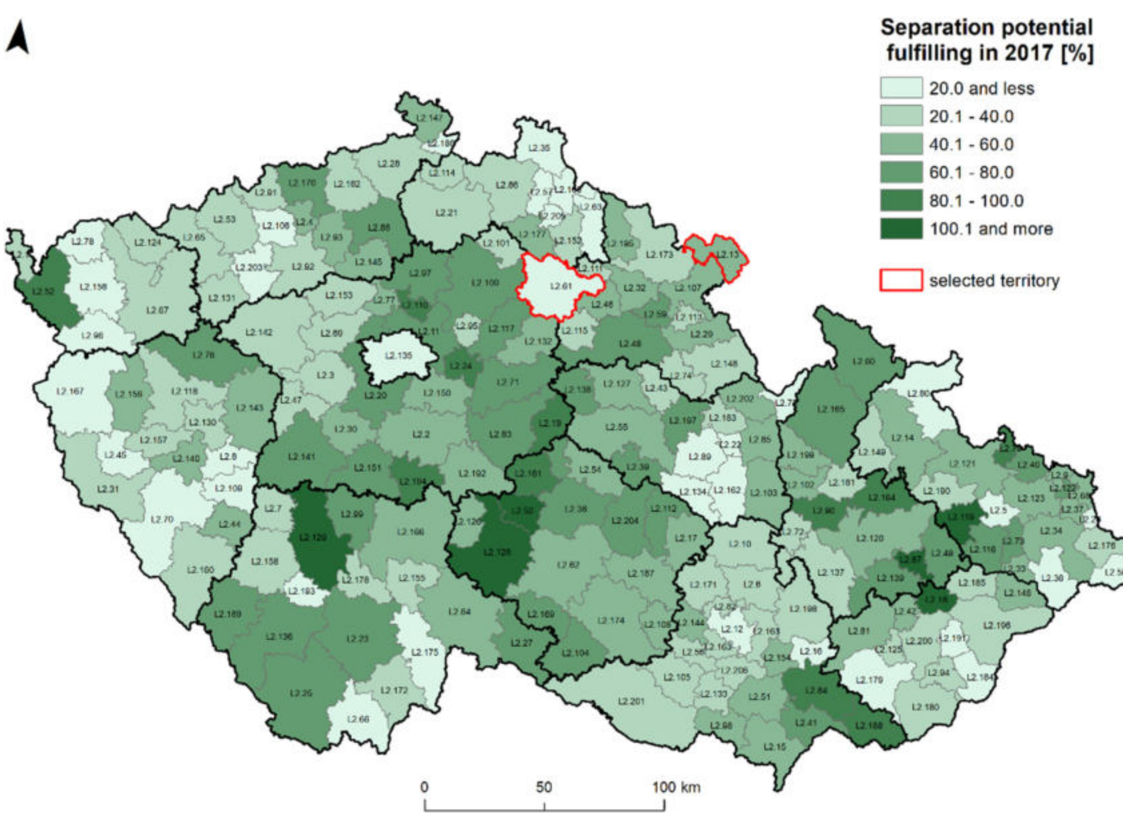

Fig. 10. Micro-regions of the Czech Republic – separation potential fulfilling in 2017.

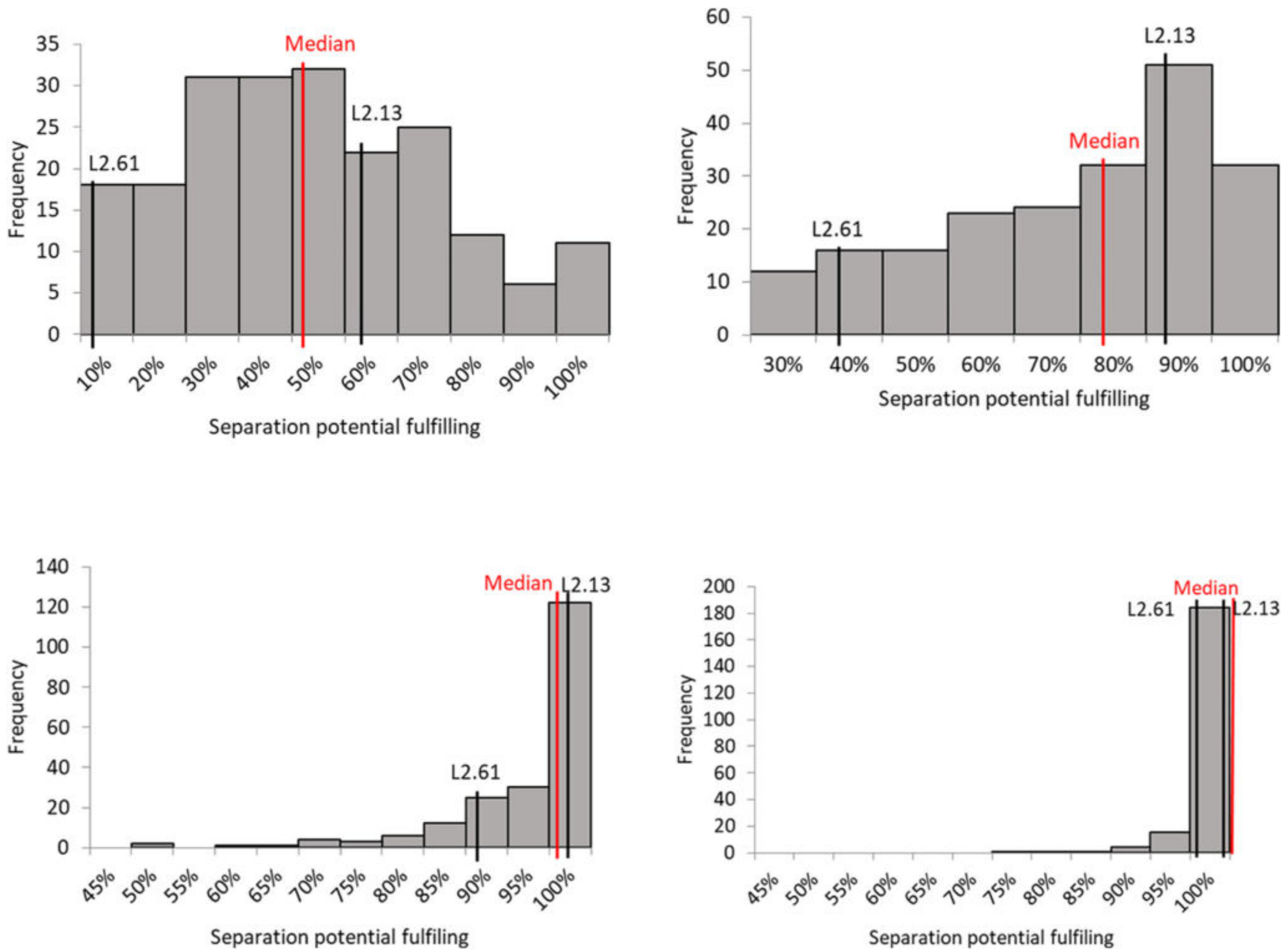

Fig. 11. Separation potential fulfilling in micro-regions.

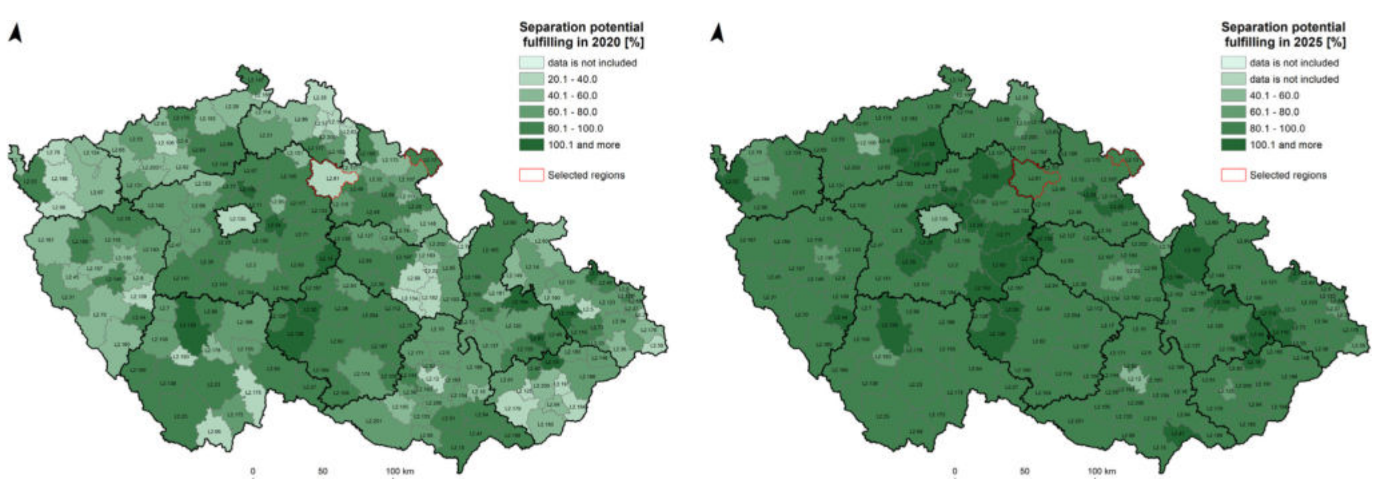

Fig. 12. Micro-regions of the Czech Republic — estimated separation potential fulfilling.

waste will slow down and then even decrease (see Fig. 13b)). It is expected that the total production will rise to 1486% by 2030 in L2.61. It is caused by almost no production at the beginning of the analysed period. Contrary, the growth of 158% is estimated in L2.13. The bio-waste generation will start declining at some point, even though the per capita production will still slowly increase.

The inclusion of the population projection in the calculation is necessary to assess the total amount of waste produced. The

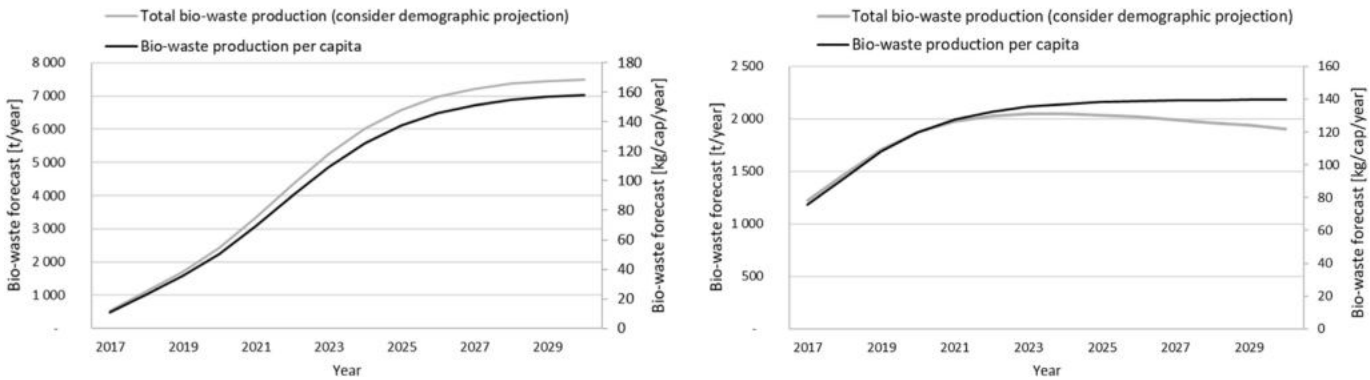

Fig. 13. Bio-waste prediction in particular micro-regions.

development of the population in a particular territory can significantly affect the total amount of waste produced. This fact must, therefore, be taken into account in Waste management plans when optimising the entire infrastructure. The effect of urbanization significantly influences the result of bio-waste production across micro-regions of the Czech Republic. Especially waste processing plant at wrong spot will result in underutilisation and economic unsustainability.

5. Conclusion

For economic, environmental and social sustainability of waste management, there are interventions of legislation and modernisation of waste treatment infrastructure. Each transition in the current system can cause a change in the trend of waste production. The presented methodology introduces the novel approach for waste production forecasting based on data with a structural break. The procedure comes from credibility theory and utilises the idea of the combination of overall and individual information. This principle forecasts the reaction on intervention also for territories, which does not show the change yet (see Fig. 6). It is expected that until 2030, a major part of micro-regions in the Czech Republic will achieve the bio-waste separation potential.

The input data about waste production are considered per capita to be possible to compare production in the territories of different size. The forecasted value based on steps 1–6 defined in sec. 2.2 is also per capita. The treatment infrastructure has to react to total waste production. So, it is important to include a population forecast to gain estimation of total future waste production. The presented approach can be applied if the following input data is available:

- waste production historical data with a structural break,
- estimation of separation potential of the modelled waste fraction,
- demographic projection.

The method works with more territories, in the case study at the micro-regional level. The important assumption is that the structural break has already manifested itself in at least some territories. Then the advantages of the method are exploited, and the individual territories take on each other's experience if they are behind the development.

The case study conducted in the Czech Republic has revealed diametrical differences between micro-regions. Based on the results, separation potential fulfilling varies from tens of percents to hundreds. It is highly dependent on the current state of the particular micro-region since some of them has already applied supportive measures to increase separation level. The average bio-waste production in micro-regions will increase from 67 kg/cap/year in 2017 to 156 kg/cap/year in 2030. Most of the micro-regions will reach 90% by 2025 and 100% by 2030 of their separation potential.

The presented approach is applicable to waste types with a structural break in historical data due to external interventions. The waste management forecasting approaches presented so far do not reflect structural break. The introduced methodology for forecasting of waste production takes into account system intervention, which can significantly refine the forecast for the future. Moreover, the response to system change can also be modelled for the territories that have not yet responded on the change. This is not possible with commonly used methods of time series analysis.

The waste production forecast for individual micro-regions and their appropriate data aggregation is used to create a forecast for any region. The mass balance of the hierarchical structure is maintained. The use of the presented approach can be applied for other wastes where changes are underway within the EU, such as cooking oil and textiles. A literature review indicates that a suitable methodology has not yet been introduced for these wastes.

It should be noted that uncertainty is not only in the population prognosis. Uncertainty is also part of waste production. Setting up confidence intervals in terms of waste generation per person for each territory is a major challenge for further research. For an adequate use of the presented approach, it is necessary to base on a quality estimate of the separation potential, which is a challenging task. Setting the separation potential will be the subject of further research.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Veronika Smejkalová: Software, Writing - original draft, Methodology, Data curation. **Radovan Šomplák:** Conceptualization, Methodology, Supervision. **Vlastimír Nevrlý:** Validation, Writing - review & editing, Visualization. **Boris Burcin:** Resources, Writing - review & editing. **Tomáš Kučera:** Resources, Data curation, Writing - original draft.

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References

Adriyanti, N.P., Gamal, A., Dewi, O.C., 2018. Solid waste management models: literature review. *2nd international Conference on Smart Grid and Smart cities*. ICSGSC 2018, 37–40. https://doi.org/10.1109/ICSGSC.2018.8541350 art. no. 8541350.

AFFIDAVIT, 2017. Landesagentur für Umwelt Bozen. Landesweite Restmüllanalyse Südtirol 2016/2017 [online]. [cit. 2018-11-22]. https://umwelt.provinz.bz.it/downloads/06_relazione_ultima_con_PP_de.pdf.

Amendment to the Waste Management Law in the Czech Republic (in Czech), 229/2014, §17, paragraph 3.

Ayeleru, O.O., Okonta, F.N., Ntuli, F., 2018. Municipal solid waste generation and characterization in the City of Johannesburg: a pathway for the implementation of zero waste. Waste Manag. 79, 87–97. https://doi.org/10.1016/j.wasman.2018.07.026.

Barbosa-Póvoa, A.P., da Silva, C., Carvalho, A., 2018. Opportunities and challenges in sustainable supply chain: an operations research perspective. Eur. J. Oper. Res. 268 (2), 399–431. https://doi.org/10.1016/j.ejor.2017.10.036.

Bayard, R., Benbelkacem, H., Gourdon, R., Buffière, P., 2017. Characterization of selected municipal solid waste components to estimate their biodegradability. J. Environ. Manag. 216, 4–12. https://doi.org/10.1016/j.jenvman.2017.04.087.

Beigl, P., Lebersorger, S., Salhofer, S., 2008. Modelling municipal solid waste generation: a review. Waste Manag. 28 (1), 200–214. https://doi.org/10.1016/j.wasman.2006.12.011.

Beyer, H.J., Krämer, A., 2016. Sperrmüllanalyse 2015 im Großherzogtum Luxemburg [online]. [cit. 2018-12-31]. https://download.data.public.lu/resources/gestion-des-dechets-et-ressources-dechetsmunicipaux/20180206-103118/SMA-2015-Bericht-3.pdf.

Boldrin, A., Andersen, J.K., Christensen, T.H., 2010. Seasonal generation and composition of garden waste in Aarhus (Denmark). Waste Manag. 30, 551–557. https://doi.org/10.1016/j.wasman.2009.11.031.

Bühlmann, H., 1967. Experience rating and credibility. ASTIN Bulletin 199–207.

Burcin, B., Kučera, T., Kuranda, J., 2019. Population projections of administrative districts of municipalities with extended powers of the Hradec Králové Region for the period 2018–2050. In: Internal Research Report for the Office of Hradec Králové Region. Praha 2019. In Czech.

Cole, Ch, Quddus, M., Wheatley, A., Osmani, M., Kay, K., 2014. The impact of Local Authorities' interventions on household waste collection: a case study approach using time series modelling. Waste Manag. 34 (2), 266–272. https://doi.org/10.1016/j.wasman.2013.10.018.

Cornellisen, A.A.J., et al., 1993. Physical investigation of the composition of household waste in The Netherlands [online]. [cit. 2018-09-12]. https://www.rivm.nl/dsresource?objectid=0ee6d4f7-8def-49f2-ac6bb1ae2feb4e5c&type=org&disposition=inline.

Den Boer, E., Jedrczak, A., Kowalski, Z., Kulczycka, J., Szpadt, R., 2010. A review of municipal solid waste composition and quantities in Poland. Waste Manag. 30 (3), 369–377. https://doi.org/10.1016/j.wasman.2009.09.018.

Denafas, G., Ruzgas, T., Martuzevičius, D., Shmarin, S., Hoffmann, M., Mykhaylenko, V., Ogorodnik, S., Romanov, M., Neguliaeva, E., Chusov, A., Turkadze, T., Bochoidze, I., Ludwig, Ch, 2014. Seasonal variation of municipal solid waste generation and composition in four East European cities. Resour. Conserv. Recycl. 89, 22–30. https://doi.org/10.1016/j.resconrec.2014.06.001.

Dennison, G.J., Dodd, V.A., Whelan, B., 1996. A socio-economic based survey of household waste characteristics in the city of Dublin, Ireland — I. *Waste composition*. Resour. Conserv. Recycl. 17 (3), 227–244. https://doi.org/10.1016/0921-3449(96)01070-1.

Directive (EU) 2018/850 of the European Parliament and of the Council of 30 May 2018 Amending Directive 1999/31/EC on the Landfill of Waste (Text with EEA Relevance).

Directive (EU) 2018/851 of the European Parliament and of the Council of 30 May 2018 Amending Directive 2008/98/EC on Waste (Text with EEA Relevance).

Directive 2008/98/EC of the European Parliament and of the Council of 19 November 2008 on Waste and Repealing Certain Directives (Text with EEA Relevance).

Edjabou, M.E., Jensen, M.B., Gotze, R., Pivnenko, K., Petersen, C., Scheutz, Ch, Astrup, T.F., 2015. Municipal solid waste composition: Sampling methodology, statistical analyses, and case study evaluation. Waste Manag. 36, 12–23. https://doi.org/10.1016/j.wasman.2014.11.009.

Engeland, J.V., Beliën, J., Boeck, L.D., Jaeger, S.D., 2018. Literature review: strategic network optimization models in waste reverse supply chains. Omega 91. https://doi.org/10.1016/j.omega.2018.12.001.

Eunomia, 2010. Assessment of the Options to Improve the Management of Bio-Waste in the European Union. Eunomia. ARCADIS Project number – 11/004759.

Eurostat, 2019. European statistical Office. https://ec.europa.eu/eurostat/databrowser/view/ten00110/default/table?lang=en.

Farahani, R.Z., Asgari, N., Heidari, N., Hosseininia, M., Goh, M., 2012. Covering problems in facility location: a review. Comput. Ind. Eng. 62 (1), 368–407. https://doi.org/10.1016/j.cie.2011.08.020.

Ganesh, K., Mohapatra, S., Malairajan, R.A., Punniyamoorthy, M., 2015. Resource Allocation Problems in Supply Chains. Emerald Group Publishing, ISBN 9781785603983.

Ghinea, C., Drăgoi, E.N., Comăniţă, E.-D., Gavrilescu, M., Câmpean, T., Curteanu, S., Gavrilescu, M., 2016. Forecasting municipal solid waste generation using prognostic tools and regression analysis. J. Environ. Manag. 182 https://doi.org/10.1016/j.jenvman.2016.07.026.

Goel, S., Ranjan, V.P., Bardhan, B., Hazra, T., 2017. Forecasting solid waste generation rates. In: Modelling Trends in Solid and Hazardous Waste Management, vols. 35–64. Springer Singapore, Singapore. https://doi.org/10.1007/978-981-10-2410-8_3.

Haas, W., Krausmann, F., Wiedenhofer, D., Heinz, M., 2015. How circular is the global economy?: an assessment of material flows, waste production, and recycling in the European Union and the world in 2005. J. Ind. Ecol. 19 (5), 765–777. https://doi.org/10.1111/jiec.12244.

Hajjari, M., Tabatabaei, M., Aghbashlo, M., Ghanavati, H., 2017. A review on the prospects of sustainable biodiesel production: a global scenario with an emphasis on waste-oil biodiesel utilization. Renew. Sustain. Energy Rev. 72, 445–464. https://doi.org/10.1016/j.rser.2017.01.034.

Hoornweg, D., Bhada-Tata, P., 2012. What a Waste: A Global Review of Solid Waste Management. The World Bank.

Innocent, N.M., Dieudonné, B., Jose, S.N., 2016. Modeling the temporal variations of municipal solid waste generation for future projection in the Douala municipality, Camerron. Journal of Multidisciplinary Engineering Science and Technology 3 (7), 5288–5295.

Intharathirat, R., Salam, P.A., Kumar, S., Untong, A., 2015. Forecasting of municipal solid waste quantity in a developing country using multivariate grey models. I 39, 3–14. https://doi.org/10.1016/j.wasman.2015.01.026.

Jiang, P., Liu, X., 2016. Hidden Markov model for municipal waste generation forecasting under uncertainties. Eur. J. Oper. Res. 250 (2), 639–651. https://doi.org/10.1016/j.ejor.2015.09.018.

Kern, M., Siepenkothen, H.-J., 2010. Restabfallanalysen für die AWSH Abfallwitschaft Südholstein GmbH [online]. [cit. 2019-01-29]. https://www.awsh.de/fileadmin/media/PDFs/AWK/Abfallanalyse_AWSH.pdf.

Khatib, I.A., 2011. Municipal solid waste management in developing countries: future challenges and possible opportunities. Integrated Waste Management 2, 37–48. https://doi.org/10.5772/16438.

Kováčová, A., Louda, J., Rybová, K., 2011. Demographic changes and prediction of municipal waste. Waste forum 4, 208–2017. In Czech.

Kučera, T., 1998. Doctoral disseration. Regional Population Forecasts: Theory and Practice of Forecasting the Development of Human Resources in the Territory, vol. 1998. Masaryk University Faculty of Science, Brno, p. 101 (In Czech).

Lebersorger, S., Schneider, F., 2011. Discussion on the methodology for determining food waste in household waste composition studies. Waste Manag. 31 (9–10), 1924–1933. https://doi.org/10.1016/j.wasman.2011.05.023.

Li, X., Du, J., Long, H., 2019a. Dynamic analysis of international green behavior from the perspective of the mapping knowledge domain. Environ. Sci. Pollut. Control Ser. 26 (6), 6087–6098. https://doi.org/10.1007/s11356-018-04090-1.

Li, X., Du, J., Long, H., 2019b. Theoretical framework and formation mechanism of the green development system model in China. Environmental Development 32, 100465. https://doi.org/10.1016/j.envdev.2019.100465.

Liikanen, M., Sahimaa, O., Hupponen, M., Havukainen, J., Sorvari, J., Hortanainen, M., 2016. Updating and testing of a Finnish method for mixed municipal solid waste composition studies. Waste Manag. 52, 25–33. https://doi.org/10.1016/j.wasman.2016.03.022.

Mahler, H.C., Dean, C.G., 2001. Foundation of Casualty Acturial Science, Chapter 8: Credibility, fourth ed., ISBN 978-0-96247-622-8, pp. 485–659.

Marandi, F., Ghomi, S.M.T.F., 2016. Time series forecasting and analysis of municipal solid waste generation in Tehran city. Proceedings of the 12th International Conference on Industrial Engineering, ICIE 2016, 14–18. https://doi.org/10.1109/INDUSENG.2016.7519343.

Mwenda, A., Kuznetsov, D., Mirau, S., 2014. Time-series forecasting of solid waste generation in Arusha – Tanzania. Math. Theor. Model. 4 (8), 2224–5804.

Orbit association, 2008. Compost Production and Use in the EU.

Owusu-Sekyere, E., Harris, E., Bonyah, E., 2013. Forecasting and planning for solid waste generation in the Kumasi metropolitan area of Ghana: an ARIMA time series approach. International Journal of Sciences 2, 2305–3925.

Palomar, A.A.U., Sundo, M.B., Velasco, P.P., Camus, D.R.D., 2019. End-of-pipe waste analysis and integrated solid waste management plant. Civil Engineering Journal I5 (9), 1970–1982. https://doi.org/10.28991/cej-2019-03091386.

Pavlas, M., Šomplák, R., Smejkalová, V., Nevrlý, V., Zavíralová, L., Kůdela, J., Popela, P., 2017. Spatially distributed production data for supply chain models - forecasting with hazardous waste. J. Clean. Prod. 161, 1317–1328. https://doi.org/10.1016/j.jclepro.2017.06.107.

Pavlas, M., Šomplák, R., Smejkalová, V., Stehlík, P., 2020. Municipal solid waste fractions and their source separation: forecasting for large geographical area and its Subregions. Waste and Biomass Valorization 11 (2), 725–742. https://doi.org/10.1007/s12649-019-00764-0.

Petersen, C.M., Berg, P.E.O., Ronnegard, L., 2006. Quality control of waste to incineration – waste composition analysis in Lidköping. Sweden [online]. [cit. 2019-01-29]. https://www.researchgate.net/publication/7392462_Quality_control_ of_waste_to_incineration_-_Waste_composition_analysis_in_Lidkoping_Sweden.

Petridis, N.E., Stiakakis, E., Petridis, K., Dey, P., 2016. Estimation of computer waste quantities using forecasting techniques. J. Clean. Prod. 112 (4), 3072–3085. https://doi.org/10.1016/j.jclepro.2015.09.119.

Poll, J., 2004. Greater London Authority waste composition Scoping study, 2004. [online]. [cit. 2019-01-29]. https://statesassembly.gov.je/scrutinyreviewresearches/2007/s-11220-1189-1972007.pdf.

Prieto-Sandoval, V., Jaca, C., Ormazabal, M., 2018. Towards a consensus on the circular economy. J. Clean. Prod. 179, 605–615. https://doi.org/10.1016/j.jclepro.2017.12.224.

Razza, F., D'Avino, L., L'Abate, G., Lazzeri, L., 2018. The role of compost in bio-waste management and circular economy. Designing Sustainable Technologies, Product and Policies. https://doi.org/10.1007/978-3-319-66981-6.

Rimaitytė, I., Ruzgas, T., Denafas, G., Račys, V., Martuzevicius, D., 2012. Application and evaluation of forecasting methods for municipal solid waste generation in an eastern-European city. Waste Manag. Res. 30 (1), 89–98. https://doi.org/10.1177/0734242X10396754.

Rybová, K., Slavík, J., Burcin, B., Soukopová, J., Kučera, T., Černíková, A., 2018. Socio-demographic determinants of municipal waste generation: case study of the Czech Republic. J. Mater. Cycles Waste Manag. 20 (3), 1884–1891. https://doi.org/10.1007/s10163-018-0734-5.

SAEFL - Swiss Agency for the Environment, Forests and Landscape, 2003. A survey of the composition of household waste 2001/02 [online]. [cit. 2019-01-29]. https://www.bafu.admin.ch/bafu/en/home/topics/waste/publications-studies/publications/composition-household-waste-2001-02.html.

Shi, Y., Ge, Y., Chang, J., Shao, H., Tang, Y., 2013. Garden waste biomass for renewable and sustainable energy production in China: potential, challenges and development. Renew. Sustain. Energy Rev. 22, 432–437. https://doi.org/10.1016/j.rser.2013.02.003.

Smejkalová, V., Šomplák, R., Nevrlý, V., Holec, T., 2019. Forecasting of waste production data with changes in credibility and trend. Chemical Engineering Transactions 76, 1243–1248. https://doi.org/10.3303/CET1976208.

Smejkalová, V., Šomplák, R., Nevrlý, V., Pavlas, M., 2017. Heuristic methodology for forecasting of quantities in waste management. Mendel 23 (11), 185–192.

Šomplák, R., Nevrlý, V., Smejkalová, V., Šmídová, Z., Pavlas, M., 2019. Bulky waste for energy recovery: analysis of spatial distribution. Energy 181, 827–839. https://doi.org/10.1016/j.energy.2019.05.175.

Song, J., He, J., 2014. A multistep chaotic model for municipal solid waste generation prediction. Environ. Eng. Sci. 31 (8), 461–468. https://doi.org/10.1089/ees.2014.0031.

Vogel, E., Steiner, M., Quickert, A., 2009. Siebgestützte Restmüllanalysen im Land Steiermark, 2009. [online]. [cit. 2019-01-29]. http://www.abfallwirtschaft.steiermark.at/cms/dokumente/10168259_4336659/4dfe9a05/Endbericht%20Steiermark_2008.pdf.

Wu, H., Wang, J., Duan, H., Ouyang, L., Huang, W., Zuo, J., 2016. An innovative approach to managing demolition waste via GIS (geographic information system): a case study in Shenzhen city, China. J. Clean. Prod. 112, 494–503. https://doi.org/10.1016/j.jclepro.2015.08.096.

Xu, L., Gao, P., Cui, S., Liu, Ch, 2013. A hybrid procedure for MSW generation forecasting at multiple time scales in Xiamen City, China. Waste Manag. 33 (6), 1324–1331. https://doi.org/10.1016/j.wasman.2013.02.012.

Yi, S., Jang, Y.-C., An, A.K., 2018. Potential for energy recovery and greenhouse gas reduction through waste-to-energy technologies. J. Clean. Prod. 176, 503–511. https://doi.org/10.1016/j.jclepro.2017.12.103.

Younes, M.K., Nopiah, Z.M., Basri, N.E.A., Basri, H., 2014. Medium term municipal solid waste generation prediction by autoregressive integrated moving average. AIP Conference Proceedings 1613, 427–435. https://doi.org/10.1063/1.4894366.

Zaman, A.U., 2016. A comprehensive study of the environmental and economic benefits of resource recovery from global waste management systems. J. Clean. Prod. 124, 41–50. https://doi.org/10.1016/j.jclepro.2016.02.086.

Příloha 6: Článek [A9] Mixed-integer quadratic optimization for waste flow quantification

Mixed-integer Quadratic Optimization for Waste Flow Quantification

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ABSTRACT

The transition to a circular economy can be realized with higher waste recycling. With the knowledge of waste flows and the links between them, it is possible to plan the infrastructure of the entire system and set the goals needed for the transition to a circular economy. If the statistical analysis does not provide quality models, it is possible to describe waste flows using basic balance relationships. This contribution presents an optimization model based on quadratic programming. The output of the model is an estimate of the waste amount that was managed to divert from mixed municipal waste to separate fractions in the past period. A key input is an estimate of the composition of mixed municipal waste. For more detailed territorial model, composition estimates are often not available, so an optimization model using the principle of credibility has been proposed. Uncertain information for lower territorial units is corrected by aggregated results for the national level. The resulting optimization models were tested on the data of the Czech Republic for the period 2010-2018 in annual detail. The result interprets what part of the newly separated waste comes from mixed municipal waste. For the significant monitored fractions this value is low, 0.26 for bio-waste in the Czech Republic. On the contrary, the high part of the shift from mixed municipal waste is for plastic, 0.82. The results showed the advantage of correction at lower territory levels due to the high variability of the input data.

KEYWORDS

Data reconciliation, mixed-integer quadratic optimization, data aggregation, waste production, mixed municipal waste, waste flow.

1. Introduction

The adoption of the EU circular economy package (CEP) leads to several changes in municipal waste management (MSW). The preferred method of MSW treatment is recycling, according to the waste hierarchy (Directive 2008/98/EC). Increasing MSW recycling is also part of the recycling targets contained in the CEP (Directive EU 2018/851). Interventions promoting MSW recycling are being introduced into the waste management (WM) system to achieve these goals in individual EU countries. The tools for increasing MSW recycling include collecting new waste fractions, increasing the density of collection points, or using new materials. The consequence of these measures is an increase in waste separation (sorting), i.e., the shift of mixed municipal waste (MMW) into separately collected waste fractions. At the same time, new waste streams (a mass that did not previously end up in the waste bin) are being formed in MSW. There are ways to increase MSW separation and streamline waste treatment (higher density of collection points, door-to-door collection system, financial incentives, etc.). To properly set the conditions of WM, it is appropriate to understand the system of waste production and the links that affect the production of individual fractions.

The goal of the EU member states is to increase the efficiency of MSW management and find potential gaps for positive changes (Tomić and Schneider, 2020). In order to target the system support, it is necessary to understand the links affecting the generation of individual waste fractions. Extensive databases about waste production make it possible to study the links between waste fractions. The description of these links will allow more detailed insight into the system's functioning and, thus, more effective planning in WM. It can be assumed that the separated waste (SEP) was originally included in the MMW, and the waste was transferred from MMW to SEP. The main waste streams representing the largest share of MSW are expected to shift the most. These are paper (PAP), plastic (PLA), glass (GLA), bio-waste (BIO), metal (MET) and textile (TEX). Other SEP fractions (electrical waste, fats and cooking oil, wood etc.) form rather minor fractions of waste and will not be taken into account in the following analyses. The illustration of waste data and potential links will be provided later in the text for the Czech Republic data.

If the established trend of recycling efficiency is not directed in time to meet recycling targets, it must include in the system procedures of improvement (Smejkalová et al., 2020). When planning in WM, it is desirable to consider the context of streams between waste fractions. The questions can be as follows:
- What proportion is the newly SEP from MMW, i.e., to what extent the SEP increase, and to what extent is it represented by fractions from MMW?
- How much is the RE affected by the new waste stream?
- In what proportion the individual fractions in the MMW change if total MMW production decreases?
- Is the change in the amount of MSW due to a complex change or the result of one fraction that forms a new waste stream?

This contribution will address the above-mentioned questions. The individual waste streams arise, disappear and pass between the SEP and the MMW. From the point of view of the treatment chain, the amount of MMW is related to the capacity of the waste-to-energy facilities. Simultaneously, it is necessary to ensure sufficient capacity of sorting stations and recycling lines for SEP treatment. The composition of the SEP determines the rate of final recycling and indicates the backflows for which adequate capacities are needed (Pluskal et al., 2021). It is necessary to estimate waste flows to understand the changes in MSW composition and determine the potential for more appropriate WM.

1.1. Production modelling with respect to waste fractions

Strategic decision-making is supported by elaborate WM plans. Member states authorities are required to draw up WM plans (Malinauskaite et al., 2017). Waste production models are becoming essential information for such plans. Methods for WM modelling use both classical approaches and advanced machine learning methods. Based on a review (Beigl et al., 2008) on waste production modelling, the most frequently used approaches are sample survey method, linear regression, and time-series analysis. A newer study from 2017 (Goel et al., 2017) has already shown a greater variety of models. The classical methods mentioned in the review (Beigl et al., 2008) were also prominent in (Goel et al., 2017). But there are also abundant machine learning methods: factor models, artificial neural network, fuzzy logic, or support vector machines (Jiang and Liu, 2016).

A number of articles presented the modelling methods on multiple waste fractions. These are universal models that do not take into account the specific behaviour of individual waste fraction (Xiao et al., 2017). Thus, the fractions are modelled individually, and their production is expected to be independent of other waste fractions (Oribe-Garcia et al., 2015). The effect of waste separation on MMW production was considered in the model presented by Diaz-Farina et al. (2020). The regression model of MMW production was created with four influential independent variables, one of which is the amount of production of SEP. Therefore, a link between these waste fractions has been taken into account. The link between the waste fractions was included in a completely different way by Pavlas et al. (2020). Using the principles of data reconciliation for waste production forecasting, the data was corrected to maintain the links in the system. It was assumed that the total production of a certain waste stream (PAP, PLA, GLA) is equal to the SEP amount of this fraction and its amount in MMW. The link between the SEP and MMW was assumed absolute in the paper (Denafas et al., 2014). The link between MMW and SEP was considered 100% with a simultaneous change in total waste production (sum of particular waste fraction in MMW and SEP).

Most approaches to modelling waste production do not consider links between waste fractions or the absolute transition. But these assumptions are not consistent with reality because of new waste fractions, technology development, consumers' behaviour, waste production prevention etc. As separation efficiency increases, a shift of waste from MMW to SEP can be expected. Modelling waste flows between MMW and SEP or new waste flows suppose more realistic models of waste production. Common or case-tailored statistical approaches find great application in the field of waste quantity estimation.

2. Motivation

In order to be able to describe the links between MMW and SEP, it is necessary to have an extensive database. Waste production data are essential and also explanatory variables that have a major impact on waste production. The presented model is applied on waste production data in the Czech Republic. Data from the database *Waste management information system* managed by *Czech environmental information agency*[1] were used for the analysis. The explanatory variables were from collection network infrastructure. In the year 2018, 5,782 kt of MSW were produced in the Czech Republic. Unfortunately, about 46% of all MSW is still landfilled. Fig. 1 demonstrates the change in waste generation for the Czech Republic in a specific period. Annual data on the production of MMW and SEP (PAP + PLA + GLA + TEX + MET + BIO) in 2010–2018 are available. Fig. 1 shows the change in MMW (*black*) and SEP (*green*) since 2010. SEP production increased by 58 kg/cap between 2010 and 2018 (value a). MMW production decreased approx. 18 kg/cap between 2010 and 2018 (value *b*). The grey value shows the change in the production of MMW and SEP fractions together. From the aggregated point of view, the change between 2010 and 2018 is approx. 30 kg/cap.

Based on Fig. 1, it can be assumed that there is a link between MMW and SEP. The question is what is the extend of the waste shift from MMW to SEP and for which waste fractions.

[1] Czech Environmental Information Agency https://www.cenia.cz/odpadove-a-obehove-hospodarstvi/isoh/

Individual waste fractions of SEP can have a different effect on MMW, and newly produced wastes interfere in various ways as well. Fig. 1 provides an example of one European country that is affected by efforts to increase recycling. However, authors expect that similar links will be evident in the data of other countries.

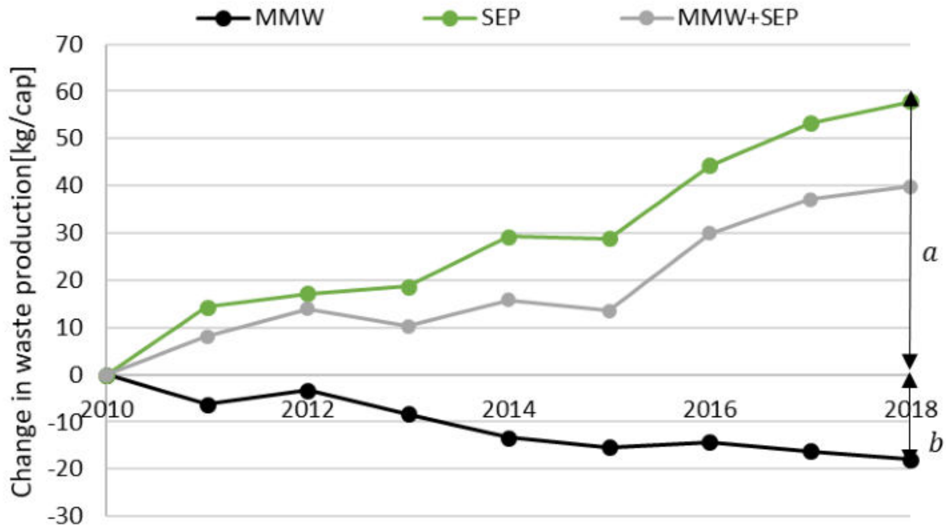


Fig. 1. Change in waste production 2010–2018, Czech Republic, data source: Waste management information system

2.1. Statistical analysis of links in data on waste production, Czech Republic

To describe the links between SEP and MMW, the authors statistically evaluated data at the level of state, regions, micro-regions and municipalities. Only main fractions from SEP were considered – PAP, PLA, GLA, TEX, MET and BIO. The available data on waste production were in annual detail from the period 2014–2018. Models were designed using correlation analysis and linear regression at the different territorial level using available explanatory variables (collection network infrastructure, type of heating, type of buildings etc.). A description of statistical methods and some results are available in the paper (Rosecký et al., 2021).

Statistically significant models have been developed at the national level for all waste fractions. However, the problem is the small amount of data dependent variables (waste production). For this reason, the results of the regression model at national level are considered inconclusive. For lower levels of territorial division (regions, micro-regions, municipalities), the results of the models were found to be statistically insignificant. Therefore, the cluster analysis of territorial units with similar characteristics was made. Subsequently, correlation and regression analysis were performed for individual clusters of territorial units separately. The only not rejected link resulting from the analyses is approximately 20 % transfer of BIO from MMW to SEP. The analyses performed did not show any other statistically significant links between the production of individual waste fractions based on available influencing factors. Therefore, some explanatory variables are missing in order to describe the variability in the data at the monitored territorial level with sufficient reliability. Studies from other countries also face the problem of insignificant statistical models for describing waste production. An example is the residual domestic waste at household level in Denmark (Edjabou et al., 2018), regression model for EU cities explains only unsatisfactory variance (Beigl et al., 2004). The same is true for data outside Europe, such as Brazil (Pisani et al., 2018). If the statistical analysis does not provide good results, it is possible to approach the problem by balancing quantities. This approach is influenced by a considerable degree of freedom, which can lead to errors in the mass balances. It is possible to eliminate error using territory, waste and time data aggregation. The following sec. 3 summarizes the overview of data reconciliation models.

3. Data reconciliation in waste management

In WM, the waste flow and streams are often described using optimization techniques. Balancing waste quantities might possibly model the transfer of waste from one fraction to another. This shift is mainly caused by increased waste separation or newly collected waste fractions, see regulation on textiles (Act No. 541/2020 Coll, Waste Act.). The balance approach is a promising technique if the statistical analysis of data does not provide good results for explaining links between fractions (see the previous section for details). Balancing of waste quantities should consider a high degree of freedom, which can lead to errors; however, methods based on data reconciliation can be helpful as was proved for bulky waste and its processing data (Šomplák et al., 2019). Similar examples with a limited source of information to be modelled occur in different fields. The individual tasks are so specific that it is appropriate to develop a tailor-made approach (Wang et al., 2021).

Data reconciliation includes methods for modifying data to comply with the rules and relationships in that data. Individual tasks using data reconciliation differ according to the completeness of the input information.

- The basic use of data reconciliation is to reduce errors of measured data in the system of sensors with redundant information (Galan et al., 2019). Random errors can be eliminated based on stated sensor reliability. The accuracy of individual sensors is usually taken into account by weighting in the objective function (Keller et al., 1992).
- Besides random errors, there are also systematic errors that can deflect the entire system. Approaches to minimizing random errors and detecting systematic errors have been proposed. Different strategies of weights' determination can be found, but usually, the accuracy/reliability of sensors is also considered (Chen et al., 2013).
- Data reconciliation methods are used in many industries, and this approach is no longer applied only to measuring systems. In some applications, the weight cannot be determined from sensor properties, and it is necessary to proceed with another approach to set the significance of data in the model. Data reconciliation as part of forecasting waste production enabled estimating future values (Pavlas et al., 2017). The weight was set according to the size of the input data, which ensured a percentage-even distribution of the error between the input parameters. This approach was chosen due to the absence of data accuracy.
- A specific application of reconciliation is for a system with incomplete data (to supplement the data with estimates). Paper (Imtiaz et al., 2004) compared approaches for estimating missing values. the method using the principles of data reconciliation was successful up to 13% of the missing values. The data reconciliation approach was used in the (Matyus et al., 2003) model for waste flow modelling. The goal was to replace missing data and minimize data uncertainty. Compatibility with a priori information was verified by statistical tests. In WM, it may occur when modelling the flow from the waste producer to the treatment site. The model presented in (Šomplák et al., 2019)

derived incomplete information on the method of waste treatment for a specific waste producer.

- Incomplete data can be observed in different time steps, when measurement is provided only in some time points. The aim is to estimate values also outside these measurements using dynamic optimization (Hedengren and Eaton, 2017).

The model presented in this contribution combines two last mentioned problems according to the searched values. The approach takes the form of a data reconciliation model with incomplete data. Waste transfer rate from MMW to SEP for individual waste fractions is missing value and the new waste stream is modelled. These values are estimated for individual years in time series of available historical data. Simultaneously, incomplete data in time steps occurs in the model. Information on the composition of MMW is essential. It is necessary to perform analyzes so that they are meaningful also for the aggregated territory (Šramková et al., 2021). MMW composition as an input information is available only in some years of time series. So MMW composition ensures connections between years in time series. Within the optimization model the missing MMW composition is estimated during the years.

In addition to the links between waste fractions, data on waste production are also characterized by a hierarchy of territorial units. Many optimization models use hierarchical system relationships to break down tasks. In this case, the task is simplified to more small tasks in order to simplify the calculation (Schmidt et al., 2015). As the follow-up work using the hierarchy (Schmidt et al., 2016) shows, a number of numerical problems have been eliminated. The hierarchical link can be successfully used to refine the estimates obtained using the data reconciliation model. The article (Yang, 2020) presented approaches for matching the point reconciliation estimate of the forecast in the field of solar energy. In the area of waste production forecasting, the hierarchy system was used for data reconciliation by Pavlas et al., 2020. The aim was to forecast the expected production of waste on the basis of historical development while maintaining hierarchical links. The model presented in the sec. 4 corrects estimates for lower levels using data from the parent territory. The hierarchical structure is therefore used to refine the estimates obtained by the model.

3.1. Novelty

The first phase is an attempt to describe the links between the components of MSW using statistical analysis. For various reasons, there may be situations where links cannot be detected using common procedures (variability in data, missing data from some areas – influencing factors, local influences). Two possibilities can occur, namely that there are no links in the data, or it is believed that there are links, but they have not been identified. In this case, they must be detected by other modelling approaches. The presented system uses balance equations based on weight conservation, and certain rules are expected to be followed.

1. Physical properties must hold.
2. Results must be meaningful.
3. The greater producer in terms of total quantity has less variability.
4. The waste fractions in a particular territory have homogenous behaviour.
5. If the data for some territories are not very informative, it is possible to be inspired by behaviour in parent territories (credibility model).

The presented model puts into context estimates of MMW composition. In addition, the model can take into account MMW composition estimates quality, which can be quantified by confidence intervals. This is a completely new approach, which solves the situation when we do not have enough data for the statistical model (it is not significant). Data reconciliation is done, which is a common method for detecting errors on devices. Here it will be used to obtain maximum information from available data based on a balance model. The model is supported by the idea of credibility model which combines information. The result preserves the logical properties, which supports the plausibility and usability of the obtained values. Identified transfers between waste fractions help to understand the behaviour of waste producers and make it possible to assess meeting recycling targets in respective years. It can be assumed that the trends established in the historical data will continue in the future. Therefore, it is possible to use the results in forecasting waste production (Pavlas et al., 2020). It is also possible to model scenarios that deviate from forecasts, e.g. to meet CEP targets. These results can indicate the potential for improvement and evaluate whether it is possible to meet the set targets.

4. Methods

The flow between MMW and SEP is probably due to local conditions and cannot be generalized. A number of studies have shown the influence of socio-economic and environmental aspects on the form of WM in a given area (Rosecký et al., 2021). Which also results in the efficiency of waste separation and the amount of MMW produced. For this reason, the links between the quantities of MMW and SEP will be described individually for each time series. Data of selected waste fractions – PAP, PLA, GLA, MET, BIO, TEX – will be processed.

For the subsequent phases of the calculation, it is necessary to estimate the share of fractions in the MMW each year. The symbols further used are described in Tab. 1.

Tab. 1: Notation of used symbols

Sets and indices	
$f \in F$	index for substituting specific waste fraction (PAP, PLA, GLA, MET, BIO, TEX)
$\mathrm{i} \in I = \{i_0, \dots, \bar{\imath} - 1\}$	index of the specific year
i_0	indication of the first year of the time series
$\bar{\imath}$	indication of the last year of the time series
$i' \in I' \subset \{i_0, \dots, \bar{\imath}\}$	years with available data about the MMW composition
$\mathrm{j} \in J$	index for investigated territorial units
Parameters	
$\Delta SEP_{f,i,j}$	year-on-year change in production of separated fraction f [t] $\Delta SEP_{f,i,j} = SEP_{f,i+1,j} - SEP_{f,i,j}$, where $SEP_{f,i,j}$ is waste f production in the year i and territorial unit j
$\overline{MMW_{i,j}}$	total MMW production [t]
$\widetilde{MMW}^{\%}_{f,i',j}$	estimate of MMW composition in the years with available data
φ	the highest permissible change in the percentage composition of fraction f in MMW [%]
$\sigma_{f,j}$	standard deviation $\Delta SEP_{f,i}$ in the years i [t]
$o_{f,j}$	fraction f weight for the balance model $[1/t^2]$, $o_{f,j} = 1/\sigma^2_{f,j}$
$w_{f,j}$	fraction f, territorial unit j weight for the correction model [-]
m_j	number of unsatisfied inequalities
M	big-M constant
$\overline{\delta_f}$	aggregate waste transfer rate for higher hierarchical unit [%]
$\overline{\Delta SEP_{f,i}}$	year-on-year change in production of separated fraction f fir higher hierarchical unit [t]

Variables	
$\delta_{f,j}$	waste transfer rate from MMW to SEP [%]
$MMW_{f,i,j}^{\%}$	percentage amount of the fraction f in MMW in year i [%]
$u_{f,i,j}$	external waste stream [t]
$y_{f,i,j}$	constraint satisfaction, binary variable [-]
$\lambda_{f,j}$	correction variable [-]
$\delta_{f,j}^{*}$	corrected waste transfer rate [%]

If the statistical analysis does not provide significant results, it is possible to describe the transfer of waste from MMW to SEP for a given territorial unit j using a data reconciliation model in terms of weight. As a percentage, the diversion of waste from MMW to SEP is given by the variable $\delta_{f,j}$. Furthermore, the separation of fraction f interferes with the external waste stream $u_{f,i,j}$, which is a waste that did not previously occur in MSW. The situation is shown in Fig. 2.

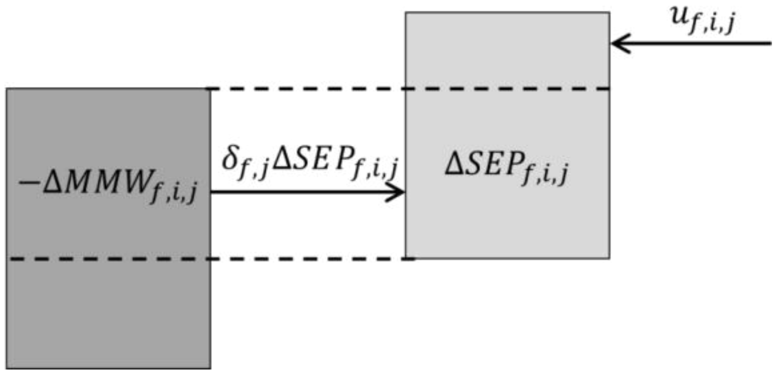


Fig. 2. Schematic representation of waste transfer from MMW to SEP

For given compositions of MMW in years i and $i+1$, the equation describing the flow from $\Delta MMW_{f,i,j}$ to $\Delta SEP_{f,i,j}$ has the following form:

$$\delta_{f,j}\Delta SEP_{f,i,j} \leq -\left(MMW_{f,i+1,j}^{\%}\overline{MMW}_{i+1,j} - MMW_{f,i,j}^{\%}\overline{MMW}_{i,j}\right). \quad (1)$$

The issue with this formulation is that for some input data (that most probably stem from erroneous data collection) the inequality cannot be satisfied, which would lead to an infeasible problem. A way to overcome this is by introducing binary variables $y_{f,i,j}$ which control if the corresponding inequality should ($y_{f,i,j} = 0$) or should not ($y_{f,i,j} = 1$) be satisfied. This is achieved by using the following big-M formulation:

$$\delta_{f,j}\Delta SEP_{f,i,j} + MMW_{f,i+1,j}^{\%}\overline{MMW}_{i+1,j} - MMW_{f,i,j}^{\%}\overline{MMW}_{i,j} \leq My_{f,i,j}. \quad (2)$$

Naturally, we would like to have the number of $y_{f,i,j}$ that are equal to one as small as possible. This could be achieved by considering an objective that would minimize the sum of $y_{f,i,j}$, transforming the problem into a multiobjective one. Instead, we use a version of the ε-constraint method, where the number of unsatisfied constraints will be bounded by a parameter m_j, that will be iteratively increased, until the optimization model becomes feasible (Algorithm 1). The mixed-integer quadratic optimization model for estimating the value of $\delta_{f,j}$ and the composition of MMW on historical data has the following form:

$$\min \sum_{i\in I} \sum_{f\in F} o_{f,j} u^2_{f,i,j} \tag{3}$$

s.t.

$$\delta_{f,j} \Delta S\mathrm{EP}_{f,i,j} + MMW^{\%}_{f,i+1,j} \overline{MMW}_{i+1,j} - MMW^{\%}_{f,i,j} \overline{MMW}_{i,j} \le M y_{f,i,j}, , \quad \forall f \in F, \forall \mathrm{i} \in I, \tag{4}$$

$$\Delta SEP_{f,i,j} = \delta_{f,j} \Delta SEP_{f,i,j} + u_{f,i,j}, \quad \forall f \in F, \forall \mathrm{i} \in I, \tag{5}$$

$$MMW^{\%}_{f,i',j} = \widehat{MMW}^{\%}_{f,i',j}, \quad \forall f \in F, \forall \mathrm{i}' \in I', \tag{6}$$

$$MMW^{\%}_{f,i+1,j} \le (1+\varphi) MMW^{\%}_{f,i,j}, \quad \forall f \in F, \forall \mathrm{i} \in I, \tag{7}$$

$$MMW^{\%}_{f,i+1,j} \ge (1-\varphi) MMW^{\%}_{f,i,j}, \quad \forall f \in F, \forall \mathrm{i} \in I, \tag{8}$$

$$\sum_{i\in I} \sum_{f\in F} y_{f,i,j} \le m_j, \tag{9}$$

$$0 \le \delta_{f,j} \le 1, \quad \forall f \in F, \tag{10}$$

$$y_{f,i,j} \in \{0,1\}, \quad \forall f \in F, \forall \mathrm{i} \in I, \tag{11}$$

The objective (3) is to minimize the sum of the weighted external waste streams. Constraints (4) and (5) describe the flow of waste into $\Delta SEP_{f,i,j}$ (see Fig. 2). Constraint (6) prescribes the composition of MMW for years with available data. Constraints (7) and (8) limit the possible change in MMW composition from one year to the next. Constraint (9) sets the maximum number of unsatisfied constraints (4). The natural ranges of variables $\delta_{f,j}$ and $y_{f,i,j}$ are described in (10) and (11), respectively.

Algorithm 1
1: Set $m_j := 0$.
2: Solve (1)-(9).
3: **If** (1)-(9) is infeasible
then $m_j := m_j + 1$, **go to** 2
else terminate.

Algorithm 1 is run for all territorial units separately, to obtain their respective values of $\delta_{f,j}$. The quality (or the correctness) of these individual estimates can be judged based on several factors. First, for territorial units that needed high values of m_j to have a feasible optimization model, it is expected that their respective "true" values of $\delta_{f,j}$ may be far off the estimate provided by the optimization model. Also, for territorial units for which the results displayed high variability in the needed amount of external flows $u_{f,i,j}$, there may be well-founded doubts about the precision of the corresponding estimate $\delta_{f,j}$. On the other hand, the estimates for territorial units with high flows of $SEP_{f,i,j}$, or territorial units in a higher hierarchy that are an aggregate of smaller ones (such as a country that can be thought of as a collection of municipalities) should be trusted more.

To correct some of the possible erroneous estimates of $\delta_{f,j}$ for some territorial units j, the following optimization model is proposed. It uses the aggregate results from a higher hierarchical territorial unit to find the corrected estimates $\delta^*_{f,j}$. The weights of the individual territorial units (inside the aggregate) are computed by the following formula:

$$w_{f,j} = \frac{E_i\left(\left|\Delta SEP_{f,i,j}\right|\right)}{\sigma_i\left(u_{f,i,j}\right)\left(1+m_j\right)}. \tag{12}$$

The correction model, separate for each waste fraction f, has the following form:

$$\min \sum_{j\in J} w_{f,j}^2 \lambda_{f,j}^2 \tag{13}$$

$$\text{s.t.} \quad \delta^*_{f,j} = \left(1-\lambda_{f,j}\right)\delta_{f,j} + \lambda_{f,j}\overline{\delta_f}, \qquad \forall j \in J, \tag{14}$$

$$\sum_{j\in J} \delta^*_{f,j}\Delta SEP_{f,i,j} = \overline{\delta_f}\,\overline{\Delta SEP_{f,i}}, \qquad \forall i \in I, \tag{15}$$

$$0 \le \lambda_{f,j} \le 2, \qquad \forall j \in J, \tag{16}$$

$$0 \le \delta^*_{f,j} \le 1, \qquad \forall j \in J, \tag{17}$$

where the objective (13) is the weighted sum of squares of the correction variables. Constraint (14) is the equation describing the correction and constraint (15) is a mass balance equation. We set the upper bound on $\lambda_{f,j}$ to 2 on purpose - for some of the municipalities with very noisy data (and, consequently, with a lower weight $w_{f,j}$) the "real" $\delta^*_{f,j}$ could lie on the "opposite side" of $\overline{\delta_f}$ from its computed value $\delta_{f,j}$. The individual parts of the calculation follow each other. The Tab. 2 summarizes the individual steps.

Tab. 2: Summary of the calculation procedure

Step	Operation	Input data	Remark
1	Statistical analysis, sec. 2.1	Waste production Influence factors (infrastructure, sociology, economy etc.)	If it is not possible to describe the production well by influential factors, the statistical model is insignificant. Then it is necessary to proceed to step 2.

2	Data reconciliation model, equations (3)–(11)	Waste production MMW composition	It is necessary to have an estimate of the MMW composition for at least one year. In the case of lower territorial units, it is recommended to proceed with the correction in step 3.
3	Correction of data reconciliation, equations (13)–(17)	Waste production Results of the data reconciliation model from step 2	The corrected value is considered to be the result of the lower level.

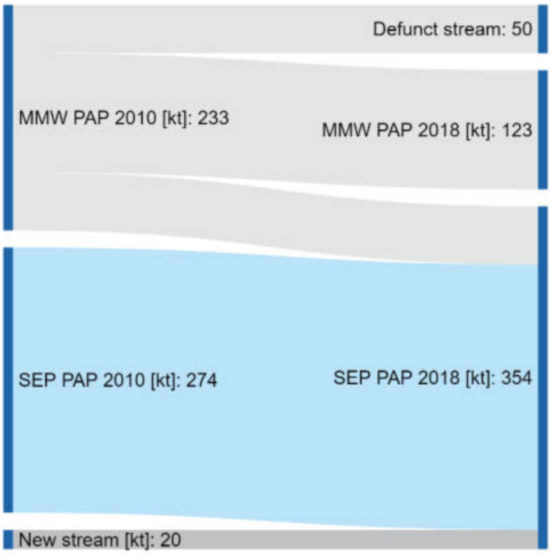
It could be interesting to have several hierarchical units and compute (13)-(17) for all of them at once (e.g., municipality-province-country). However, the transition into several hierarchical units would mean that the parameters $\overline{\delta_f}$ would become variables (for the units in the middle of the hierarchy). The constraint (14) would then become a quadratic equality, which would break the convexity of the optimization problem.

5. Case study – CZECH REPUBLIC

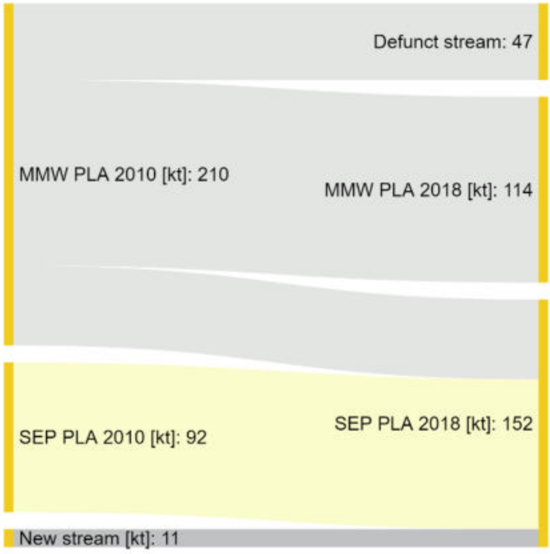
The model was applied to data on waste production in the Czech Republic. The available dataset for SEP is from the period 2010-2018, but information on the composition of waste is only from 2018. The estimate of MMW composition is the result of analyses carried out according to the stratification of the territory (Šramková et al., 2021). Subsequently, the composition of MMW for other territorial units was recalculated according to the type of housing. The aim of the model is therefore to estimate the rate of waste transfer from MMW to SEP and to estimate the composition of MMW in 2010-2017. The results below are shown for the national, regional and micro-regional level, of which there are 206 in the Czech Republic.

5.1. Results for the aggregated territories

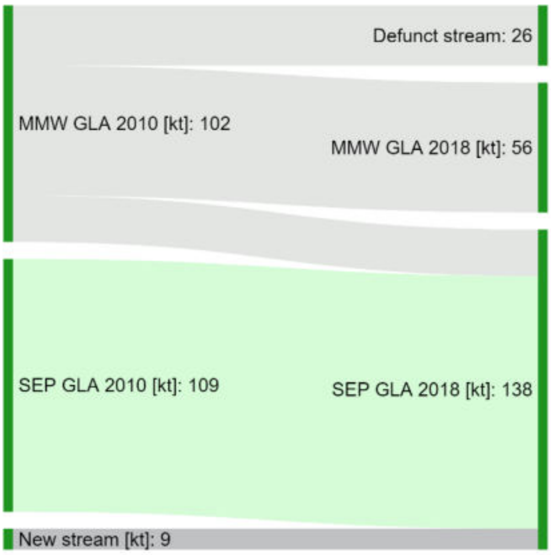
The initial part of the procedure according to Algorithm 1 was first calculated. The result is value $\delta_{f,j}$ estimating the magnitude of the flow between MMW and SEP and the new waste stream at $u_{f,i,j}$. At the same time, the number of unsatisfied inequalities was monitored using the parameter m_j. At the national level, inequality (1) was met for all monitored parameters, so the parameter m_j is zero. The Fig. 3 below graphically shows the waste streams between MMW and SEP for all 6 monitored fractions, this is the expected flow from 2010 to 2018 in the Czech Republic. The designation MMW PAP indicates the amount of paper in MMW and SEP PAP is the amount of separated PAP, analogous to other waste fractions. It can be seen that defunct and new waste streams are interfering with the system.



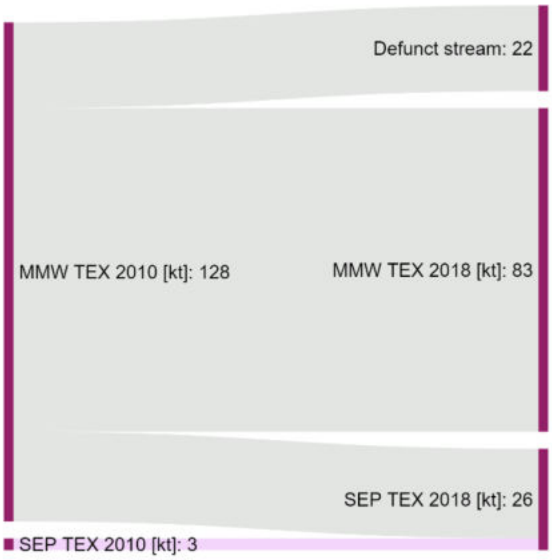
a) *PAP separation*



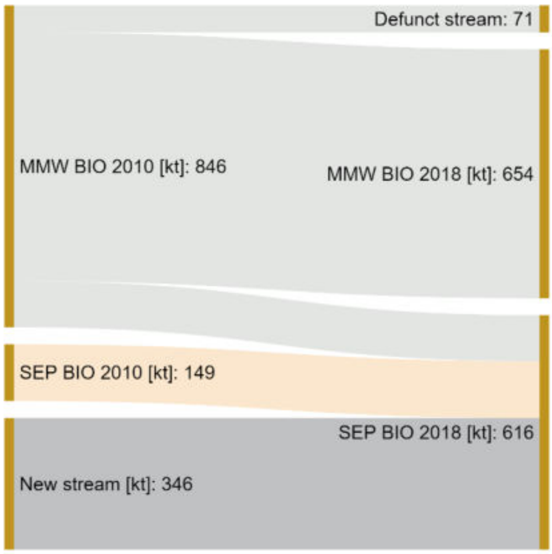
b) *PLA separation*



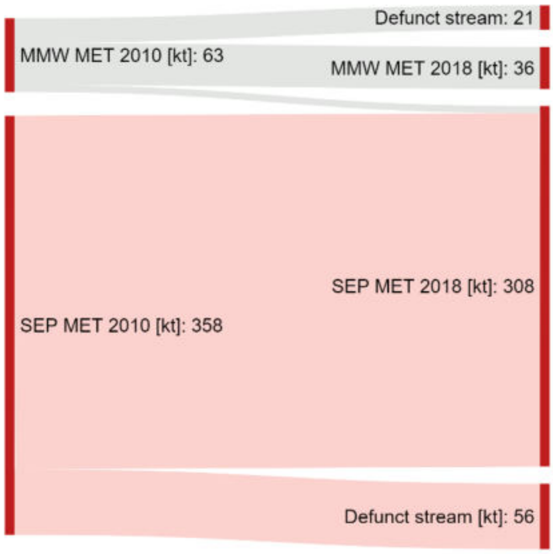
c) *GLA separation*



d) *TEX separation*



e) BIO separation



f) MET separation

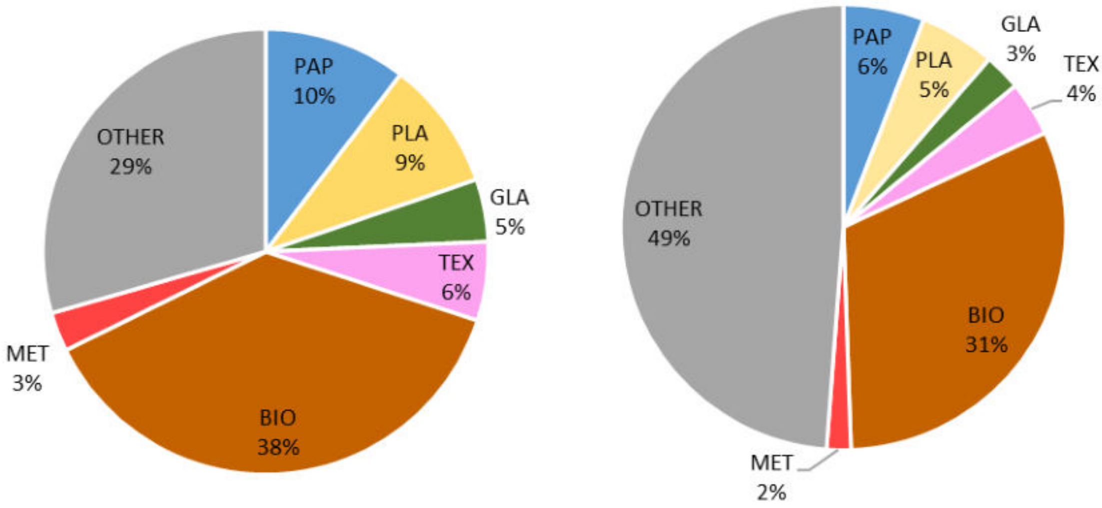
Fig. 3. Diagrams of stream between MMW and SEP in the period 2010-2018, national level

The numerical values of the results for the national and regional level are in the Tab. 3. The stated value indicates what part of the newly separated waste originates in MMW. Particularly, in the Capital City of Prague is estimated that 55 % of SEP PAP originates from MMW. However, this particular result is burdened by great variability over time, which requires more research in these areas. The results show relatively significant variability across the monitored waste fractions. At the level of the Czech Republic, the lowest estimated transfer between MMW and SEP is 11 % for MET. The highest value resulted for TEX (98 %). A low value of $\delta_{f,j}$ means the effect of a new waste stream, which can be understood as a change in consumer behavior. A high value of $\delta_{f,j}$ indicates that waste separation is increasing, but the total MSW production as a whole does not change significantly. The last part of Tab. 3 indicates the weighted average of $\delta_{f,j}$ in regions and weighted standard deviation of $\delta_{f,j}$. It is evident that the assessment $\delta_{f,j}$ at the level of the Czech Republic reaches a higher value than their weighted average across regions in all waste fractions except GLA. The values for the aggregated data of the Czech Republic are significantly more reliable. MET shows the lowest variability from the monitored waste fractions. This result shows that MET separation is least affected by local conditions compared to PAP, PLA, GLA, TEX and BIO. It is possible to find significant differences in the results at the regional level. The result for the South Bohemian region can be mentioned as unsuccessful. This output is not a model error, but an input dataset. It would be necessary to have better estimates of the composition of MMW. This output points to the need to correct the delta result for lower territorial units, see (13)–(17). The results of the statistical analysis (see sec. 2.1) estimate a $\delta_{f,j} = 0.2$ for BIO. The results of the model calculation at the national level are $\delta_{f,j} = 0.26$, the weighted average for regions is $\delta_{f,j} = 0.21$ and for micro-regions $\delta_{f,j} = 0.22$. The results from two ways of calculation are close and therefore model results are supported by the statistical analysis. However statistical analysis is not always applicable, the presented model has wider use. The results show that lower levels of territorial division achieve higher variability (see Tab. 3). The only exception is PLA, where the variability of the results (weighted standard deviation) is the same for the regions and micro-regions.

Tab. 3: Estimates of waste transfer ($\delta_{f,j}$)

	PAP	**PLA**	**GLA**	**TEX**	**BIO**	**MET**
Czech Republic	0.75	0.82	0.69	0.98	0.26	0.11
Regions						
Capital City of Prague	0.55	0.46	0.74	1.00	0.36	0.32
Central Bohemian	0.38	0.29	0.99	0.91	0.00	0.02
South Bohemian	0.09	0.11	0.07	0.74	0.01	0.07
Pilsen	0.28	0.05	0.74	0.07	0.03	0.07
Karlovy Vary	0.65	0.85	0.98	0.93	0.41	0.11
Ústí and Labem	0.46	0.95	0.97	0.97	0.39	0.20
Liberec	0.33	0.64	0.22	0.45	0.11	0.11
Hradec Králové	0.43	0.61	0.42	0.92	0.34	0.06
Pardubice	0.36	0.95	0.68	0.98	0.39	0.04
Vysočina	0.35	0.56	0.47	0.98	0.11	0.05
South Moravian	0.50	0.89	0.67	0.99	0.57	0.05
Olomouc	0.39	0.95	0.96	0.99	0.11	0.06
Zlín	0.50	0.72	0.80	0.96	0.51	0.06
Moravian-Silesian	0.83	0.91	0.97	0.98	0.20	0.03
Weighted average of regions	0.46	0.61	0.72	0.88	0.21	0.06
Weighted standard deviation of regions	0.17	0.30	0.27	0.21	0.20	0.05
Micro-regions						
Weighted average of micro-regions	0.33	0.60	0.51	0.57	0.22	0.04
Weighted standard deviation of micro-regions	0.24	0.30	0.30	0.31	0.22	0.06

Higher waste separation also entails a change in the composition of MMW. Information on the MMW composition is essential for estimating the potential for increasing separation and thus planning in waste management. MMW composition is very beneficial information for treatment infrastructure planning. The model uses available MMW composition and on that basis it forms an estimate for other years. The Fig. 4 shows the composition of MMW in 2010 and 2018. The composition in 2018 was input information and previous years, including 2010, are the output of the model. The Fig. 4 shows a decrease in the proportion of separable fractions over time compared to a higher proportion of other components. However, it should be noted that due to separation and prevention of waste, the total amount of MMW production decreased by about 7 % in the period under review. It is also evident from the Fig. 4 that changing the composition of MMW also influence the potential for further increase in separation. Assuming that the established trends in the composition of MMW will continue in the future, the results can be used for waste production forecasts. Information on the expected composition of MMW in the future is essential for modelling scenarios with increased separation to meet CEP targets.



a) Year 2010 *b) Year 2018*

Fig. 4. MMW composition estimate, national level

5.2. Results for the lower territorial units

As was already mentioned, lower territorial units have significantly less quality historical data. At lower levels, it is therefore recommended to make a correction according to (13)–(17). This correction was made for the Czech Republic at the level of micro-regions. Fig. 5 below shows a histogram of these parameters m_j for 206 micro-regions. For each micro-region the met inequalities (1) are evaluated for individual monitored years (2010-2018) and monitored fractions (PAP, PLA, GLA, TEX, MET, BIO). The results show that for most areas, namely 140 micro-regions, this inequality has been met. An extreme case is the micro-region, where the inequality was not met for 21 assessed values out of a total of 54 (9 time periods and 6 waste fractions). It is a micro-region with very variable data and the resulting value $\delta_{f,j}$ is therefore debatable.

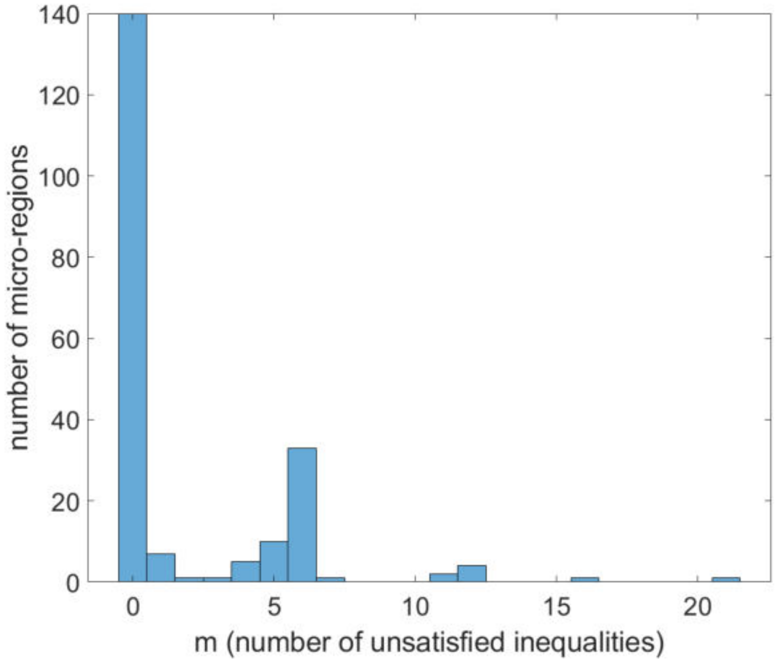


Fig. 5. Number of unsatisfied inequalities at the level of micro-regions, Czech Republic

The next part of the calculation of (13)-(17) is devoted to the correction of the results for lower territorial units of hierarchical structure to ensure the highest possible reliability. In the case of high data variability, the $\delta_{f,j}$ for micro-regions is corrected by the aggregated information for national level $\overline{\delta_f}$ (see 5.1). The correction rate is expressed as a $\lambda_{f,j}$ value. If the $\lambda_{f,j}$ is zero, the model trusts absolutely its own data, so it uses the original $\delta_{f,j}$. If $\lambda_{f,j}$is equal to one, the own data for micro-region is considered very unreliable and only aggregated information is used in the form of $\overline{\delta_f}$. If $\lambda_{f,j}$ is higher than 1, the result at the micro-region level is corrected to a higher value than for the aggregated territory. The corrected value is denoted as $\delta^*_{f,j}$. The histogram in Fig. 6 shows the $\lambda_{f,j}$ for micro-regions and it is clear that the degree of credibility of the own data is different for individual waste fractions. For most waste fractions, it is clear that the model largely adheres to its own original $\delta_{f,j}$ values ($\lambda_{f,j}$ close to zero).

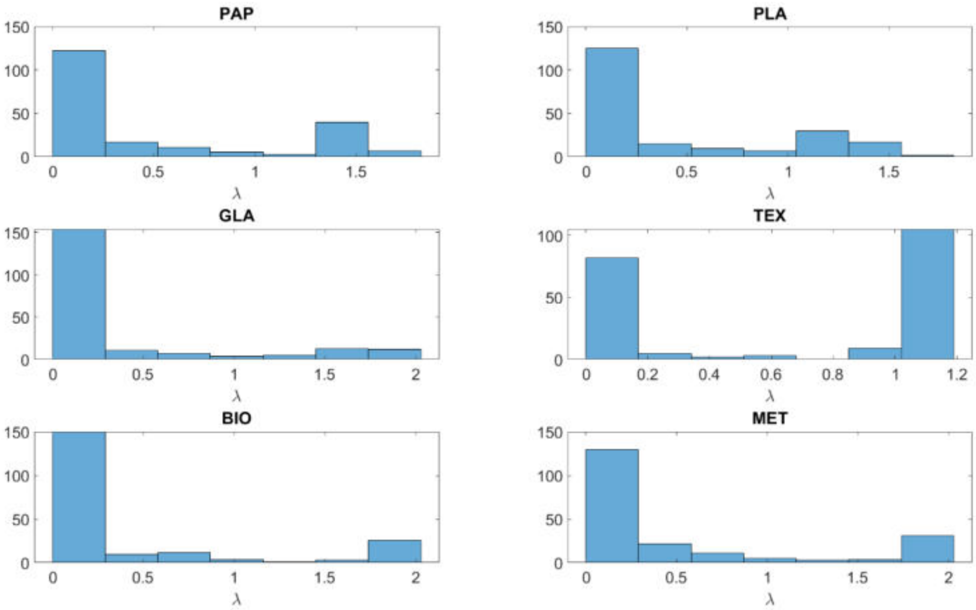


Fig. 6. Histogram of degree of correction using aggregated information at the micro-regional level

The histograms Fig. 7 show the original $\delta_{f,j}$ value (blue colour) and its correction in the form of $\delta^*_{f,j}$ (brown colour). In most cases, it is a shift of the $\delta_{f,j}$ to higher values within correction. The vertical line shows the national results, so it is aggregated information $\overline{\delta_f}$.The value of $\delta^*_{f,j}$ is the final result for micro-regions.

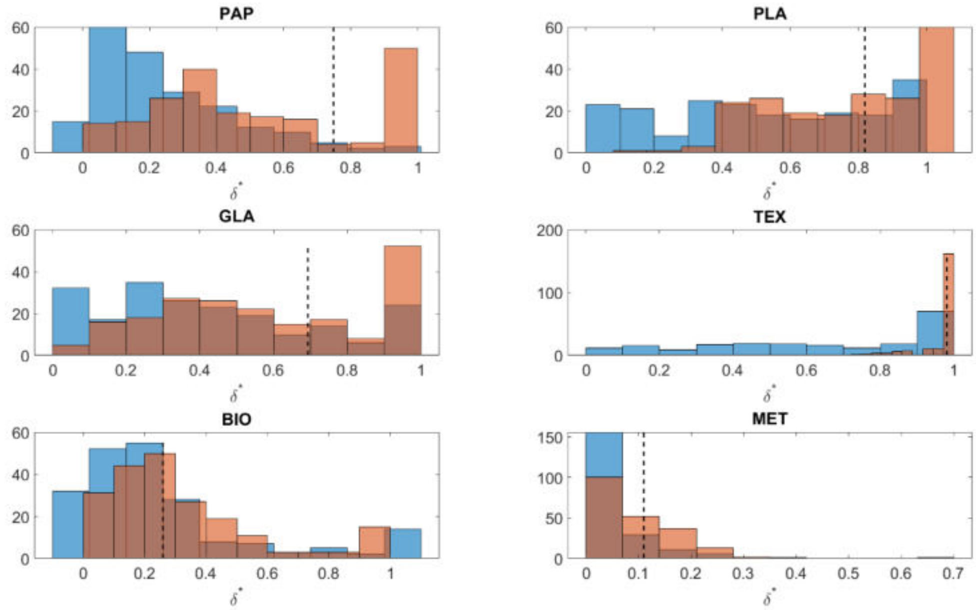


Fig. 7. Histogram of estimate correction $\delta_{f,j}$ (blue) to $\delta^*_{f,j}$ (brown) at the level of micro-regions, Czech Republic

By correcting the estimate to $\delta^*_{f,j}$, the estimation variability decreased, yet it is relatively high. This is due to the very small amount of data on MMW composition analyses and for most regions these are only rough estimates. As the number of composition analyses will increase in future, the results of the model will achieve better quality. In general, the results are less variable for higher territorial units, see Tab. 4.

Tab. 4: Corrected estimates of waste transfer at national and regional level ($\delta^*_{f,j}$)

	PAP	PLA	GLA	TEX	BIO	MET
Czech Republic	0.75	0.82	0.69	0.98	0.26	0.11
Regions						
Weighted average of regions	0.74	0.82	0.69	0.98	0.26	0.11
Weighted standard deviation of regions	0.14	0.15	0.13	0.02	0.06	0.01
Micro-regions						
Weighted average of micro-regions	0.61	0.82	0.67	0.98	0.28	0.11
Weighted standard deviation of micro-regions	0.26	0.20	0.26	0.04	0.20	0.07

6. CONCLUSION

The presented approach made it possible to define the relationship between waste transfer from MMW to SEP. The results show significant differences between the different types of waste. The most accurate estimates can be made in higher territorial units (country level), where data from the relevant sub-areas are aggregated. The input for the model is the amount of individual waste fractions in MMW. The advantage of the approach is that all monitored waste fractions are modelled simultaneously. Therefore, the change in the composition of MMW due to higher separation is taken into account. A weakness of the model is dependence on the quality of the MMW composition estimate. The effect of poor input values is an effort to eliminate through correction taking into account different levels of the territory.

The model can be refined by using additional studies on the composition of MMW from a specific area, which are the output of MMW composition analyses. Calculated results can help estimate the fulfilment of recycling targets set by legislation. If the goals are not achieved in the set years, it is possible to react in advance to the situation through intervention or support in problematic fractions or localities. In the further development of the model would be appropriate to take into account the hierarchical structure of data on multiple levels simultaneously (micro-regions, regions, state) and use these links for more accurate estimation. With a sufficient data set, it would be appropriate to examine whether there is a change in the rate of waste movement over time. For output users, the estimated values should be supplemented by confidence intervals. However, this is the subject of further research because there are currently no exact approaches for the design of the reliability belts of such a model.

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Data Availability

The data about municipal solid waste used in the case study are available from the database of Waste Management Information System of Czech Republic called ISOH (ISOH 2021).

Author contributions

All authors contributed to the presented study. Conceptualisation was provided by Radovan Šomplák. Formal analysis was performed by Veronika Smejkalová. Methodology was performed by Radovan Šomplák and Jakub Kůdela. Validation of results was performed by Veronika Smejkalová, Radovan Šomplák and Jakub Kůdela. The figures visualisation was performed by Veronika Smejkalová and Jakub Kůdela. The first draft of the manuscript was written by Veronika Smejkalová. The review and editing were provided by Radovan Šomplák and Jakub Kůdela. All authors read and approved the final manuscript.

REFERENCES

Act No. 541/2020 Coll, Waste Act. In Czech.https://www.zakonyprolidi.cz/cs/2020-541?fbclid=IwAR0S-zW5CJaPL_35Xh_vB1lt2ybfcRH20r73qsDtKfhOqE4VZSZBjmqG6A

Beigl P, Lebersorger S, Salhofer S (2008) Modelling municipal solid waste generation: A review. Waste Management 28(1):200-214. https://doi.org/10.1016/j.wasman.2006.12.011

Beigl P, Wassermann G, Schneider F, Salhofer S (2004) Forecasting municipal solid waste generation in major European cities. International Congress on Environmental Modelling and Software. 83.

Chen J, Peng Y., Munoz JC (2013) Correntropy estimator for data reconciliation. Chemical Engineering Science 104:1019-1027. https://doi.org/10.1016/j.ces.2013.09.034.

Denafas G, Ruzgas T, Martuzevičius D, Shmarin S, Hoffmann M, Mykhaylenko V, Ogorodnik S, Romanov M, Neguliaeva E, Chusov A, Turkadze T, Bochoidze I, Ludwig C (2014) Seasonal variation of municipal solid waste generation and composition in four East European cities. Resources, Conservation and Recycling 89:22-30. https://doi.org/10.1016/j.resconrec.2014.06.001

Diaz-Farina E, Díaz-Hernández JJ, Padrón-Fumero N (2020) The contribution of tourism to municipal solid waste generation: A mixed demand-supply approach on the island of Tenerife. Waste Management 102: 587-597. https://doi.org/10.1016/j.wasman.2019.11.023

Directive (EU) 2018/851 of the European Parliament and of the Council of 30 May 2018 amending Directive 2008/98/EC on waste (Text with EEA relevance), accessed 23.06.2020.

Directive [2008/98/EC] of the European Parliament and of the Council on waste.

Edjabou ME, Boldrin A., Astrup TF (2018) Compositional analysis of seasonal variation in Danish residual household. Resources, Conservation & Recycling 130:70-79. https://doi.org/10.1016/j.resconrec.2017.11.013

Galan A, de Prada C, Gutierrez G, Sarabia D, Grossmann IE, Gonzalez R (2019) Implementation of RTO in a large hydrogen network considering uncertainty. Optimization and Engineering 20:1161–1190. https://doi.org/10.1007/s11081-019-09444-3

Goel S, Ranjan VP, Bardhan B, Hazra T (2017) Forecasting solid waste generation rates. Modelling Trends in Solid and Hazardous Waste Management 35-64. https://doi.org/10.1007/978-981-10-2410-8_3.

Hedengren JD, Eaton AN (2017) Overview of estimation methods for industrial dynamic system. Optimization and Engineering 18:155–178. https://doi.org/10.1007/s11081-015-9295-9

Imtiaz SA, Shah SL, Narasimhan S (2004) Missing data treatment using iterative PCA and data reconciliation. *IFAC* Proceedings Volumes (IFAC-PapersOnline) 37(9):197-202.

Jiang P, Liu X (2016) Hidden Markov model for municipal waste generation forecasting under uncertainties. European Journal of Operational Research 250(2):639-651. https://doi.org/10.1016/j.ejor.2015.09.018

Keller JY, Zasadzinski M, Darouach M (1992) Analytical estimator of measurement error variances in data reconciliation. Computers and Chemical Engineering, 16(3):185-188. https://doi.org/10.1016/0098-1354(92)85005-S

Malinauskaite J, Jouhara H, Czajczyńska D, Stanchev P, Katsou E, Rostkowski P, Thorne RJ, Colón J, Ponsá S, Al-Mansour F, Anguilano L, Krzyżyńska R, López IC, Vlasopoulos A, Spencer N (2017) Municipal solid waste management and waste-to-energy in the context of a circular economy and energy recycling in Europe. Energy 141: 2013-2044. https://doi.org/10.1016/j.energy.2017.11.128

Matyus T, Gleiß A, Gruber K., Bauer G (2003) Data reconciliation, structure analysis and simulation of waste flows: Case study Vienna. Waste Management and Research 21(2). 93-109. https://doi.org/10.1177/0734242X0302100203

Oribe-Garcia I, Kamara-Esteban O, Martin C, Macarulla-Arenaza AM, Alonso-Vicario A (2015) Identification of influencing municipal characteristics regarding household waste generation and their forecasting ability in Biscay. Waste Management 39:26-34. https://doi.org/10.1016/J.WASMAN.2015.02.017

Pisani R, de Castro MCAA, da Costa AA (2018). Influence of population, income and electricity consumption on per capita municipal solid waste generation in Sao Paulo State, Brazil. Journal of Material Cycles and Waste Management 20:1216-1227. https://doi.org/10.1007/s10163-017-0687-0

Pavlas M, Šomplák R, Smejkalová V, Nevrlý V, Zavíralová L, Kůdela J, Popela P (2017) Spatially distributed production data for supply chain models - Forecasting with hazardous waste. Journal of Cleaner Production 161:1317-1328. https://doi.org/10.1016/j.jclepro.2017.06.107

Pavlas M, Šomplák R, Smejkalová V, Stehlík P (2020) Municipal Solid Waste Fractions and Their Source Separation: Forecasting for Large Geographical Area and Its Subregions. Waste and Biomass Valorization 11:725–742. https://doi.org/10.1007/s12649-019-00764-0

Pluskal J, Šomplák R, Nevrlý V, Smejkalová V, Pavlas M (2021) Strategic decisions leading to sustainable waste management: Separation, sorting and recycling possibilities. Journal of Cleaner Production 278:123359. https://doi.org/10.1016/j.jclepro.2020.123359

Rosecký M, Šomplák R, Slavík J, Kalina J, Bulková G, Bednář J (2021) Predictive modelling as a tool for effective municipal waste management policy at different territorial levels. Journal of Environmental Management 291:112584. https://doi.org/10.1016/j.jenvman.2021.112584

Schmidt M, Steinbach MC, Willert BM (2015) High detail stationary optimization models for gas networks. Optimization and Engineering 16(1):131-164. https://doi.org/10.1007/s11081-014-9246-x

Schmidt M, Steinbach MC, Willert BM (2016) High detail stationary optimization models for gas networks: validation and results. Optimization and Engineering 17(2):437-472. https://doi.org/10.1007/s11081-015-9300-3

Smejkalová V, Šomplák R, Rybová K, Nevrlý V, Rosecký M, Burcin B, Kučera T (2020) Waste Production and Treatment Modelling for EU Member States. Chemical Engineering Transactions 81:691-696. https://doi.org/10.3303/CET2081116

Šomplák R, Nevrlý V, Smejkalová V, Šmídová Z, Pavlas M (2019) Bulky waste for energy recovery: Analysis of spatial distribution. Energy 181:827-839. https://doi.org/10.1016/j.energy.2019.05.175

Šramková K, Šomplák R, Nevrlý V, Jirásek P, Smejkalová V, Popela P (2021) Stratification and multi-representative optimization approach to waste composition analysis. Optimization and Engineering 22:1727-1754. https://doi.org/10.1007/s11081-021-09645-9

Tomić T, Schneider DR (2020) Circular economy in waste management – Socio-economic effect of changes in waste management system structure. Journal of Environmental Management 267:110564. https://doi.org/10.1016/j.jenvman.2020.110564

Wang L, Zheng W, Tang L, Zhang S, Liu Y, Ke X (2021) Spatial optimization of urban land and cropland based on land production capacity to balance cropland protection and ecological conservation. Journal of Environmental Management 285. https://doi.org/10.1016/j.jenvman.2021.112054

Xiao L, Lin T, Chen S, Zhang G, Ye Z, Yu Z (2017) Characterizing urban household waste generation and metabolism considering community stratification in a rapid urbanizing area of China. PloS ONE 102(12). https://doi.org/10.1371/journal.pone.0145405

Yang D (2020) Reconciling solar forecasts: Probabilistic forecast reconciliation in a nonparametric framework. Solar Energy 210:49-58. https://doi.org/10.1016/j.solener.2020.03.095

Příloha 7: Článek [A12] Pricing and advertising strategies in conceptual waste management planning

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Pricing and advertising strategies in conceptual waste management planning

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The paper presents a new model for integration of circular economy strategies into the municipal solid waste management. The goals are to reduce the waste produced, recycle at the highest rate as possible (material recovery) and to use the resultant residual waste for energy recovery. Such a strategy utilizes both pricing and advertising principles in the mixed integer linear programming model while accounting two criterions - assessment of greenhouse gas (GHG) and cost minimization. The aim is to design the optimal waste management grid to suggest a sustainable economy with environmental concerns. The government, municipalities and/or authorized packaging company decide about the investments to the propagation of waste prevention and to advertising of waste recycling, while investors decide about new facility location and technological parameter. The availability of waste is projected in pricing method as well as in the location of the facility. The mathematical model will consider randomness in the form of waste production. The suggested non-linear functions of pricing and advertising are replaced by piecewise linear approximation to reduce computational complexity. The proposed multi-objective model is applied in a case study for the Czech Republic in the area of waste treatment infrastructure planning to support decision-making at the micro-regional level. The integration of circular economy principles, considering also the total amount of produced GHG, revealed the existing potential in waste prevention. On the other hand, the increase of recycling is limited, landfills are not supported and the energy recovery is preferred. However, the planning of the complex system relies on the decision-maker.

1. Introduction

Waste treatment has gained major attention in recent years (Liu et al., 2018). Although material and energy recovery from waste has been steadily growing (Malinauskaite et al., 2017), many countries still resort to landfilling (Lino and Ismail, 2017). Sadly, many countries refuse to deal with the issue of waste treatment altogether (Wang et al., 2018). Some of the most startling examples may be seen in the oceans which are filled with plastics; this plastic then enters the food chain of sea animals (Gutow and Bergmann, 2018). In addition to that, the decrease in the availability of primary sources has become a subject of serious discussion (Hofmann et al., 2018). Several countries have taken steps to amend relevant legislation in order to reduce inefficient waste treatment and consequently also the negative impact of waste on the environment (Gharfalkar et al., 2015). At the same time, there are strong efforts to use a hidden potential of waste as the secondary source of materials and energy (Silva et al., 2017). Circular Economy Package (Directive (EU) 2018/849, 2018/850, 2018/851, 2018/852) may serve as an example of these efforts. This package aims to shift from a linear pattern (raw material, product, waste) to the circular pattern which strives for maximum reuse and minimum amounts of residual

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flows (Tomić and Schneider, 2018).

Circular economy (CE) provides a powerful approach to combat environmental challenges and promote sustainable development (Korhonen et al., 2018). Some developed European as well as Asian countries have advanced in the development of policies that support the CE in their society (Ormazabal et al., 2018). Waste treatment hierarchy defined in EU (Directive, 2008/98/EC) must be observed to comply with the targets of the CE. The waste hierarchy prioritizes prevention to waste production, followed by waste recycling, material and energy recovery and last - waste disposal (Fonseca et al., 2018).

The efficient CE requires the establishment of necessary processing infrastructure. Mathematical modelling may serve as a powerful tool for its start and design. This issue is rather complex and covers all stages of waste hierarchy, siting of processing capacities, the design of transportation infrastructure, including transfer stations and so on. Therefore, sophisticated methods and tools are required. The paper by Barbosa-Póvoa et al. (2018) provides an in-depth research study for planning in supply chain systems, including waste management (WM). Papers discussed in the research study discuss various types of sustainability of the system. Specific decision-making criteria relate to the following aspects.

1.1. Economic aspects

Minimization of total costs is a basic and most frequently used indicator of economically oriented calculations of the sustainable supply chain (Tong et al., 2014). Costs seem to be a sufficient indicator, especially if the network is stable and only tactical decisions are made; moreover, costs are the easiest metric value. Net Present Value or Internal Rate of Return are less frequently assessed (Amin and Zhang, 2012), especially when strategic decisions, i.e. new facility establishment, are made.

1.2. Environmental aspects

There is a significant difference between indicators in terms of environmental assessment of the system. A lot of attention is paid to emissions of carbon dioxide, by direct evaluation of carbon footprint (Byrne et al., 2010), or by calculation of greenhouse gases (GHGs), see (d'Amore and Bezzo, 2016). Global warming potential (GWP) is an indicator used for comparison of the impact of particular pollutants on the environment changes, see (De Meyer et al., 2015). Climate change is another commonly applied indicator, see (Boukherroub et al., 2015). All of these indicators help evaluate the environmental impact of the systems in relation to global warming. Waste reduction and recycling is another important category of environmental impacts, see (Gilli et al., 2018). The papers and publications mentioned above focus exclusively on one of the indicators; however, this may significantly distort final results. The so-called life cycle assessment (LCA) approach usually incorporates more than one environmental aspect and the method is crucial for transition to a CE, see (Cellura et al., 2012). LCA represents a complex method for environmental impact assessment.

1.3. Social aspects

Job creation, safety, health and others are among the most frequently assessed indicators of the social aspects category, see (Bouchery et al., 2012). In addition, the so-called NIMBY (Not-In-My-BackYard) effect becomes evident as mentioned by (Ren et al., 2016). The public perception of modern waste infrastructure is investigated by (Kirkman and Voulvoulis, 2017).

1.4. Multi-criteria approaches

There are several decisions that have to be made when operating an integrated system of WM; these include waste collection planning, siting of processing facilities, selection of proper waste treatment technologies, etc (Yadav et al., 2017). A complex approach to the whole system has to consider more than just one aspect discussed above. Hu et al. (2017) examined a bi-objective model for the design of Waste-to-Energy (WtE) plants siting. The authors analyse economic and environmental aspects; total costs and emission production are minimized in the objective function. Multi-objective model is explored by (Asefi and Lim, 2017) for the design of integrated solid WM. The authors strive to minimize waste transport related costs. Suitability of the whole system is further assessed by evaluation of system components which include social and environmental criteria. A model presented in a paper by (Jabbarzadeh et al., 2016) represents another multi-objective method for design of a WM system consisting of customers, transfer stations, landfills and waste collection vehicles. The model incorporates three objective functions: minimization of total costs, minimization of total GHG production, and the total rate of energy consumption.

Many papers usually focus only on particular fractions of municipal solid waste (MSW) and related technologies which are suitable for their processing. Residual MSW (RES) is the main waste flow suitable for processing by the energy recovery infrastructure, see (Fiorentino et al., 2015). Biowaste is another topic that deserves mentioning, see (Neri et al., 2018). Some of the studies aspire for a more complex method and assume MSW as a whole, see (Chen et al., 2019) in China or (Malinauskaite et al., 2017) in certain European countries. These authors consider the separation of utilizable fractions (for material recovery) and subsequent energy recovery of RES. Relatedness of waste prevention, material recovery, energy recovery and waste disposal are only theoretical in these papers; the authors may only focus on small, aggregated areas with little practical applicability. Following sections of this paper presents a new complex method for design of optimization of MSW treatment related to WM hierarchy. Fig. 1 displays a scheme of intended borders of the MSW processing system which includes economic and environmental aspects. Since ignoring uncertainties often leads to insufficient results (Yadav et al., 2017), uncertainty in the amount of produced waste is expressed using a scenario-based approach which leads to a stochastic model.

Basic layer analysed in this paper is related to RES and relevant optimization of processing infrastructure. Pricing and advertising methods are used to describe relationships between this RES layer and its surroundings, incl. layers focused on prevention of waste production, material recovery, and waste disposal. Fig. 2 shows a complex view of the balance for one node of the network. The method combines economic and environmental criteria, a detailed description is in Section 3. The aim is to design an effective plan for waste transport and subsequent waste processing, provided that the total waste production (reduced thanks to prevention) and recycling rate (material recovery) may be affected by targeted investments.

Prevention of waste production and recycling is usually taken into account very generally in most of the studies that determine the means for change, i.e. assessment of main factors using regression in (Gilli et al., 2018). However, there is not a quantification of links between economic factors and real data about waste production and its management.

This paper presents functional relationships based on real data about waste production and processing in the Czech Republic in 2015, see Section 2. The introduced dependencies are inputs to the mathematical model (see Section 3) for WM planning, which takes

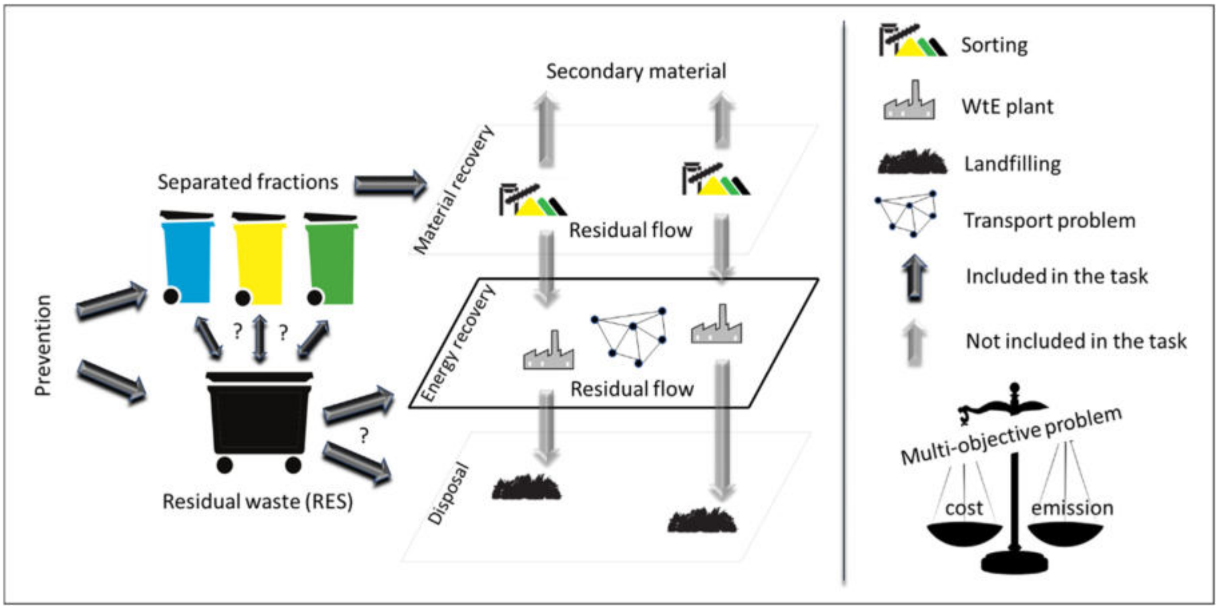


Fig. 1. Scheme of the MSW processing system includes economic and environmental criteria.

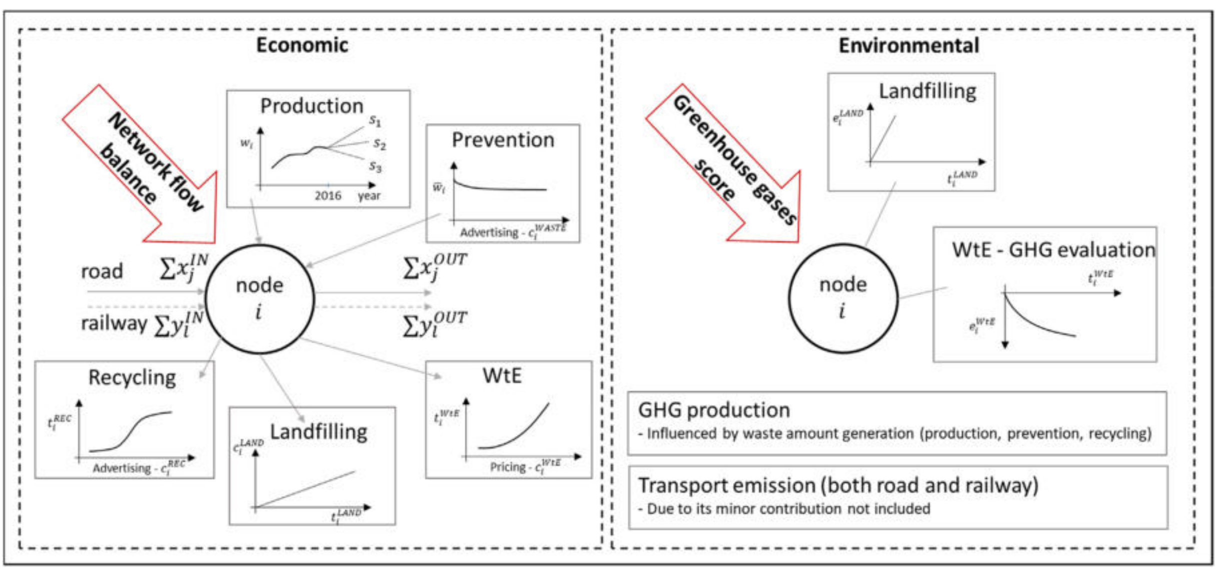


Fig. 2. Scheme of the proposed integrated system consisting of an economic and environmental component.

into account both economic and environmental aspects. Next part (Section 4) of the paper presents the case study on waste data from the Czech Republic and the current situation in the year 2015 is analysed. Finally, the paper concludes with Section 5.

2. Description of economic and environmental relationships in the system

The aim is to suggest the optimal waste strategy for waste suitable processing and to find an optimal waste transportation scheme with respect to the total cost and GHG. The proposed procedure assumes the possibility of influencing the waste production and recycling investments in advertising. Economic sustainability of the new projects is a crucial aspect for actually implemented case studies. Functional dependencies from Fig. 2 were estimated based on the real data.

Motivation based solely on economic profitability has limited opportunities for more efficient MSW management. Since there is a link to the environment and the quality of life, state intervention is needed to support material and energy recovery. Non-profit organizations and associations can also play an important role in fulfilling the waste management hierarchy (Fonseca et al., 2018).

2.1. Waste prevention

One of the influencing factors of waste generation is a certain extent by investment to prevent waste production such as education and environmental projects (washable cups for events, etc.), (Corvellec, 2016). Now, there is still a serious potential for improvements in waste prevention, which may be held back by lack of public awareness, willingness and absence of relevant information, see (Zorpas and Lasaridi, 2013). Investments in waste prevention can be approached by pricing-like principles (Hrabec et al., 2016).

S-curves are usually used in waste management for modelling by regression (Ghinea et al., 2016) and forecasting of waste generation (Lu et al., 2016). Waste production is in obvious relation with the waste prevention. Amount of waste production as a dependent variable is described by a regression model in the form of logistic function (S-shaped curve) Eq. (1):

$$\overline{w}_i\left(c_i^{WASTE}\right) = (w_{max} - w_{min})\left(1 - \frac{1}{1 + e^{-\left(a + bc_i^{WASTE}\right)}}\right) + w_{min}, \tag{1}$$

where $\overline{w}_i$ is the estimation of waste production based on the independent variable c_i^{WASTE} which indicates the investment in the waste prevention at node i and a, b are regression parameters. The parameters w_{min} and w_{max} sets the minimum and maximum possible waste generation. Estimate of minimum and maximum MSW* production (MSW* is a sum of particular MSW fractions: paper, plastics, glass, RES) in the Czech regions is set to 200 kg/cap respectively 400 kg/cap, which corresponds to the best and worst regions in applying a prevention strategy. Similar situation was also observed in Austria, see (Lebersorger and Beigl, 2011). Waste processing price has a major impact on the amount of produced waste (MSW*). S-curve (see Eq. (1)) was selected due to nature of modelled prevention on the basis of waste management experts. Data from Czech regions in 2015 were used to estimate regression parameters a and b (see supplementary materials and Fig. 3a). In general, it is assumed that higher costs spent on public awareness raising are included in total costs (one of the aspects of higher unit costs). Fig. 3 illustrates the regression model of the dependence between waste prevention cost and percentage decline of waste production (see supplementary materials). The model stems from dependence illustrated at Fig. 3a. It is assumed that if additional costs (additional to current costs) are spent on waste prevention, the final effect will be at least the same as in Fig. 3a. The goal of further analysis is to improve the prevention cost definition and calculation. The S-shaped curve in Fig. 3b should lead through the point of 0% decrease of waste production in the case of no waste prevention investment. The w_i^* corresponds to MSW* production decrease for a specific node, which is further used in the model. This regression function leads to poor approximation around the point $c_i^{WASTE} = 0$ (see Fig. 3b). This inaccuracy will be reduced in a mathematical model using the special order set of type 2 (SOS2) variables, see Section 3. The mean absolute percentage error of function from Fig. 3b equals to ca 6.5% (against ca 9.7% for linear function).

It must be noted, that the data comes from the regional level although the case study is targeted at the micro-regions. Unfortunately, the economic data are available only on a regional level, more detailed data are not accessible concerning business secrets between producer and waste processors. The regression model assumes the same decision in all regions, but some of the nodes lie under the regression model. To prevent the solution from getting worse than the current situation, the local constraint is added to prohibit deterioration of waste production.

2.1.1. Recycling

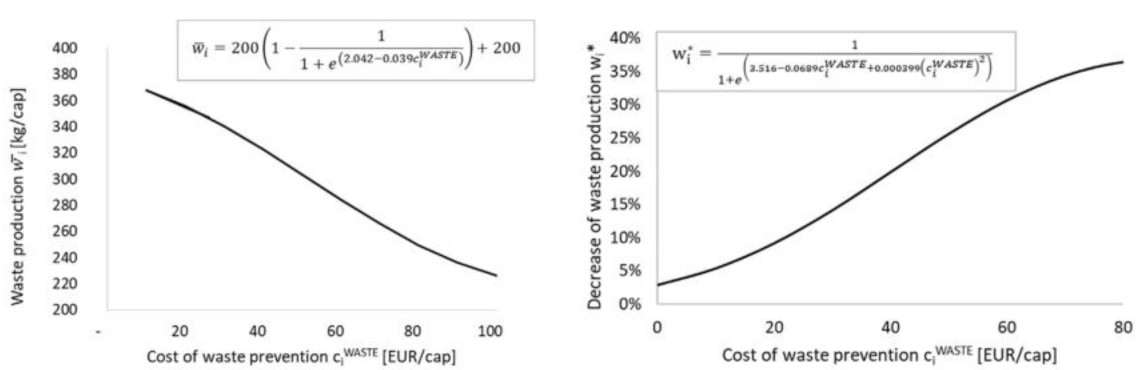
The preference of the waste processing method is controlled by the hierarchy that is anchored in Directive 2008/98/EC. The most desirable way is to prevent and reuse waste followed by waste recycling, so the waste is shifted from RES to recycled MSW. A number of control mechanisms and investments were identified by authors to increase recycling. They can be divided based on the target side: producer of products side, consumer side and operator side. An illustrative division into qualitative and quantitative groups is based on different points of view of participants in the system.

2.1.2. Quantitative

- Producer of products – Adequate size packaging with regard to the product; Aggregation of products into a smaller number of packages.
- Consumer – Denser net of containers.
- Operator – Separation of larger amounts of fractions.

2.1.3. Qualitative

- Producer of products – Eco-design and utilization of recyclable materials.
- Consumer – Changes in the collection system; Fees related to production: PAYT – pay as you throw (Elia et al., 2015); Separation of larger amounts of fractions.
- Operator – The technological level of the facility.



a) Dependence of the waste production on the waste prevention cost *b) Dependence of waste production decline on the waste prevention cost*

Fig. 3. Impact of waste prevention investments on waste production.

The investments are described by advertising cost in this text. The term is generally used in mathematical programming. In the context of recycling, it expresses investment and operating costs associated with a larger number of collection points, the cost of a deposit refund system (e.g. returning PET, cans, glass bottles) and/or the costs of school promotion etc. The advertising efficiency is commonly described by S-shaped function, see (Hrabec et al., 2017). The dependence of the separation efficiency on investment is characterized according to Fig. 4a by three phases:

I. Phase, when it is advantageous to recycle. Such waste constitutes an income (material recovery).
II. Phase, when it is advantageous to support recycling, i.e., it is possible to increase the ratio of separated fractions and residual waste by investments in infrastructure and promotion for a general awareness of recycling benefits to the environment.
III. Phase presents an area of technological constraint for further increases of the recycling ratio, alternatively, it presents a depleted potential of separable components of the RES.

Fig. 4b shows the S-shaped regression model of the relationship between recycling ratio and advertising costs based on real data. Curve at Fig. 4b models efficiency of separation of consumer's part. Increase in separation depending on investments is very slow, which reflects the need to focus on other participants of the chain.

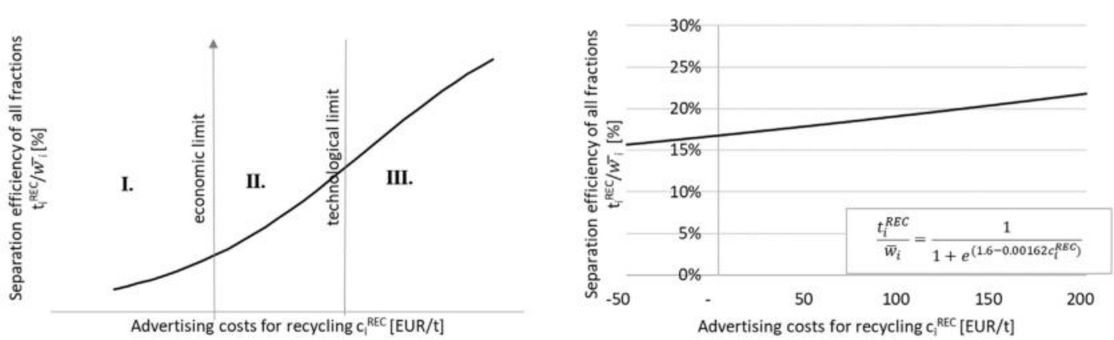
As the separation efficiency increase, the composition of the residual RES changes which is processed in WtE, see (Ferdan et al., 2017). Waste composition, which is treated in the WtE, is at the same time linked with high impact on GHG contribution. As stated by Chen (2018) incinerating plastic MSW emitted the most GHG followed by paper waste, whose GHG production is almost negligible compared to plastic. The waste composition is valuable information in a number of applications and is the subject of research (Baawain et al., 2017), especially with regards to the amount of plastic which leads to the increased contribution of GHG. In the case study, the authors worked with the average waste composition in the Czech Republic where plastics represented 9.32 percent in 2015.

Based on real data in the Czech Republic, about 16.7% of waste can be separated without additional investment, so-called advertising cost for recycling (see Fig. 4b), which corresponds to the current separation efficiency. This value is marked as an economic limit in the scheme in Fig. 4a. Fig. 4b shows a segment of the S-shaped regression model for 14 regions in the Czech Republic. Only selected components of MSW are considered for the purposes of this paper. The analysis is targeted at sorted paper, plastic, glass and RES; other types of waste represent a completely new flow of produced waste in the Czech Republic. The relationship between the amount of separated biowaste or metal and quantity of RES has not been established. Others waste types, such as textile, wood, etc. constitute only negligible parts of MSW.

2.2. Treatment

The treatment cost is determined as dependent on WtE facility capacity, see (Hrabec et al., 2018). In the case of landfills, the processing cost is assumed constant. The treatment cost is based on the so-called gate fee, which is given as a cost per unit of processed waste. In this paper, the annual treatment cost is considered and it has to be assessed for each locality separately due to dependence on the local heat demand and on attributes of WtE facility, see (Putna et al., 2018b). The following figures describe the annual treatment cost depending on the capacity of WtE plant for a particular territory. The area covers ca. 40,000 inhabitants and advanced industrial production with total heat supply of ca. 1,900 TJ/year. Fig. 5 illustrates treatment cost as a function of WtE capacity in particular locality. Both the investment and operating costs are included. These costs are different for each (see supplementary material). Construction is expected in the premises of existing heating plants (see supplementary material for potential sites), where it is possible to ensure the sales of heat produced. In addition, some old boilers are expected to be shut down.

(Fan et al., 2018b) further examined the efficiency of the process and its integration in the plant for cleaner production. In the waste processing as well as in other businesses, there is an emphasis on emissions as GHG. The amount of GHG is given by a function of waste amount processed in the WtE facility. This dependence has a different course for each area because it depends on the heat demand (Putna et al., 2018b) as depicted in Fig. 6.



a) Three phases of dependency between waste separation investment and waste separation

b) S-shaped regression function (based on real data

Fig. 4. Functional relationships associated with the recycling rate in terms of investment in increased recycling.

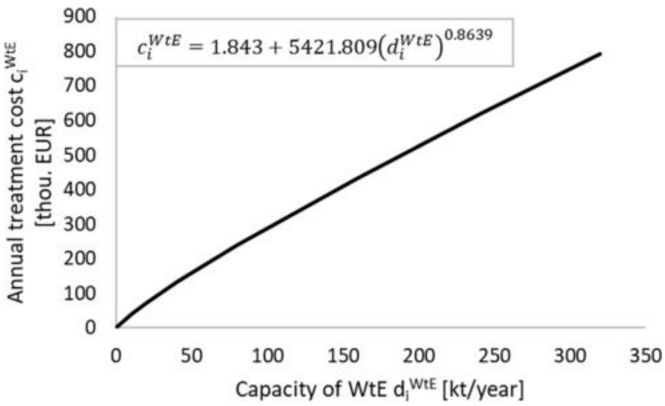


Fig. 5. Annual treatment cost as a function of WtE facility capacity.

Fig. 6a illustrates the heat demand during a year for the same area as in Fig. 5 with an obvious decrease in summer months, marked by line 1. The increased heat demand, when covered by WtE, has the positive effect on the GHG contribution, see Fig. 6b, which describes the reduction of GHG contribution when replacing fossil fuels (gas, coal) for heating. In addition, several heat supply levels from WtE are displayed by horizontal lines in Fig. 6a. Two break points 1 and 2 are highlighted and indicate three parts of graph A, B and C. In part A, the all heat produced in the WtE is absorbed. WtE covers the base, whereas peaks are supplied by additional heat sources. In some months, the demand is lower than WtE maximum capacity. As a result, some heat cannot be utilized. In part C, the heat demand is completely covered by WtE. Since that point, heat delivery reached its maximum. Annual GHG production does not change with increased WtE capacity considering power production is GHG neutral, see (Ferdan et al., 2018). The electricity production does not change and balance is approximately zero. So higher WtE capacity is not beneficial from GHG point of view.

The most significant cost and environmental impact come from MSW processing. The preferred form of energy use is considered in the model, but the model also includes the possibility of landfilling. This cost was set to 160 EUR/t. It includes processing costs itself (about 30 EUR/t) and landfill tax, which is the main motivator for better ways to use RES, see (European Commission (DG ENV). 2012).

In the case of WtE facility, it is necessary to determine the gate-fee with regard to the disposition of the site. This is mainly about demand and the price of heat (Putna et al., 2018a). The link between WtE capacity and gate-fee is described by function separately for each locality. GHG contribution is evaluated in terms of GWP, based on specific attributes of each WtE plant. Therefore, it is assessed for each territorial area apart.

2.3. Transportation

Waste transport is planned using both roads and railways, while rail transport is preferred for the transportation of large quantities of waste over long distances. The economic aspect of these modes of transport is taken into account by the transportation costs (Gregor et al., 2017). Traffic emissions are neglected in the model due to its minor production compared to a processing facility. A respective air emission analysis has been proposed by (Fan et al., 2018a).

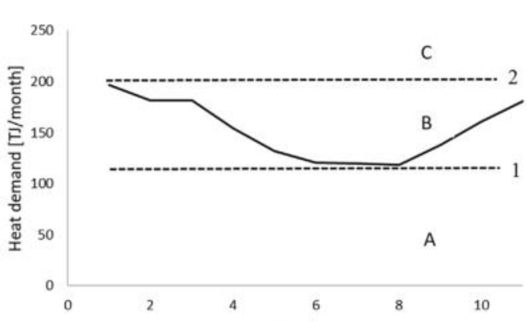
For the road transport, a constant price is considered 0.16 EUR/km.t. In view of the disposition of the regional calculation, the effect of the distance and the quantity transported on the unit price is minimal (Gregor et al., 2017). In the case of rail transport, the distance plays a key role in unit prices. The following equation was used to describe the price:

$$c_l^{RAIL} = 0.005 + 6.26h^{-1}, \tag{2}$$

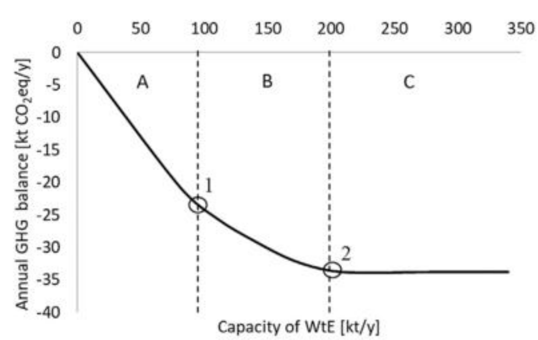
where parameter h **represents the distance in km and** c_l^{RAIL} **defines the unit cost in EUR/t. The relationships** are set according to information from company ČD Cargo, a.s. The unit cost decreases with distance, which is due to the lower weight of the total cost for cargo handling. Furthermore, it is possible to optimize the use of the rail more effectively, making transport more efficient and reducing unit prices. Compared to disposal methods, transport also plays a minor role in terms of GHG production for WM strategy planning (Ferdan et al., 2017). The reason is that GHGs from transport are the same for every kind of waste processing.

3. Modelling approach

In this section, a mathematical model for transport planning and WM is introduced. The previously mentioned contexts are taken into account due to both economic and environmental impacts. Therefore, the objective of the model is to create appropriate waste transport and management plan with minimal cost and emission production.



a) Heat demand during a year



b) Annual GHG balance as a function of the amount of processed waste in the WtE facility

Fig. 6. Functional dependence between the capacity of WtE and GHG contribution with respect to heat demand.

3.1. Notation used

The following notation is used in the model to formulate the general scheme as was described before. The main goal of the model is to identify decision variables and SOS2 variables. SOS2 variables corresponds to the established capacity of WtE plant, investments for recycling and investments for prevention of waste generation. Other decision variables mostly define the waste flows on edges and the amount of waste processed in a certain way.

Sets	
$i\in I$	nodes in the network
$l\in L$	edges which connect nodes i by railway
$j\in J$	edges which connect nodes i by road
$s\in S$	scenarios representing the amount of waste production
$k\in K$	points for linearization – for each k the value on axis x and axis y is defined
Decision variables	
f	weighted multi-objective function
f_1,f_2,f_3,f_4	individual parts of objective function
y_l^s	amount of flow on rail edge l in the scenario s
x_j^s	amount of flow on road edge j in the scenario s
$t_i^{WtE;s}$	amount of processed waste in the WtE plant in the node i in the scenario s
t_i^{REC}	amount of recycled waste in the node i
$t_i^{LAND;s}$	amount of landfilled waste in the node i in the scenario s
w_i^s	waste production in the node i in the scenario s
d_i^{WtE}	planned capacity of WtE plant in the node i
$\overline{w}_i$	average waste production in the node i
$\omega_i^{WtE;s}$	non-utilised capacity in the WtE plant in the node i and scenario s
δ_l	activation of rail edge l, a binary variable
Parameters	
M	big constant
$a_{i,j}$	incidence matrix for road transportation
$b_{i,l}$	incidence matrix for rail transportation
c_i^{LAND}	cost of landfilling in the node i
$c_i^{WtE,PEN}$	cost of loss within electricity and heat generation in the node i in WtE plant
c_l^{RAIL}	cost of transportation on edge l
c_j^{ROAD}	cost of transportation on edge j
$c_l^{RAIL,PEN}$	penalization cost for railways
d_i^{LAND}	existing capacity of landfill in the node i
A_l	minimal amount of waste transported through rail edge l
ε_i^s	random value generated for scenario s in the node i
p^s	probability of scenario s
λ	weight of the objective functions
w_i^C	current production in the reference year in the node i
$f_{i,k}^{WtE}$	potential capacities of each linearization point k for WtE plant in node i
$f_{i,k}^{REC}$	possible advertising investments k for recycling in node i
$f_{i,k}^{WASTE}$	possible advertising investments k for waste production reduction in node i
$c_{i,k}^{WtE}$	cost for processing in the WtE plant in node i
$c_{i,k}^{REC}$	cost for recycled waste in the node i,b
$c_{i,k}^{WASTE}$	cost for waste reduction in the node i
$e_{i,k}^{WtE}$	GHG contribution in the WtE plant in the node i.
e_i^{LAND}	GHG contribution for landfilling in the node i
SOS2 variables	
$\alpha_{i,k}^{WtE}$	the variable of special order set 2 type; indicates the activation of specific capacity k of WtE for all nodes i
$\alpha_{i,k}^{REC}$	the variable of special order set 2 type; indicates the use of specific advertising investment k for recycling in all nodes i
$\alpha_{i,k}^{WASTE}$	the variable of special order set 2 type; indicates the use of specific advertising investment for prevention of waste production k in all nodes i

3.2. Model formulation

On the basis of the above notation, a model consists of multi-objective function Eq. (3) – Eq. (7) and set of constraints Eq. (8) – Eq. (17).

3.2.1. Objective function

The mathematical model is built as a multi-objective optimization problem. It involves objective functions, listed below, which minimize total cost Eq. (3) – Eq. (5) and GHG contribution Eq. (6) which are weighted in the objective function Eq. (7).

Each functional relationship described in the Section 2 given by non-linear expression disrupt the model linearity and hence solvability. All of these non-linear functions are substituted by piecewise linear function using SOS2 variables to restore the linear property of the model in the way as was described in (Hrabec et al., 2018).

The linearization mentioned uses the so-called SOS2 variables, which ensures that at most two adjacent in the ordering given to the set can be non-zero and they must add up to 1.

$$f_1 = \sum_{i \in I}\sum_{k \in K}\alpha_{i,k}^{WtE}c_{i,k}^{WtE} + \sum_{i \in I}\omega_i^{WtE;s}c_i^{WtE,PEN} \tag{3}$$

$$f_2 = \sum_{l \in L} y_l^s c_l^{RAIL} + \sum_{l \in L}\delta_l c_l^{RAIL,PEN} + \sum_{j \in J} x_j^s c_j^{ROAD} \tag{4}$$

$$f_3 = \sum_{i \in I}\sum_{k \in K}\alpha_{i,k}^{REC}c_{i,k}^{REC} + \sum_{i \in I}\sum_{k \in K}\alpha_{i,k}^{WASTE}c_{i,k}^{WASTE} + \sum_{i \in I} t_i^{LAND;s}c_i^{LAND} \tag{5}$$

$$f_4 = \sum_{i \in I}\sum_{k \in K}\alpha_{i,k}^{WtE}e_{i,k}^{WtE} + \sum_{i \in I} t_i^{LAND;s}e_i^{LAND} \tag{6}$$

$$f = \sum_{s \in S} p_s[\lambda(f_1 + f_2 + f_3) + (1-\lambda)f_4] \tag{7}$$

The Eq. (3) is an objective function for presents the processing cost in WtE plants, where the first summation is the linearized price. In the case of unused capacity $\omega_i^{WtE;s}$, the penalty is paid as a loss in electricity and heat generation, the amount is a result of balance according to Fig. 2. Within the minimization of the cost, the optimal location and capacities of WtE plants are suggested. The Eq. (4) includes the transportation cost for both types of transport considered (road and rail). The operation fees for the use of railways $c_l^{RAIL,PEN}$ are also taken into account. The objective function Eq. (5) summarizes the advertising investments for recycling and waste prevention. The relations for these investments (introduced in Section 2) were linearized again using SOS2 variables. The last summation in this objective function f_3 includes the cost for landfilling. The Eq. (6) deals with emissions, so it includes GHG contribution from WtE plants and landfilling, while the replacing of fossil fuels is considered. The methodology is described in more detail in (Ferdan et al., 2018). The last part, Eq. (7) is the weighted multi-objective function which connects all mentioned objective functions Eqs. (3)– (6). Depending on the value of the weight λ, the objective function moves its focus between the costs (corresponding to higher values of λ) and emissions (lower values of λ).

The waste production is modelled in the form of scenarios s with the probability p^s. In this way, the stochasticity is included in the model so the parameters and variables can acquire different values for individual scenarios.

3.2.2. Constraints

$$w_i^s + \sum_{j \in J} a_{i,j}x_j^s + \sum_{l \in L} b_{i,l}y_l^s = t_i^{WtE;s} + t_i^{REC} + t_i^{LAND;s} \quad \forall i \in I, \tag{8}$$

$$\delta_l A_l \le y_l^s \le \delta_l M \quad \forall j \in J, \tag{9}$$

$$w_i^s = \overline{w}_i \varepsilon_i^s \quad \forall i \in I, \tag{10}$$

$$\overline{w}_i \le w_i^C \quad \forall i \in I, \tag{11}$$

$$t_i^{WtE;s} + \omega_i^{WtE;s} = d_i^{WtE} \quad \forall i \in I \tag{12}$$

$$t_i^{LAND;s} \le d_i^{LAND} \quad \forall i \in I, \tag{13}$$

$$y_l^s \ge 0 \quad \forall l \in L, \tag{14}$$

$$x_j^s \ge 0 \quad \forall j \in J, \tag{15}$$

$$t_i^{WtE;s}, t_i^{REC}, t_i^{LAND;s}, \overline{w}_i, w_i^s, \omega_i^{WtE;s} \ge 0 \quad \forall i \in I, \tag{16}$$

$$\delta_l \in \{0,1\} \quad \forall l \in L. \tag{17}$$

The first constraint Eq. (8) defines the total balance of each node. The amount of waste that is transported to the node i and produced in the node i has to be equal to amount transported from the node i and processed there in some way (WtE, REC, LAND). The summations $\sum_{j \in J} a_{i,j}x_j^s$ and $\sum_{l \in L} b_{i,l}y_l^s$ define flows to the node and also from the node through incidence matrix $a_{i,j}$ and $b_{i,l}$.The inequality Eq. (9) gives the minimum waste transport by rail in order to reduce the density of road transport. The Eq. (10) defines waste production w_i^s, which is given by average waste production $\overline{w}_i$ and random value generated for each scenario ε_i^s. The waste production is determined on the basis of an average value $\overline{w}_i$ (its change by investing to the waste prevention is further decribed) and it is randomized for each scenario s by ε_i^s. Eq. (11) forbids the increase of waste production beside the current production w_i^c (for the explanation, see Section 2). In Eq. (12), the planned capacity of the facility is set and divided into utilised and not used according to individual scenarios. The Eq. (13) indicates the maximum amount of landfilled waste which is limited by the capacity d_i^{LAND}. All flows have to be non-negative both for the road Eq. (14) and for the rail Eq. (15). The amount of processed waste, production, average production, and non-utilised capacity have to be non-negative as stated in Eq. (16). Activation of rail edge l is performed by binary variable δ_l Eq. (17).

3.2.3. Additional constraints for SOS2

The constraints listed below are added due to the linearization of the non-linear expressions from Section 2.

$$d_i^{WtE} = \sum_{k \in K}\alpha_{i,k}^{WtE}f_{i,k}^{WtE} \quad \forall i \in I, \tag{18}$$

$$t_i^{REC} = \sum_{k \in K}\alpha_{i,k}^{REC}f_{i,k}^{REC} \quad \forall i \in I, \tag{19}$$

$$\overline{w}_i = \sum_{k \in K}\alpha_{i,k}^{WASTE}f_{i,k}^{WASTE} \quad \forall i \in I, \tag{20}$$

$$\sum_{k \in K}\alpha_{i,k}^{WtE} = 1, \ \sum_{k \in K}\alpha_{i,k}^{REC} = 1, \sum_{k \in K}\alpha_{i,k}^{WASTE} = 1 \quad \forall i \in I \tag{21}$$

Eq. (18) gives the WtE plant capacity d_i^{WtE} based on SOS2 variable $\alpha_{i,k}^{WtE}$ in order to linearize the cost function. In the same way, Eq. (19) and Eq. (20) deal with linearization of functions which describe advertising for recycling and investments for waste reduction. Eq. (21) indicate conditions for SOS2 variables.

4. Case study

The introduced approach given by Eqs. (3)–(21) is applied to the data from 2015 in the Czech Republic. The analysed area includes 206 nodes with existing WtE plants in 4 of them, with a combined capacity of 741 kt. In the rest of nodes, the model allows the construction of new facilities. The input data is shown in Fig. 7, including the 1,898 road edges connecting the individual nodes.

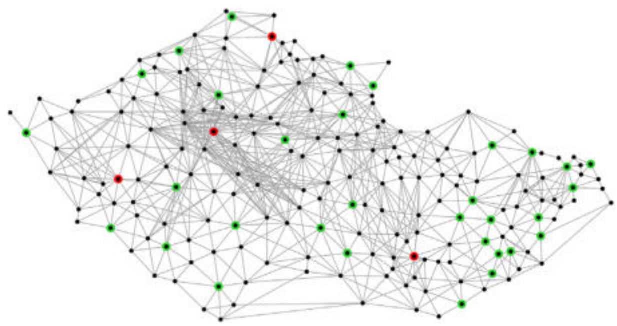


Fig. 7. Problem layout. Nodes are denoted as black dots, existing WtE plants as red rings, possible places for new WtE plants as green rings. Road network (incidence matrix $\boldsymbol{a}_{i,j}$) is marked by grey lines. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

The considered railway network consisted of 2,966 possible edges (these are not included in Fig. 7 as it would make it rather hard to read). There are 48 possible places for new WtE plants in 32 different nodes (in some of the nodes, it is possible to build more WtE plants). The details regarding the input data are provided in the supplementary materials.

The model considered 500 different waste production scenarios to adequately capture the uncertainty involved. The uncertain values ε_i^s are drawn from a uniform distribution on the interval [0.9,1.1]. The probability of a scenario is the same for all scenarios $p^s = \frac{1}{|S|}$. The problem was solved for varying values of λ (cf. the numerical results) to identify the trade-off between the overall optimal costs and the amount of produced GHG emissions. The algorithm that was used to solve the problem was the Benders decomposition scheme, thoroughly reviewed in (Rahmaniani et al., 2017), utilizing the warm-start cuts developed in (Kůdela and Popela, 2017). The optimization model and the decomposition algorithm were programmed in the high-performance dynamic language JULIA (Bezanson et al., 2017) with the JuMP package for mathematical optimization (Dunning et al., 2017), that is well suited for large-scale scientific computing. The solver CPLEX 12.6.3 (CPLEX, 2019) was used to compute the consecutive mixed-integer problems (in the Benders decomposition scheme). The optimality gap was set to 1.5% and the computations took around 8 h to complete (for each value of λ) on an ordinary machine (3.2 GHz i5-4460 CPU, 16 GB RAM). The resulting optimal decisions were subsequently tested on a separate set of 10,000 different scenarios and the average costs, the amount of produced emissions are reported in Table 1, whereas the average amount of waste prevented, recycled, treated and landfilled are reported in Table 2 (the reference average waste production is a constant value 2,661 kt). The tests took around 1.5 h to compute (for each value of λ).

The results of the computations are summarized in Tables 1 and 2 Although the optimal decisions depend quite profoundly on the chosen value of λ, they have one thing in common – in all the cases (and all the considered scenarios) the amount of installed WtE capacity is robust enough to process nearly all of the generated waste and less than 0.2% of the waste is being landfilled. It means that the decision to build and use the WtE plants is both economic and ecological (in terms considered in this paper). The two extreme cases for the value of the weight λ correspond to the two opposite solutions. For $\lambda = 0$ the model emphasizes the amount of produced emissions over everything else, resulting in rather disastrous transporting decisions and enormous costs. On the other hand, the model with $\lambda = 1$ completely disregards the production of emissions and advises to build a comparatively large number of smaller WtE plants. These two, in fact, single-objective, solutions are useful as reference points rather than grounds for actual decision support, as the main strength of the model comes from the possible trade-off between these two extremes. Small capacities of WtE have economic advantages due to easier slag waste management, flue gas cleaning etc.

As depicted in Fig. 8, even very small deviations from the boundary values of λ yield solutions that are much better in one of the objectives while being only marginally worse in the other objective. These trade-off decisions retain some of the qualities of the extreme ones – i.e. the decision to build a small number of high-capacity WtE plants and increased spending in prevention for the lower values of λ. The solution for $\lambda = 0$ is not depicted in Fig. 8, since it would distort the overall insight – compared to all other solutions, it has extremely high cost with very marginal improvement in the amount of produced emissions.

The considered railway transport is utilized in all the solutions. Because of the relationship for the computation of the railway transport costs Eq. (2) the model seems to prefer longer and medium-sized journeys to be conducted by the trains, whereas the shorter ones are left for the road transport. This can be seen in Fig. 9 and Fig. 10. What can also be seen (especially in Fig. 9) is that some of the nodes serve as a "transfer hubs" where the waste is being concentrated from nearby nodes by the road transport and subsequently loaded on a train and shipped to a node with a WtE plant.

The usage of different advertising investments varies greatly. The recycling investments (at least in the presented form) are too expensive to be used and, therefore, are advised only when costs are completely neglected. On the other hand, the waste-prevention investments are utilized to a greater extent, mainly in places with high per capita waste production, as the investment in waste prevention in these places has a higher impact compared to places with already low per capita waste production (see Fig. 3a). What can be seen from the results in Table 1 is that the waste-prevention investments are being used to decrease the need for landfilling, without the need to increase the WtE capacity. These investments are most prominent for lower values of λ as they help to decrease the amount of GHG emissions while being rather costly.

Table 1
The numerical results for different values of λ – decisions and costs.

λ	Cost [MEUR]	Emissions [Mt]	# of rail connections	Transport by rail [%]	Additional recycling costs [MEUR]	Additional prevention costs [MEUR]	Installed new WtE capacity [kt]	# of new WtE plants
0	801.262	134.400	2,966	42.27	16.084	31.614	1,280	4
0.001	209.340	134.401	31	22.41	0	29.722	1,280	4
0.25	202.078	134.487	16	19.76	0	23.231	1,280	4
0.375	197.089	135.097	37	27.15	0	19.086	1,280	4
0.5	193.796	137.419	47	29.76	0	15.128	1,280	4
0.625	181.931	153.050	49	29.49	0	0.033	1,320	5
0.75	160.303	204.275	46	29.99	0	0.033	1,320	7
0.875	148.850	255.371	28	19.00	0	0.033	1,320	9
1	146.445	307.757	26	15.86	0	0.054	1,326	15

Table 2
The numerical results for different values of λ – waste disposal.

λ	Prevention [kt]	Prevention [%]	Recycling [kt]	Recycling [%]	Energy recovery [kt]	Energy recovery [%]	Landfilling [kt]	Landfilling [%]
0	89.98	3.38	604.57	22.72	1,966.61	73.90	<0.01	<0.01
0.001	87.55	3.29	602.57	22.64	1,971.03	74.07	<0.01	<0.01
0.25	71.59	2.69	602.57	22.64	1,986.99	74.66	<0.01	<0.01
0.375	60.69	2.28	602.57	22.64	1,997.19	75.05	0.72	0.03
0.5	49.45	1.86	602.57	22.64	2,006.38	75.39	2.78	0.10
0.625	5.68	0.21	602.57	22.64	2,048.79	76.99	4.14	0.16
0.75	5.68	0.21	602.57	22.64	2,048.79	76.99	4.14	0.16
0.875	5.68	0.21	602.57	22.64	2,048.79	76.99	4.14	0.16
1	5.81	0.22	602.57	22.64	2,050.47	77.05	2.32	0.09

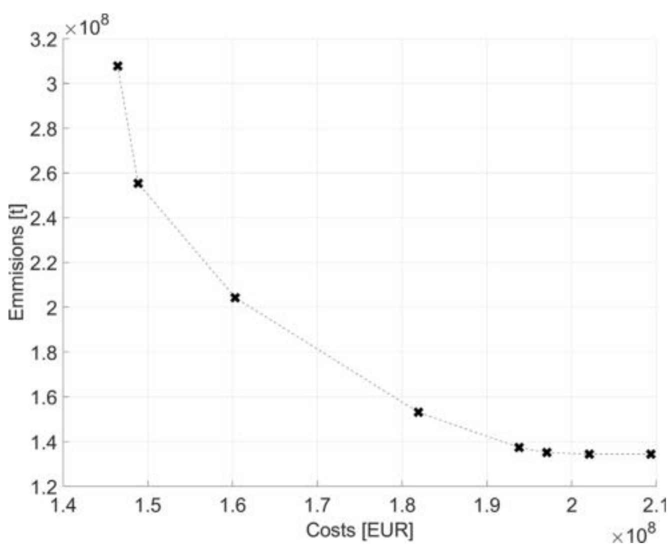


Fig. 8. The Pareto frontier describing the trade-off between the optimal costs and the amount of produced emissions. The dashed line has only a visual purpose.

As it is with most optimization computations, especially the ones that are working with random quantities, the results should be taken cautiously. It is up to the decision-maker to choose the desired trade-off between expected costs and environmental impacts and to carefully weigh the advantages, disadvantages, and applicability of the decisions suggested by the results of the optimization.

5. Conclusion

The paper presents a new method to apply some of CE concepts within the WM sector. The approach is based on the multi-objective mixed integer linear model, which comprises both the economic and environmental aspects. It utilizes the pricing and advertising principles in the form of waste prevention and recycling investments. These principles are implemented through the developed dependencies defined in the Section 2. The functions are further approximated by piecewise linear functions to reduce the computational complexity and thus to ensure the solvability of the problem. Moreover, the approach contains the stochasticity in the unknown future waste production, which also makes the model more robust and complex. The resulting large-scale problem was subsequently solved with the well-known Benders decomposition.

The developed methods were applied in a case study for municipalities from the Czech Republic. The results revealed the existing potential in the waste prevention (a few percent according to the λ parameter). On the other hand, the increase of recycling is limited, at least from the economic point of view. The recommendation to make an investment was only for λ equal to 0, which corresponds to the absolute preference of the environmental aspect. Energy recovery is at a high level irrespective of preference.

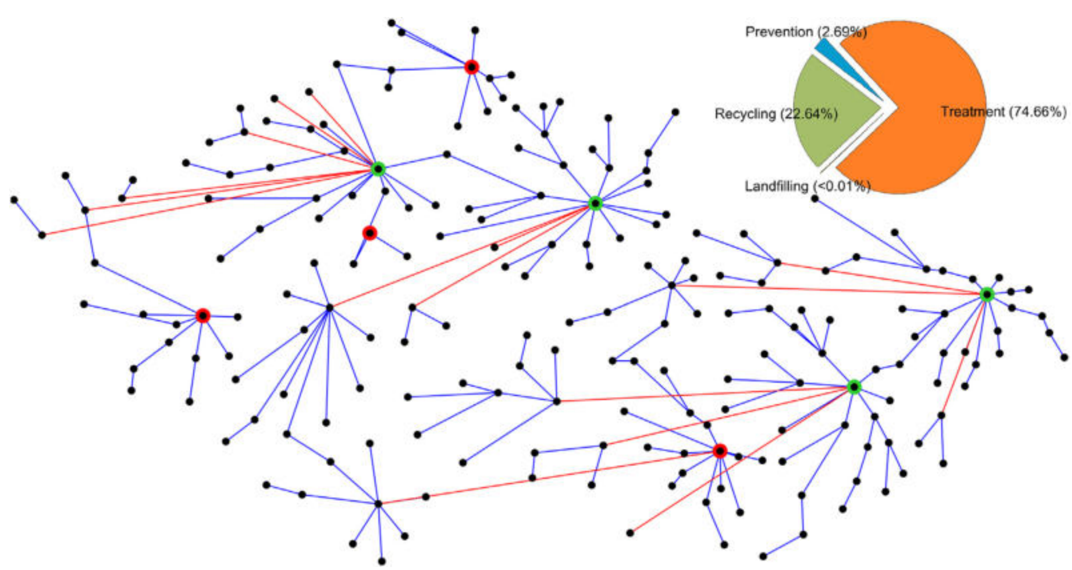


Fig. 9. The optimal solution for $\lambda = 0.25$ (one scenario). Red lines correspond to the used rail connections, blue lines to the road connections. Green rings denote the newly build WtE plants, red rings the already existing ones. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

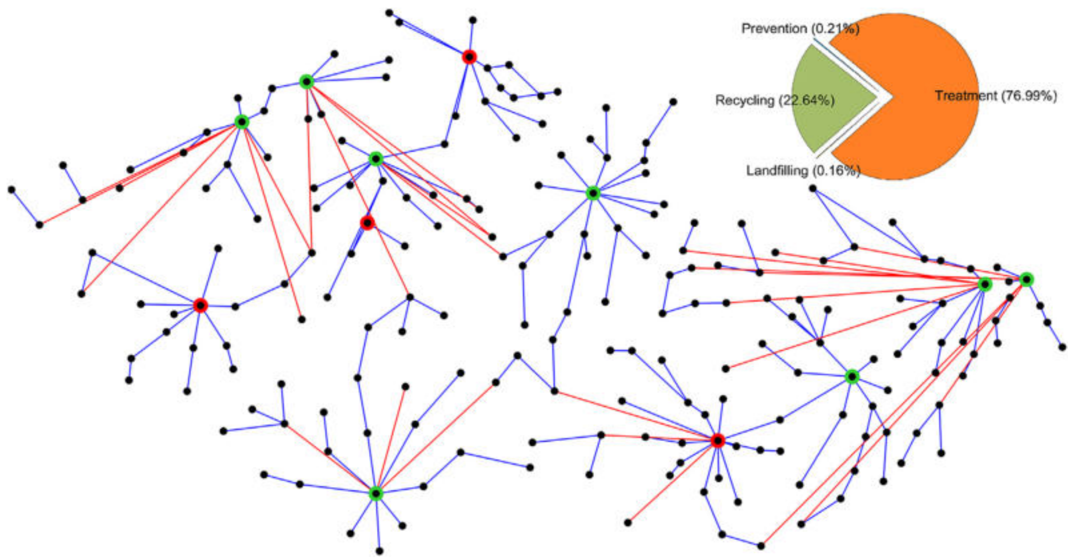


Fig. 10. The optimal solution for $\lambda = 0.875$ (one scenario).

Landfilling is not supported, resulting in less than one percent utilization for all considered situations. However, the final realization is upon the decision-maker.

Since the CE way of thinking receives a rapidly increasing attention, the proposed model has also some limitations, such as it does not cover the whole cycle and it also misses other objectives (besides used economic and environmental aspects) that are recently used. The main such objective is the social aspect(s) including, e.g., harmful effects of waste processing, nuisance or people density and resistance; see, e.g., (Asefi and Lim, 2017).

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2019.118068.

References

Amin, S.H., Zhang, G., 2012. An integrated model for closed-loop supply chain configuration and supplier selection: multi-objective approach. Expert Syst. Appl. 39 (8), 6782—6791. https://doi.org/10.1016/j.eswa.2011.12.056.
Asefi, H., Lim, S., 2017. A novel multi-dimensional modelling approach to integrated municipal solid waste management. J. Clean. Prod. 186 https://doi.org/10.1016/j.jclepro.2017.08.061, 1331-1143.
Baawain, M., Al-Mamun, A., Omidvarborna, H., Al-Amri, W., 2017. Ultimate composition analysis of municipal solid waste in Muscat. J. Clean. Prod. 148, 355—362. https://doi.org/10.1016/j.jclepro.2017.02.013.
Barbosa-Póvoa, A.P., da Silva, C., Carvalho, A., 2018. Opportunities and challenges in sustainable supply chain: an operations research perspective. Eur. J. Oper. Res. 268 (2), 399—431. https://doi.org/10.1016/j.ejor.2017.10.036.
Bezanson, J., Edelman, A., Karpinski, S., Shah, V.B., 2017. Julia: a fresh approach to numerical computing. SIAM Rev. 59, 65—98.
Bouchery, Y., Ghaffari, A., Jemai, Z., Dallery, Y., 2012. Including sustainability criteria into inventory models. Eur. J. Oper. Res. 222 (2), 229—240. https://doi.org/10.1016/j.ejor.2012.05.004.
Boukherroub, T., Ruiz, A., Guinet, A., Fondrevelle, J., 2015. An integrated approach for sustainable supply chain planning. Comput. Oper. Res. 54, 180—194. https://doi.org/10.1016/j.cor.2014.09.002.
Byrne, P.J., Heavey, C., Ryan, P., Liston, P., 2010. Sustainable supply chain design: capturing dynamic input factors. J. Simul. 4 (4), 213—221. https://doi.org/10.1057/jos.2010.18.
Cellura, M., Ardente, F., Longo, S., 2012. From the LCA of food products to the environmental assessment of protected crops districts: a case-study in the south of Italy. J. Environ. Manag. 93 (1), 194—208. https://doi.org/10.1016/j.jenvman.2011.08.019.
Chen, Y., 2018. Evaluating greenhouse gas emissions and energy recovery from municipal and industrial solid waste using waste-to-energy technology. J. Clean. Prod. 192, 262—269. https://doi.org/10.1016/j.jclepro.2018.04.260.
Chen, G., Wang, X., Li, J., Yan, B., Wang, Y., Wu, X., Velichkova, R., Cheng, Z., Ma, W., 2019. Environmental, energy, and economic analysis of integrated treatment of municipal solid waste and sewage sludge: a case study in China. Sci. Total Environ. 647, 1433—1443. https://doi.org/10.1016/j.scitotenv.2018.08.104.
Corvellec, H., 2016. A performative definition of waste prevention. Waste Manag. 52, 3—13. https://doi.org/10.1016/j.wasman.2016.03.051.
CPLEX, 2019. IBM ILOG CPLEX Optimization Studio. https://www.ibm.com/analytics/cplex-optimizer. (Accessed 22 April 2019).
De Meyer, A., Cattrysse, D., Van Orshoven, J., 2015. A generic mathematical model to optimise strategic and tactical decisions in biomass-based supply chains (OPTIMASS). Eur. J. Oper. Res. 245 (1), 247—264. https://doi.org/10.1016/j.ejor.2015.02.045.
Directive 2008/98/EC of the European Parliament and of the Council of 19 November 2008 on Waste and Repealing Certain Directives
Directive (EU) 2018/849 of the European Parliament and of the Council of 30 May 2018 Amending Directives 2000/53/EC on End-Of-Life Vehicles, 2006/66/EC on Batteries and Accumulators and Waste Batteries and Accumulators, and 2012/19/EU on Waste Electrical and Electronic Equipment, 93—99.
Directive (EU) 2018/850 of the European Parliament and of the Council of 30 May 2018 Amending Directive 1999/31/EC on the Landfill of Waste (Text with EEA Relevance), 100—108.
Directive (EU) 2018/851 of the European Parliament and of the Council of 30 May 2018 Amending Directive 2008/98/EC on Waste, 109—140.
Directive (EU) 2018/852 of the European Parliament and of the Council of 30 May 2018 Amending Directive 94/62/EC on Packaging and Packaging Waste, 141—154.
Dunning, I., Huchette, J., Lubin, M., 2017. JuMP: a modeling language for mathematical optimization. SIAM Rev. 59, 295—302.
d’Amore, F., Bezzo, F., 2016. Strategic optimisation of biomass-based energy supply chains for sustainable mobility. Comput. Chem. Eng. 87, 68—81. https://doi.org/10.1016/j.compchemeng.2016.01.003.
Elia, V., Gnoni, M.G., Tornese, F., 2015. Designing Pay-As-You-Throw schemes in municipal waste management services: a holistic approach. Waste Manag. 44, 188—195. https://doi.org/10.1016/j.wasman.2015.07.040.
European Commission (DG ENV), 2012. Use of Economic Instruments and Waste Management Performances. Contract ENV.G.4/FRA/2008/0112.
Fan, Y.V., Klemeš, J.J., Perry, S., Lee, C.T., 2018a. An emissions analysis for environmentally sustainable freight transportation modes: distance and capacity.

Chem. Eng. Trans. 70, 505–510. https://doi.org/10.3303/CET1870085.
Fan, Y.V., Varbanov, P.S., Klemeš, J.J., Nemet, A., 2018b. Process efficiency optimisation and integration for cleaner production. J. Clean. Prod. 174, 177–183. https://doi.org/10.1016/j.jclepro.2017.10.325.
Ferdan, T., Pavlas, M., Šomplák, R., Nevrlý, V., Klemeš, J.J., Pitschke, T., 2017. Allocation analysis of waste treatment nodes for economic optimisation considering reduced greenhouse gas emissions. Chem. Eng. Trans. 61, 967–972. https://doi.org/10.3303/CET1761159.
Ferdan, T., Pavlas, M., Nevrlý, V., Šomplák, R., Stehlík, P., 2018. Greenhouse gas emissions from thermal treatment of non-recyclable municipal waste. Front. Chem. Sci. Eng. 12 (4), 815–831. https://doi.org/10.1007/s11705-018-1761-4.
Fiorentino, G., Ripa, M., Protano, G., Hornsby, C., Ulgiati, S., 2015. Life cycle assessment of mixed municipal solid waste: multi-input versus multi-output perspective. Waste Manag. 46, 599–611. https://doi.org/10.1016/j.wasman.2015.07.048.
Fonseca, L.M., Domingues, J.P., Pereira, M.T., Martins, F.F., Zimon, D., 2018. Assessment of circular economy within Portuguese organizations. Sustainability 10 (7), 2521. https://doi.org/10.3390/su10072521.
Gharfalkar, M., Court, R., Campbell, C., Ali, Z., Hillier, G., 2015. Analysis of waste hierarchy in the European waste directive 2008/98/EC. Waste Manag. 39, 305–313. https://doi.org/10.1016/j.wasman.2015.02.007.
Ghinea, C., Drăgoi, E.N., Comăniţă, E.-D., Gavrilescu, M., Câmpean, T., Curteanu, S., Gavrilescu, M., 2016. Forecasting municipal solid waste generation using prognostic tools and regression analysis. J. Environ. Manag. 182, 80–93. https://doi.org/10.1016/j.jenvman.2016.07.026.
Gilli, M., Nicolli, F., Farinelli, P., 2018. Behavioural attitudes towards waste prevention and recycling. Ecol. Econ. 154, 294–305. https://doi.org/10.1016/j.ecolecon.2018.08.009.
Gregor, J., Šomplák, R., Pavlas, M., 2017. Transportation cost as an integral part of supply chain optimisation in the field of waste management. Chem. Eng. Trans. 56, 1927–1932. https://doi.org/10.3303/CET1756322.
Gutow, L., Bergmann, M., 2018. Contamination of our oceans by plastics. In: Encyclopedia of the Anthropocene, pp. 43–49. https://doi.org/10.1016/B978-0-12-809665-9.09976-6.
Hofmann, M., Hofmann, H., Hagelüken, Ch, Hool, A., 2018. Critical raw materials: a perspective from the materials science community. Sustain. Mater. Technol. 17 https://doi.org/10.1016/j.susmat.2018.e00074.
Hrabec, D., Popela, P., Roupec, J., 2016. WS network design problem with nonlinear pricing solved by hybrid algorithm. Lect. Notes Comput. Sci. 9921, 655–664. https://doi.org/10.1007/978-3-319-45823-6_61.
Hrabec, D., Haugen, K.K., Popela, P., 2017. The newsvendor problem with advertising: an overview with extensions. Rev. Manag. Sci. 11 (4), 767–787. https://doi.org/10.1007/s11846-016-0204-1.
Hrabec, D., Šomplák, R., Nevrlý, V., Smejkalová, V., 2018. Sustainable model integration of waste production and treatment process based on assessment of GHG. Chem. Eng. Trans. 70. https://doi.org/10.3303/CET1870268.
Hu, C., Liu, X., Lu, J., 2017. A bi-objective two-stage robust location model for waste-to-energy facilities under uncertainty. Decis. Support Syst. 99, 37–50. https://doi.org/10.1016/j.dss.2017.05.009.
Jabbarzadeh, A., Darbaniyan, F., Jabalameli, M.S., 2016. A multi-objective model for location of transfer stations: case study in waste management system of Tehran. J. Ind. Syst. Eng. 9, 109–125.
Kirkman, R., Voulvoulis, N., 2017. The role of public communication in decision making for waste management infrastructure. J. Environ. Manag. 203 (2), 640–647. https://doi.org/10.1016/j.jenvman.2016.06.002.
Korhonen, J., Nuur, C., Feldmann, A., Birkie, S.E., 2018. Circular economy as an essentially contested concept. J. Clean. Prod. 175, 544–552. https://doi.org/10.1016/j.jclepro.2017.12.111.
Kůdela, J., Popela, P., 2017. Warm-start cuts for generalized Benders decomposition. Kybernetika 53, 1012–1025. https://doi.org/10.14736/kyb-2017-6-1012.
Lebersorger, S., Beigl, P., 2011. Municipal solid waste generation in municipalities: quantifying impacts of household structure, commercial waste and domestic fuel. Waste Manag. 31, 1907–1915. https://doi.org/10.1016/j.wasman.2011.05.016.
Lino, F.A.M., Ismail, K.A.R., 2017. Incineration and recycling for MSW treatment: case study of Campinas, Brazil. Sustain. Cities Soc. 35, 752–757. https://doi.org/10.1016/j.scs.2017.09.028.
Liu, X., Hewings, G.J.D., Wang, S., 2018. Evaluating the impacts of waste treatment management modes on each sector's price in a macro economic system. J. Clean. Prod. 200, 188–195. https://doi.org/10.1016/j.jclepro.2018.07.232.
Lu, W., Peng, Y., Chen, X., Skitmore, M., Zhang, X., 2016. The S-curve for forecasting waste generation in construction projects. Waste Manag. 56, 23–34. https://doi.org/10.1016/j.wasman.2016.07.039.
Malinauskaite, J., Jouhara, H., Czajczyńska, D., Stanchev, P., Katsou, E., Rostkowski, P., Thorne, R.J., Colón, J., Ponsá, S., Al-Mansour, F., Anguilano, L., Krzyżyńska, R., López, I.C., Vlasopoulos, A., Spencer, N., 2017. Municipal solid waste management and waste-to-energy in the context of a circular economy and energy recycling in Europe. Energy 141, 2013–2044. https://doi.org/10.1016/j.energy.2017.11.128.
Neri, E., Passarini, F., Cespi, D., Zoffoli, F., Vassura, I., 2018. Sustainability of a bio-waste treatment plant: impact evolution resulting from technological improvements. J. Clean. Prod. 171, 1006–1019. https://doi.org/10.1016/j.jclepro.2017.10.082.
Ormazabal, M., Prieto-Sandoval, V., Puga-Leal, R., Jaca, C., 2018. Circular economy in Spanish SMEs: challenges and opportunities. J. Clean. Prod. 185, 157–167. https://doi.org/10.1016/j.clepro.2018.03.031.
Putna, O., Janošťák, F., Pavlas, M., 2018a. Modelling of existing heating plant replacement with a waste to energy plant and a peak-load natural gas boiler. Chem. Eng. Trans. 70, 1615–1620. https://doi.org/10.3303/CET1870270.
Putna, O., Janošťák, F., Šomplák, R., Pavlas, M., 2018b. Demand modelling in district heating systems within the conceptual design of a waste-to-energy plant. Energy 163, 1125–1139. https://doi.org/10.1016/j.energy.2018.08.059.
Rahmaniani, R., Crainic, T.G., Gendreau, M., Rei, W., 2017. The Benders decomposition algorithm: a literature review. Eur. J. Oper. Res. 259, 801–817. https://doi.org/10.1016/j.ejor.2016.12.005.
Ren, X., Che, Y., Yang, K., Tao, Y., 2016. Risk perception and public acceptance toward a highly protested Waste-to-Energy facility. Waste Manag. 48, 528–539. https://doi.org/10.1016/j.wasman.2015.10.036.
Silva, A., Rosano, M., Stocker, L., Gorissen, L., 2017. From waste to sustainable materials management: three case studies of the transition journey. Waste Manag. 61, 547–557. https://doi.org/10.1016/j.wasman.2016.11.038.
Tomić, T., Schneider, D.R., 2018. The role of energy from waste in circular economy and closing the loop concept – energy analysis approach. Renew. Sustain. Energy Rev. 98, 268–287. https://doi.org/10.1016/j.rser.2018.09.029.
Tong, K., Gleeson, M.J., Rong, G., You, F., 2014. Optimal design of advanced drop-in hydrocarbon biofuel supply chain integrating with existing petroleum refineries under uncertainty. Biomass Bioenergy 60, 108–120. https://doi.org/10.1016/j.biombioe.2013.10.023.
Wang, F., Cheng, Z., Reisner, A., Liu, Y., 2018. Compliance with household solid waste management in rural villages in developing countries. J. Clean. Prod. 202, 293–298. https://doi.org/10.1016/j.jclepro.2018.08.135.
Yadav, V., Bhurjee, A.K., Karmakar, S., Dikshit, A.K., 2017. A facility location model for municipal solid waste management system under uncertain environment. Sci. Total Environ. 603–604, 760–771. https://doi.org/10.1016/j.scitotenv.2017.02.207.
Zorpas, A.A., Lasaridi, K., 2013. Measuring waste prevention. Waste Manag. 33 (5), 1047–1056. https://doi.org/10.1016/j.wasman.2012.12.017.

Příloha 8: Článek [A13] Legislation-induced planning of waste processing infrastructure: A case study of the Czech Republic

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Legislation-induced planning of waste processing infrastructure: A case study of the Czech Republic

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ABSTRACT

Trends in the treatment of municipal solid waste are changing worldwide. In the European Union, one of the largest economies in the world, the waste treatment and management among the member states vary significantly. To support and promote environmentally friendly waste management, the European Union issued directives commonly called the Circular Economy Package. This legislative is designed to accelerate the transition to a cleaner future. It gives an obligation to member states to meet specific landfilling and recycling targets. To reach these ambitious goals will be a challenging task, especially for the member states with less developed waste management systems. An approach using multi-stage stochastic programming is suggested for solving such a problem. The developed model considers current material recovery rates and trends in municipal waste, while uncertain waste production is forecasted by possible scenarios. The model enables sequential decision-making and assessment of various strategies for different future scenarios with specific years, locations, technologies and capacities for the establishment of the waste processing infrastructure. The utilization of the model and its computational tractability is demonstrated in a case study of the Czech Republic.

1. Introduction

Sustainability of human activities is evaluated by three basic aspects: economical, environmental and social. Sustainable development is highly influenced by municipal solid waste (MSW) treatment [1]. In the European Union, the preferred ways of waste treatment are defined by *Waste hierarchy*, which is anchored in the directive [2]. Waste management is a very complex task, which encompasses the whole process of waste handling: waste collection, transportation, eventual adjustment and final treatment. Different phases of waste handling are linked with a great variety of technological options and waste management methods.

Population growth, urbanization, and the changing lifestyle of people in developing countries are connected with an increase in the production of waste worldwide [3]. If the waste cannot be recovered materially, the next preferred way of treatment is energy recovery [4]. Waste management sustainability can be supported by the utilization of hidden potential in waste, which is one of the most significant future renewable energy source [5]. It presents one of the alternatives for fossil fuels which still cover most of the global energy production [6]. Waste incineration is not available in many developing countries (except in countries with fast-growing economies such as China, Malaysia, etc.) for the following reasons [7]:

- high initial and operating costs,
- unfavorable waste composition,
- lack of technical knowledge,
- availability of easy landfilling.

In developed countries (EU, US and Japan), the waste incineration for energy production is one of the common waste treatment options [8]. The Waste-to-Energy (WtE) facilities have quite lower emissions compared to electricity production facilities from fossil fuels (except natural gas), and help to reduce further greenhouse gases emissions from landfills [9]. The increase in the utilization of WtE plants in the EU is expected in the view of strict limitations of waste landfilling that should follow from the passed legislation.

In order to reinforce interventions that change currently

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List of abbreviations, units and nomenclature

Abbreviation	*Definition Notes/Case study values*
MSW	municipal solid waste
EU	European Union
US	United States
WtE	waste-to-energy
CEP	Circular Economy Package
MBT	mechanical biological treatment
BAU	business as usual
EUR	Euro
kt	kilotonne
s, z	Indices for scenarios $s, z \in \{1, \ldots, 27\}$
i	Index for cities $i \in \{1, \ldots, 206\}$
j	Index for routes between the cities $j \in \{1, \ldots, 1898\}$
t	Index for periods $t \in \{1, \ldots, 11\}$
τ	Index for decision stages $\tau \in \{1, 6, 11\}$
o^i_{WtE}	Set of possible options for WtE plants in city *i*; For every city *i*, there are 9 options (these can differ between cities). These options have different capacities and treatment costs, based on the analysis of the candidate locations in the individual cities
o^i_{MBT}	Set of possible options for MBT plants in city *i*; For every city *i*, there are 9 options (as in the WtE case discussed above)
$k^i_{o^i_{WtE}}$	The capacity of the options for the WtE plant in city *i*
$k^i_{o^i_{MBT}}$	The capacity of the options for the MBT plant in city *i*
${}^{WtE}c^i_{o^i_{WtE}}$	Treatment cost of the options for the WtE plant in city *i*
${}^{MBT}c^i_{o^i_{MBT}}$	Treatment cost of the options for the MBT plant in city *i*
c^i_L	Landfilling cost in city *i*; Assumed static (not developing in time), around 70 EUR/t
c^j_R	Shipping cost on arc *j*; Assumed static, 0.12 EUR/(t·km). The cost of fuel did not show any significant trend in the past years. If it were the case, the augmentation of the model by adding time-dependent shipping costs would be quite straightforward.
$\xi^i_{t,s}$	Amount of produced MSW that requires treatment in city *i*, the time period *t*, scenario *s*; The most important stochastic parameter that was considered in this study. The scenario branching considers possible demographic and societal changes that affect the MSW production in individual cities
$\xi^i_{[t],s}$	Progression of MSW production up to time period *t*, city *i*, scenario s, i.e. $\xi^i_{[t],s} = (\xi^i_{1,s}, \xi^i_{2,s}, \ldots, \xi^i_{t,s})$; “Dummy” parameters used in the nonanticipativity constraints
$A^{i,j}$	Incidence matrix of the road network
pen_{WtE}	The penalty for unused WtE capacity $pen_{WtE} = 0.8$; This rather high penalty value ensures that the installed waste treatment facilities are properly utilized
pen_{MBT}	The penalty for unused MBT capacity $pen_{MBT} = 0.8$; Same as above
κ	The ratio of MBT treated MSW that needs to be landfilled $\kappa = 0.4$; Assumed static (no significant technological breakthroughts during the planning period) and independent of the MBT option
$MSW_{t,s}$	The total amount of MSW generated in the whole region/country in time period *t*, scenario *s*
p_s	The probability of scenario *s*; In the case study, all the scenarios had the same probability
g_1, g_2, g_3	Target values for the amount of landfilled MSW $g_1 = 0.3$, $g_2 = 0.2$, $g_3 = 0.1$
$x^j_{t,s}$	Flow on the arc *j*, time period *t*, scenario *s*; Real nonnegative variable
$w^{i,o^i_{WtE}}_{\tau,s}$	Building the WtE plant in city *i*, with option o^i_{WtE}, in decision stage τ, in scenario *s*; Binary variable
$m^{i,o^i_{MBT}}_{\tau,s}$	Building the MBT plant in city *i*, with option o^i_{MBT}, in decision stage τ, in scenario *s*; Binary variable
${}^{WtE}r^{i,o^i_{WtE}}_{t,s}$	Amount of MSW treated in WtE in city *i*, with option o^i_{WtE}, in time period *t*, in scenario *s*; Real nonnegative variable
${}^{MBT}r^{i,o^i_{MBT}}_{t,s}$	Amount of MSW treated in MBT in city *i*, with option o^i_{MBT}, in time period *t*, in scenario *s*; Real nonnegative variable
${}^{L}r^i_{t,s}$	Amount of MSW landfilled in city *i*, in time period *t*, in scenario *s*; Real nonnegative variable
${}^{WtE}u^{i,o^i_{WtE}}_{t,s}$	Amount of unused capacity in WtE in city *i*, with option o^i_{WtE}, in time period *t*, in scenario *s*; Real nonnegative variable
${}^{MBT}u^{i,o^i_{MBT}}_{t,s}$	Amount of unused capacity in MBT in city *i*, with option o^i_{MBT}, in time period *t*, in scenario *s*; Real nonnegative variable
f	Index for waste fraction
RR_f	recycling rate for waste fraction *f*
MAT_f	amount of materially recovered waste fraction *f*
SEP_f	amount of separated waste fraction *f*

unsustainable practices, the existing policies and legislation need to be reformed [10]. The trend in developed countries leads from the linear economy system to a circular economy. The impact of these legislative changes is an essential factor in waste management models. For example, the legislation induced changes on the gate-fee of and WtE plant were investigated in the paper [11]. To ensure the smooth transition to the circular economy in waste management, it is necessary to solve the complex tasks taking into account the different ways of waste handling and production forecasts. This contribution presents a multi-stage stochastic model as a support tool for the decision-making process. The approach is presented on the real data from the Czech Republic, which represents the country in the transition process from linear to the circular economy.

2. Literature review and theory

Waste management is a dynamically developing area that is currently subject to several changes that were outlined above. Within waste management, it is necessary to address the strategy of waste collection, waste transport and finally its treatment. The sustainability is measured along the triple bottom line [12]: economic, environmental and social impact. The following text is devoted to the literature review, which is divided into thematic parts with the final evaluation of the research gap.

2.1. Circular economy

In recent years there has been an effort to move from a linear economy to a circular economy. These tendencies arise worldwide, mainly because of the limited capacities of primary sources and environmental pollution. The study [13] pointed out that current trends in the circular economy are built on research into resource efficiency [14]. The paper [15] formulated ten common circular economy strategies: recovery, recycling, repurpose, remanufacture, refurbish, repair, re-use,

Table 1
The targets anchored in the Directives within CEP.

Action	Source	Waste stream	2025	2030	2035
Recycling/reuse (minimum)	Directive (EU) 2018/851 [18]; Directive (EU) 2018/852 [19];	Municipal solid waste	55%	60%	65%
		Packaging waste	65%	70%	
		Packaging paper	75%	85%	
		Packaging plastics	50%	55%	
		Packaging glass	70%	75%	
		Packaging ferrous metals	70%	80%	
		Packaging aluminum	50%	60%	
		Packaging wood	25%	30%	
Landfill (maximum)	Directive (EU) 2018/850 [20];	Municipal solid waste			10%
Reduction (minimum)	Directive (EU) 2018/851 [18];	Food waste	30%	50%	

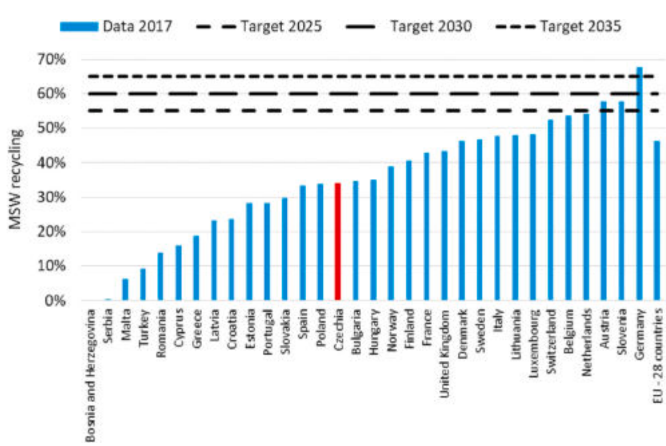


Fig. 1. Municipal waste recycling in the year 2017 and recycling targets (Eurostat, 2019 [21]).

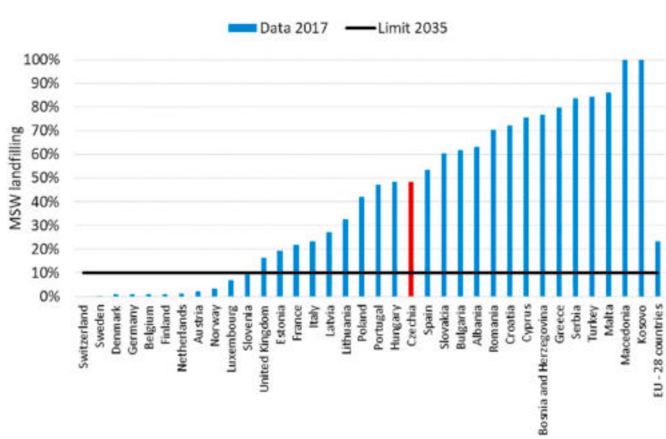


Fig. 2. Municipal waste landfilling in the year 2017 and the landfilling limit [21].

reduce, rethink, refuse. The aim is to maintain the value of the product for as long as possible to exploit its maximum utility. The principle is in the closing loops of products, product parts and materials. The transition from a linear to a circular economy brings with it a range of practical challenges for policies and companies. The paper [16] developed a framework of strategies to guide designers and business strategists in the move from a linear to a circular economy. The transition to a circular economy will be reflected throughout the production chain. Three basic principles characterize the circular business model: closing, slowing and narrowing resource loop. However, the measurement and assessment of circularity performances are not yet a common practice in companies.

The transition to a circular economy requires actions and legislative intervention. Turning waste into a resource is an essential part of increasing resource efficiency and closing the loop in a circular economy. In 2018, the European Commission accepted the Circular Economy Package (CEP) with the stated goal of "closing the cycle" of the product life cycle. It seeks to establish an action program with measures covering the whole cycle from production and consumption to waste management and the secondary raw materials market [17]. According to the CEP, the aim is to minimize waste so that once a product reaches the end of its life, its materials will be kept within the economy for as long as possible. What was previously considered as "waste" is therefore transformed into a valuable resource. The EU member states must incorporate directives included in the CEP into national legislation.

The targets included in the CEP are summarized in Table 1. The recycling targets set a minimum percentage of recycled or reused wasted, and they deal with both general municipal solid waste and particular packaging waste. The next important milestone is landfill restriction at maximal 10%, which will come into force in 2035. CEP also addresses the issue of prevention by means of food waste reduction.

The assessment of the current situation (in 2017) for European states is illustrated in Fig. 1 and Fig. 2. Fig. 1 shows the current waste recycling of 32 states in relation to the desired targets. On average, only 46.4% of MSW is recycled by the 28-EU Member States. The only country that currently meets the strictest target set for the year 2035 is Germany. Unfortunately, most countries are not very close to these recycling targets at present. The Czech Republic, as a representative of countries in the transition process from linear to the circular economy, recycles approximately 34% of MSW (red color in Fig. 1).

Alongside the recycling targets, the member states also have to react to the landfilling restrictions. A total of 11 countries already meet the landfilling limit, see Fig. 2. On average, EU-28 Member States landfill currently 23.4% of waste.

It is important to consider the different levels of development of individual EU member states and their starting position. In some cases, which are specified in the relevant Directives, a member state may request that the deadlines be postponed. The Czech Republic ranks in both the recycling and landfilling somewhere in the middle of the EU-28 countries. There has been a lack of financing in the Baltic countries to promote and operate waste incineration. Their first goal after joining the EU was to avoid dumping at uncontrolled sites and to meet the EU standards. Later on, Estonia has become the most advanced of these countries in terms of waste avoidance and recycling in the capitals, and it is ranking top even in the whole EU. The construction of WtE and MBT plants has shifted total landfilling drastically [22]. On the other hand, Poland, which is the neighbor of the Czech Republic, still has problems securing the real values of waste production. It is caused by existing gaps in landfill weighting or illegal dumping. Poland is also in the middle of the EU countries regarding landfilling, but its WtE sector has been evolving dynamically in the recent years in contrast to the Czech Republic, where new projects are waiting for greater legislative support.

Croatia, as the southern country from the EU, still landfills a significant amount of the MSW. Even though it has recently adopted the national Waste Management Plan 2017–2022, its implementation is delayed. Reaching the targets from the CEP will require substantial investment in waste infrastructure. So far, the investments and plans have not been efficient, causing the future overcapacity of MBT plants. The waste hierarchy has not been properly followed, and responsibilities among authorities were not in line with each other. One of the proposed changes is to focus on bio-waste, its composing and separation at source. Waste management centers in operation are costly and not the best option available since it only increases landfilling and produces low

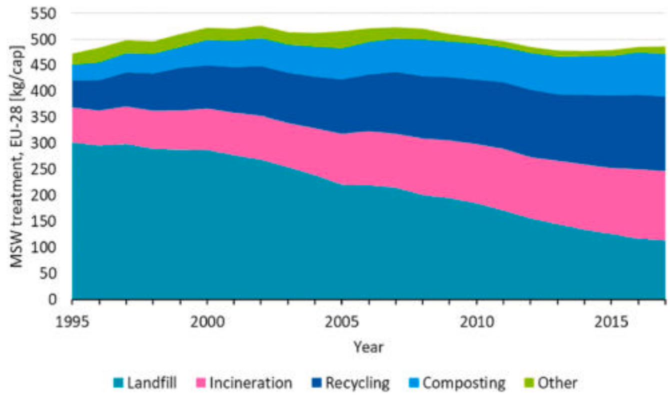


Fig. 3. Municipal waste treatment, EU-28, (kg/capita) (Eurostat, 2019 [21]).

quality refuse-derived fuel [23]. The performance of the EU-28 countries has been compared in detail [24]. The degree of transition to the circular economy is measured by defined indicators considering waste production, material reuse or recycling and their correlation with Growth Domestic Product has been proven.

In response to CEP, EU member states will make efforts to reduce the amount of landfilled MSW. Where possible, MSW is used for material or energy recovery. MSW treatment methods over the period 1995–2017 are illustrated in Fig. 3 for the EU-28 countries. Waste prevention is not reflected in historical data, although it is the most preferred method by *Waste management hierarchy* [2]. There is a clear trend in landfill reduction in the long-term. Despite the objectives of maximizing recycling, a direct transition from landfill is not possible without intermediate steps in the form of WtE, which plays a not negligible role in the circular economy [22]. Different WtE processes were clearly assigned to options in the waste hierarchy ladder [25]. However, there are concerns about undermining the waste hierarchy with respect to new incineration plants.

2.2. Waste management tasks

Waste management is concerned with adapting existing infrastructure to create a satisfactory and sustainable system. Most tasks from waste management can be classified into the following categories:

Waste collection and transport play an important role in the processing chain. Waste collection routes are the output of vehicle routing models. Because of the computational complexity, heuristic solutions are often used [26]. Most often, the minimum travel cost is the aim of optimization [27].

Location problems search for the optimum placement of new waste treatment facilities [28]. Also, the optimal location of transfer stations [29] and the deployment of waste collecting bins in the cities [30] fall into this category. There are several methods used to solve the location problems, among which are the overlay technique [28] and mixed-integer programming approaches [31].

Allocation problems deal with waste streams from producers to processing sites [32].

Facility design addresses all technological obstacles of individual subsystems. The aim is to dimension the facility so that it can process waste from the appropriate collection area [33].

The collection of MSW is highly dependent on the development level of the country in question [34]. While informal recycling and manual labor for collection and transportation of MSW are common practices in developing countries [35], in developed countries mechanical collection systems [36] of segregated MSW are more commonly practiced [37].

An extensive review of models for supply chain systems was presented by Ref. [38]. Collection and transportation represent a considerable part of the cost within the waste management system. For example, in India, which represents developing countries, the collection and transportation cost is estimated at 70–85% [39]. But collection and transportation costs are significant also for developed countries, e.g. in Sweden, they amount to 50–75% of waste management cost [40].

Transfer stations are often used to support waste transportation for long distances. Approaches for selection of appropriate transfer station locations include spatial multi-criteria analysis [41], interval optimization [42], multi-objective stochastic programming [43], and GIS-based

Table 2
Waste management tasks, data types and solution methods of the selected works.

	Task				Data type		Solution method
	Collection	Location	Allocation	Design	Deterministic	Uncertain	
Badran et al., 2006 [31];		✓			✓		MIP
Benjamin et al., 2010 [59];	✓				✓		Heuristic
Boonmee et al., 2018 [55];		✓	✓		✓		Heuristic
Cebi et al., 2016 [57];		✓				✓	Hybrid model
Chatzouridis et al., 2012 [45];	✓	✓			✓		MIP
Cheng et al., 2003 [32];		✓	✓			✓	MIP
Das et al., 2015 [27];	✓				✓		Heuristic
Gambella et al., 2019 [63];			✓			✓	MIP
Ghiani et al., 2012 [30];		✓	✓		✓		Heuristic
Ghose et al., 2006 [39];	✓				✓		Energy consumption
Hrabec et al., 2019 [65];		✓	✓			✓	MIP
Hu et al., 2017 [49];		✓				✓	MIP
Jin et al., 2019 [33];			✓	✓		✓	Fuzzy linear programming
Kim et al., 2005 [58];	✓				✓		Heuristic
Kudela et al., 2019 [43];		✓	✓			✓	MIP
Li et al., 2008 [66];			✓	✓		✓	Fuzzy MIP
Li et al., 2009 [67];			✓	✓		✓	Inexact fuzzy stoch.
Li et al., 2012 [64];			✓			✓	Fuzzy-stoch. Quadratic programming
López et al., 2008 [56];		✓			✓		Metaheuristic
Randazzo et al., 2018 [62];		✓			✓		GIS, multi-criteria analysis
Sonesson, 2000 [40];	✓				✓		Mechanistic approach
Tung et al., 2000 [26];	✓				✓		Heuristic
Yadav et al., 2016 [68];		✓			✓		MIP
Yadav et al., 2018 [29];		✓				✓	Interval programming
Yousefi et al., 2018 [28];		✓			✓		Index overlay method
Zhao et al., 2016 [53];	✓	✓			✓		MIP
this work		✓	✓			✓	MIP

Table 3
Optimization criteria and decision stages of the selected works.

	Criteria			Optimized part of the waste management chain	Objective function		Stage	
	Economical	Environmental	Social		Single	Multi	One	Multi
Badran et al., 2006 [31];	✓			Collection stations	✓		✓	
Benjamin et al., 2010 [59];	Number of vehicles			Collection	✓		✓	
Boonmee et al., 2018 [55];	✓	✓		Composting, recycling, land.		✓	✓	
Cebi et al., 2016 [57];	✓			MBT	✓		✓	
Chatzouridis et al., 2012 [45];	✓			Transfer station	✓		✓	
Cheng et al., 2003 [32];	✓	✓	✓	Landfill		✓		two
Das et al., 2015 [27];	✓			Transfer station, treatment facility, recycling, composting	✓		✓	
Gambella et al., 2019 [63];	✓			Treatment facility	✓			two
Ghiani et al., 2012 [30];	Number of collection sites			Bins	✓		✓	
Ghose et al., 2006 [39];	✓			Collection	✓		✓	
Hrabec et al., 2019 [65];	✓			Waste reduction	✓			two
Hu et al., 2017 [49];	✓	✓		WtE		✓		two
Jin et al., 2019 [33];	✓	✓		WtE, land.		✓	✓	
Kim et al., 2005 [58];	Traveling time, number of vehicles			Collection		✓	✓	
Kudela et al., 2019 [43];	✓	✓		Transfer station		✓		two
Li et al., 2008 [66];	✓			Unspecified ways of treatment	✓			two
Li et al., 2009 [67];	✓			Composting, recycling, land.	✓			✓
Li et al., 2012 [64];	✓	✓		Composting, recycling, land.		✓		✓
López et al., 2008 [56];	✓			Biomass power plant	✓		✓	
Randazzo et al., 2018 [62];	✓	✓	✓	Land.		✓	✓	
Sonesson, 2000 [40];	Energy consumption			Collection	✓		✓	
Tung et al., 2000 [26];	✓			Collection	✓		✓	
Yadav et al., 2016 [68];	✓			Transfer station	✓		✓	
Yadav et al., 2018 [29];	✓			Transfer station	✓		✓	
Yousefi et al., 2018 [28];		✓		Land.			✓	
Zhao et al., 2016 [53];	✓	✓		MBT		✓	✓	
this work	✓			WtE, MBT, land.	✓			✓

technologies [44], which can also be used together with binary optimization [1].

Based on the *Waste hierarchy*, landfilling is the least desirable way of waste treatment. Yet it still prevails in many countries, even in developed EU countries (as depicted in Fig. 2). However, current trends are gradually reducing landfilling and waste is largely used for material or energy recovery. A recent review of the WtE technologies can be found in the studies [46], which considered bio-waste, and [47], where the authors also consider the utilization of landfill gas for power production. The paper [48] reported that energy recovery from waste is an integral part of an environmentally sustainable waste management strategy. The contribution [49] developed the model for WtE location based on stochastic parameters considering economical and environmental criteria.

Recent studies [50] emphasized other advantages of incineration (apart from volume reduction and electricity generation) such as the utilization of bottom and fly ash of incineration plants in road construction and cement production, and recovery of ferrous and non-ferrous substances. This suggests that the technological development in metal recovery from dry bottom ash of incineration plants will enhance the acceptance of WtE facilities [13]. The study [51] reported on the average recoverable energy contents (in terms of electrical energy efficiency) of the different components of MSW using different WtE technologies. It was found that anaerobic digestion is the best-suited WtE option for food and yard wastes, while gasification is the best WtE option for treating plastic wastes. Incineration was found to be an attractive option amongst all the waste streams, as it can be used for energy recovery from all the reported waste streams. Other types of wastes, such as inert, metals, glass, etc., were not considered in the abovementioned study.

The study [52] focused on a Life cycle assessment of four waste management strategies in the municipality of Rome (Italy): landfill without biogas utilization; landfill with biogas combustion to generate electricity; sorting plant which splits the inorganic waste fraction from the organic waste fraction; and direct incineration of waste. Results, which they claim to be useful for most of the big European cities, show landfill systems as the worst waste management options and significant environmental savings at the global scale are achieved from undertaking energy recycling. Furthermore, waste treatments finalized to energy recovery provide an energy output that could meet 15% of Rome electricity consumption (in one of the considered case scenarios).

In the United States, for example, about 13% of power is generated from alternative electricity-production sources; of this fraction, approximately 11% of the alternative production is the contribution of biomass [53]. However, the high costs of biomass power generation, as well as the unreasonable distribution of biomass power plants [54] have led to an insufficient feedstock supply and some of the environmental issues hindering this industry from further development. Models can be targeted to exceptional situations such as in post-disaster waste management [55].

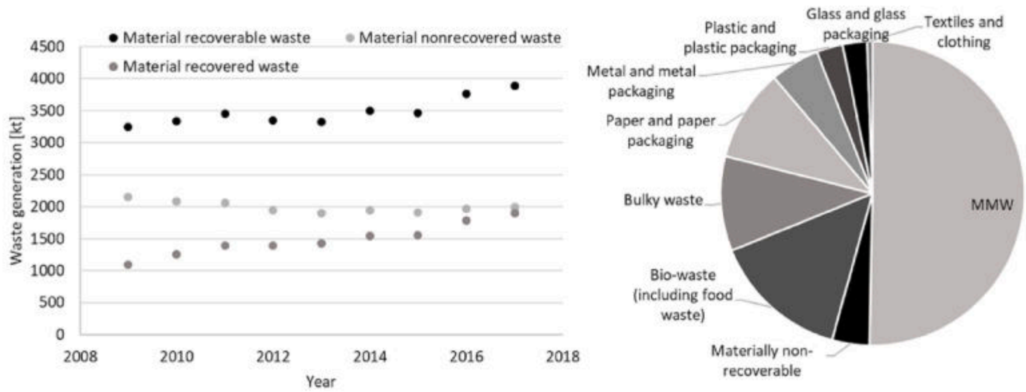
The types of waste management tasks for contributions mentioned in the literature review text are summarized in Table 2.

2.3. Optimization models

2.3.1. Single-criteria vs. multi-criteria models

When solving waste management tasks, models are often limited to just one criterion, in most cases total costs. The contribution [56] dealt with a suitable location for biomass power plant with minimum cost, where the model was solved using metaheuristic. Also [57] searched the location for a biomass power plant but with the fuzzy input information. The study [26] presented modified Solomon's insertion algorithm to solve the vehicular routing problem. The objective function sometimes minimizes other value, such as traveling time [58] or vehicles number [59].

The multi-criteria models consider not only the costs but also the environmental problems and social affairs that correspond to the different decisions [60]. The public acceptance of MSW treatment facilities can be largely driven by the social and cultural perception of the positive impact of resource recovery processes and facilities in the community. If they are perceived to foster climate change mitigation, and address local deficiencies or inefficiencies, such as employment, energy and fertilizer shortages, these are highly accepted by the community (especially in rural areas where jobs and energy supply are of greater concern) further enhancing socio-economic processes and



a) Material recoverable waste and its utilization 2009–2017, the Czech Republic   *b) The MSW composition in 2017, the Czech Republic*

Fig. 4. Material recoverable waste treatment in the Czech Republic.

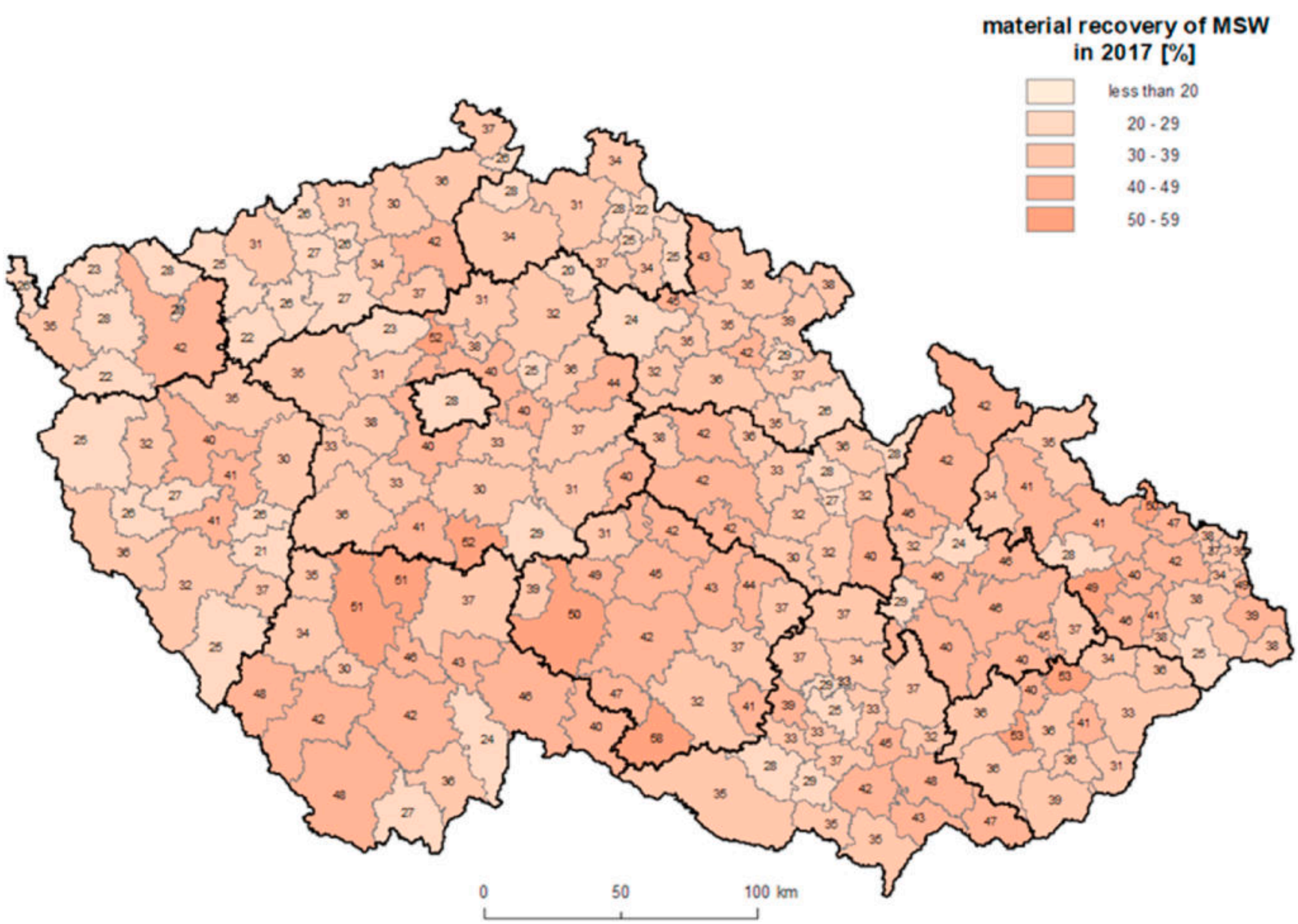


Fig. 5. Material recovery of MSW in the Czech Republic in 2017.

improving the human, social and cultural capital [61]. The operation research perspective on the strategic decision-making that takes place in designing sustainable systems was carried out [38]. The authors found that the economic and environmental aspect of the decision-making outweighed the social aspects in the majority of recent studies. One of the studies [32] that took into account economic, environmental and social impacts, where the authors created a comprehensive approach for landfill location and also dealt with waste stream allocation in the city of Regina (Canada). Similarly, the paper [62] developed an approach for landfill location in Sicily by multi-criteria analysis. The environmental assessment of the site of the landfill was discussed in the study [28] using an index overlay method.

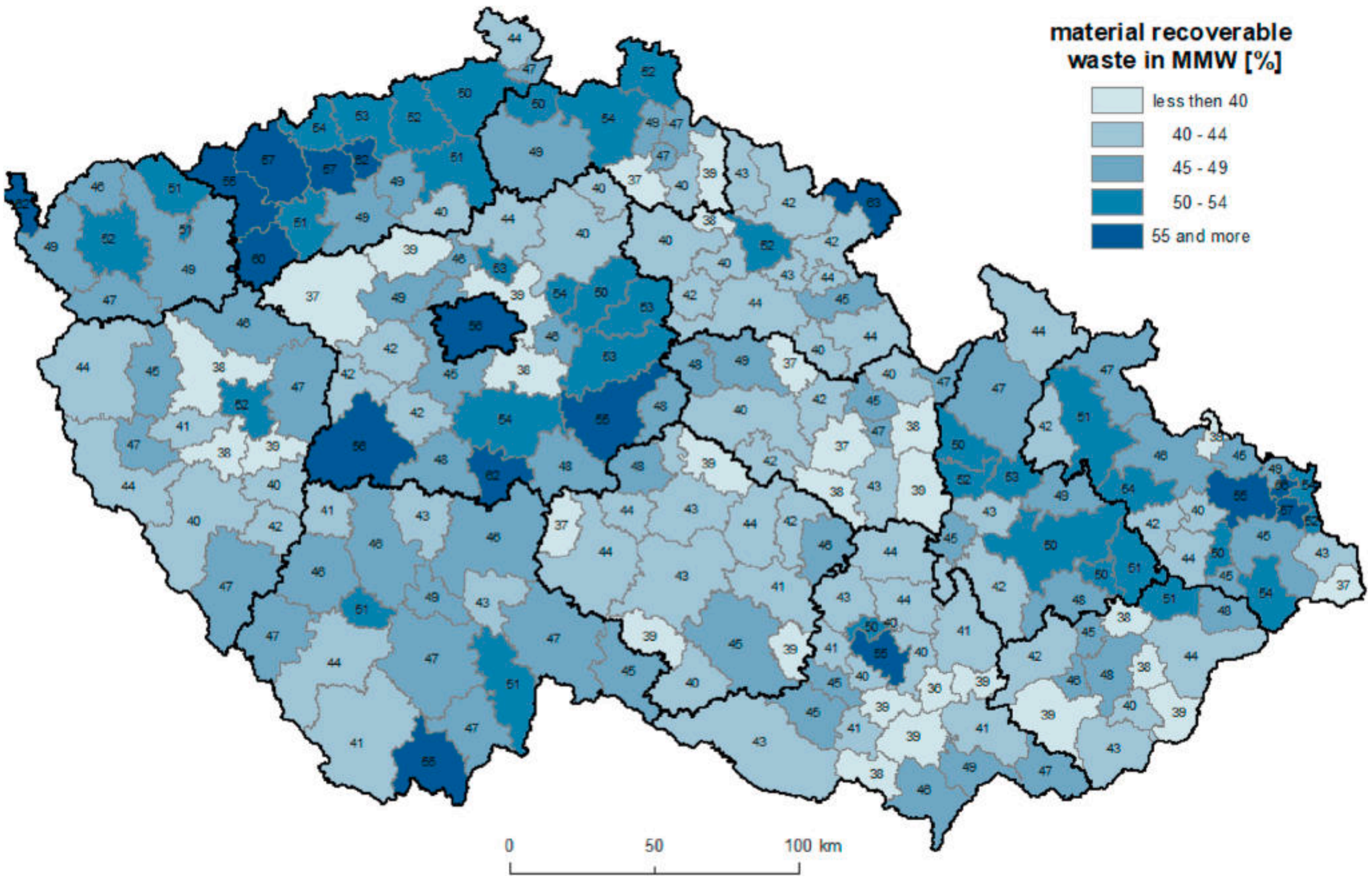


Fig. 6. Proportion of materially recoverable waste if MMW in the Czech Republic in 2017.

Table 4
Recycling rates for the different waste fractions in 2015.

Waste fraction f	RR_f
Bio-waste (including food waste)	0.91
Bulky Waste	0.17
Glass and glass packaging	0.90
Metal and metal packaging	0.87
Paper and paper packaging	0.90
Plastic and plastic packaging	0.89
Textiles and clothing	1.00

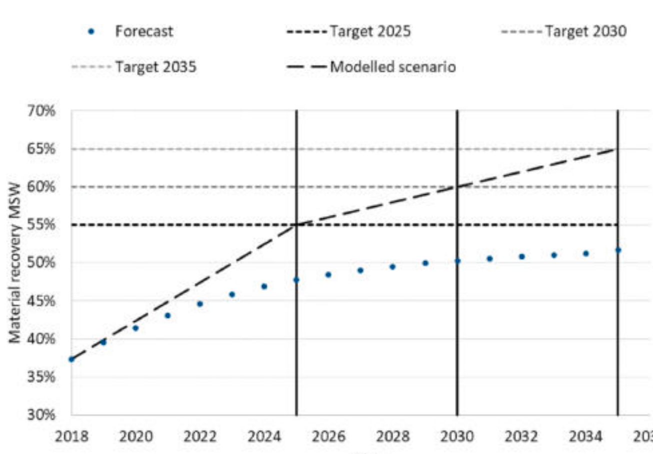


Fig. 7. Forecasting of material recovery in the Czech Republic under current conditions and scenario for targets fulfilling.

2.3.2. *Single-stage vs. multi-stage models*

The dynamic nature of the decision-making process is best captured in the use of models with several decision stages, that correspond to successive instances in time. Whereas single-stage models are best-suited to situations, where the corresponding model data are static (do not change over time), multi-stage models are more appropriate for dynamically changing environments. The difficulty with multi-stage approaches lies in an increase in computational and modelling complexity. As can be seen in Table 3, most of the relevant literature focuses on single-stage models. A sort of an intermediate step between the single-stage and multi-stage models is the two-stage model. In this setting, typically the "important decisions", such as facility locations and their design, are made in the first stage of the model. The second stage than serves to assess the impact that the "important decisions" will have in time. This approach was used in the study [63], where the authors describe a stochastic two-stage multi-period stochastic optimization model for the allocation of waste flows. Similarly, the two-stage model was used in a robust setting for a selection of WtE facilities [49] and in a stochastic setting for a design of a transfer station network [43]. The only work that presents a proper multi-stage model was the one [64] for bi-objective waste allocation in a fuzzy optimization setting.

2.3.3. *Deterministic vs. uncertain models*

A similar dichotomy, as the one between the single-stage and multi-stage models, exists in the approaches to the considered data of the model. When modelling a static situation with very little data variation, the deterministic approaches are the most sensible ones (and the ones most widely used). However, when the system that should be managed is dynamically changing and there are multiple possible paths of development, uncertain models are the most reasonable choice. This naturally means that there are very few contemporary works that are in

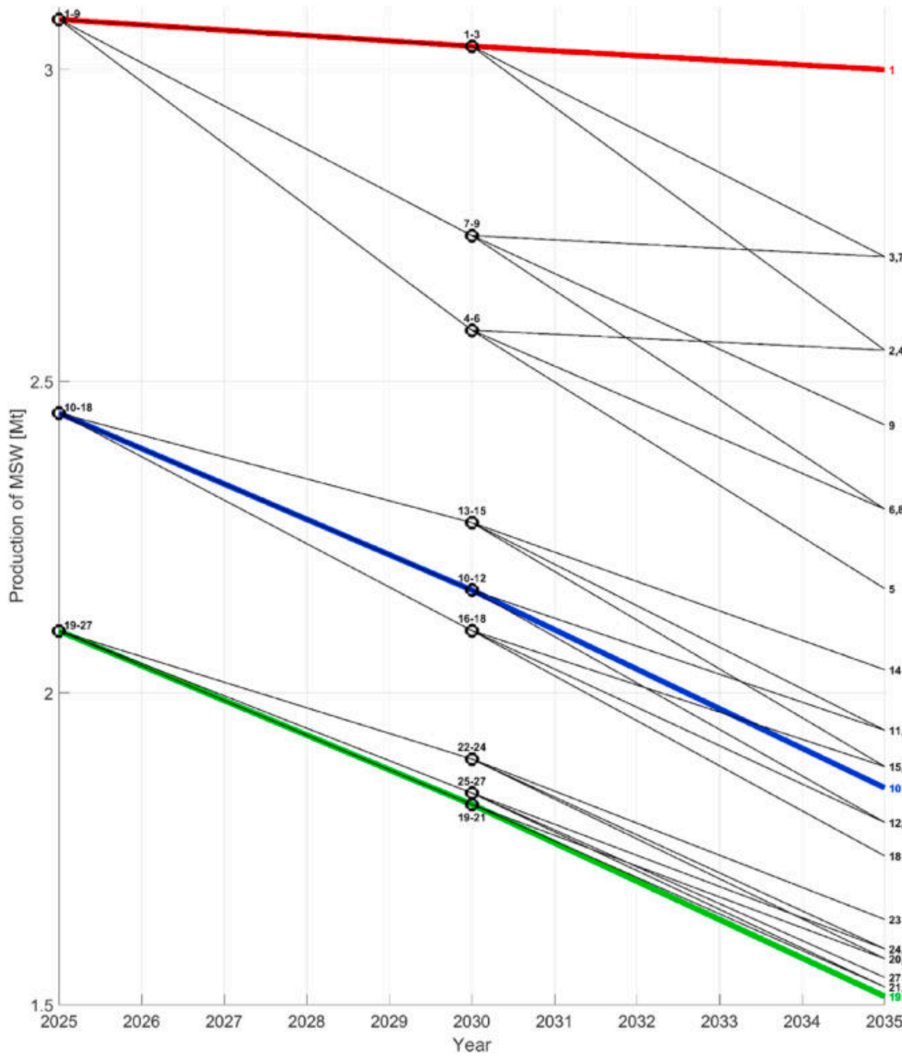


Fig. 8. Scenario branching. Red scenario (1) – BAU, blue scenario (10) – middle, green scenario (19) – on target. Aggregate data for the whole republic. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

a multi-stage setting with deterministic data. Three major approaches try to deal with uncertainty in the data: fuzzy programming, robust programming and stochastic programming. Fuzzy programming was used for waste allocation [33] and facility design [64]. Robust programming was used for waste reduction [65] and a bi-objective selection of WtE facilities [49]. Stochastic programming approaches were used in transfer station planning [43] and waste flow allocation models [63].

2.4. Research gap and novelty

Most contributions deal with setting up individual parts of the processing chain. There are also papers with a comprehensive approach to waste management, but the sequence of steps with regards to time is often disregarded. The dynamical decision-making process that is enabled by the multi-stage models increases the likelihood of a successful deployment of the system, compared to radical changes that correspond to the one-stage models. Since the legislation-induced changes that are coming into effect will significantly alter the production of MSW and its possible treatment options, this dynamic setting is well justified. This paper presents a stochastic multi-period and multi-stage model that captures the planning and decision-making process of selecting the locations and sizes of waste treatment plants, and the subsequent waste flow allocation. Sequential decision-making during the time horizon represents a significant benefit of the model. Despite the complexity of the model, it remains computationally tractable even for real-world instances, which is demonstrated in a case study of the Czech Republic. The approach represents a suitable supporting mathematical apparatus for the “smooth” transition from linear to the circular economy.

3. Multi-stage stochastic optimization model

The presented optimization model falls into the category of multi-stage multi-period stochastic mixed-integer optimization models. There are several monographs dedicated to stochastic programming, with [69] offering the standard more theoretical treatment, and [70] with a more hands-on modelling focus. The goal is to select the optimal locations and sizes of waste treatment facilities in selected cities. Two types of facilities are considered: WtE plants where the waste is incinerated to produce heat and electricity, and mechanical biological treatment (MBT) plants where the MSW is sorted and then either treated with anaerobic digestion or landfilled (the proportion of MBT that needs to be landfilled is denoted as κ). The relationship between the size and cost of treatment in a facility is not simply linear. To model it efficiently, the sizes of the facilities can be chosen only from a predefined set of values. In this way, the linearity of the model can be preserved, although at the cost of introducing new binary variables.

The objective function is purely economical and expresses the ex-

Table 5
The results of the computations. (PG – progressive goals).

	year 2025		year 2030		year 2035	
	with PG	without PG	with PG	without PG	with PG	without PG
max landfilling [%]	29.85	40.15	19.92	38.57	10	10
mean landfilling [%]	21.03	31.61	13.25	26.65	7.35	8.78
max # of new facilities	9	0	6	0	5	16
mean # of new facilities	9	0	2	0	1.89	10.66
mean installed WtE capacity [kt]	981	741	981	741	1099	1074
min used WtE capacity [%]	100	100	100	100	72.31	79.14
mean used WtE capacity [%]	100	100	100	100	97.14	96.69
mean installed MBT capacity [kt]	600	0	883	0	890	822
min used MBT capacity [%]	100	–	100	–	76.30	69.15
mean used MBT capacity [%]	100	–	100	–	96.33	96.80

pected costs of the whole waste treatment system over the considered time period (transportation costs, gate fees at the WtE and MBT plants, penalties for unused capacity, and landfilling fees):

$$\min \sum_s p_s \left[\sum_{j,t} c_R^j \cdot x_{t,s}^j + \sum_{i,t} c_L^i \cdot {}^L r_{t,s}^i \right.$$
$$+ \sum_{i,o_{WtE}^i,t} {}^{WtE}c_{o_{WtE}^i}^i \left({}^{WtE}r_{t,s}^{i,o_{WtE}^i} + pen_{WtE} \cdot {}^{WtE}u_{t,s}^{i,o_{WtE}^i} \right) \tag{1}$$
$$\left. + \sum_{i,o_{MBT}^i,t} {}^{MBT}c_{o_{MBT}^i}^i \left({}^{MBT}r_{t,s}^{i,o_{MBT}^i} + pen_{MBT} \cdot {}^{MBT}u_{t,s}^{i,o_{MBT}^i} \right) \right]$$

The constraints can be grouped into a few categories. The first one comprises of the "conservation of mass" constraints, which enforce that the waste generated in or shipped into city i is either shipped away or disposed of (through one of the treatment options):

$$\sum_j A^{i,j} x_{t,s}^j - \sum_{o_{WtE}^i} {}^{WtE}r_{t,s}^{i,o_{WtE}^i} - \sum_{o_{MBT}^i} {}^{MBT}r_{t,s}^{i,o_{MBT}^i} - {}^L r_{t,s}^i + \xi_{t,s}^i = 0, \quad \forall i, \forall t, \forall s. \tag{2}$$

Another set of constraints restricts building new facilities. If there already is a facility of the given type (WtE or MBT), another one cannot be built:

$$\sum_{o_{WtE}^i} \sum_\tau w_{\tau,s}^{i,o_{WtE}^i} \leq 1, \quad \forall i, \forall s, \tag{3}$$

$$\sum_{o_{MBT}^i} \sum_\tau m_{\tau,s}^{i,o_{MBT}^i} \leq 1, \quad \forall i, \forall s. \tag{4}$$

Next are the constraints that compute the amount of used and unused capacity in the waste treatment facilities in different cities:

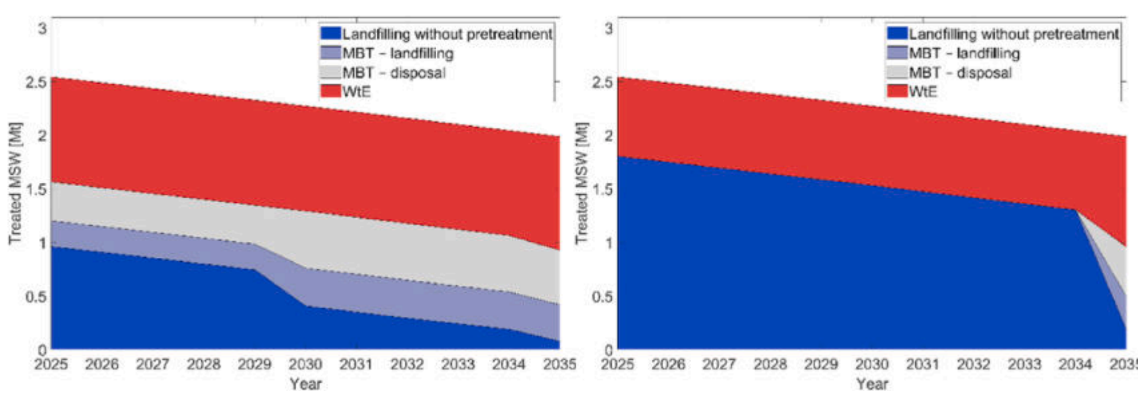


Fig. 9. The volume of MSW treated by the different options in 2025–2035. Solution with progressive goals on the left, the one without progressive goals on the right.

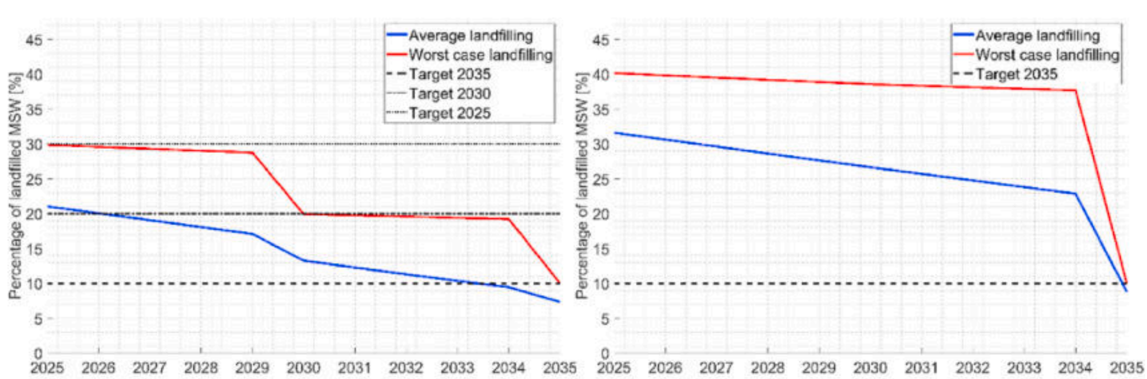


Fig. 10. Percentage of landfilled MSW in 2025–2035. Solution with progressive goals on the left, the one without progressive goals on the right.

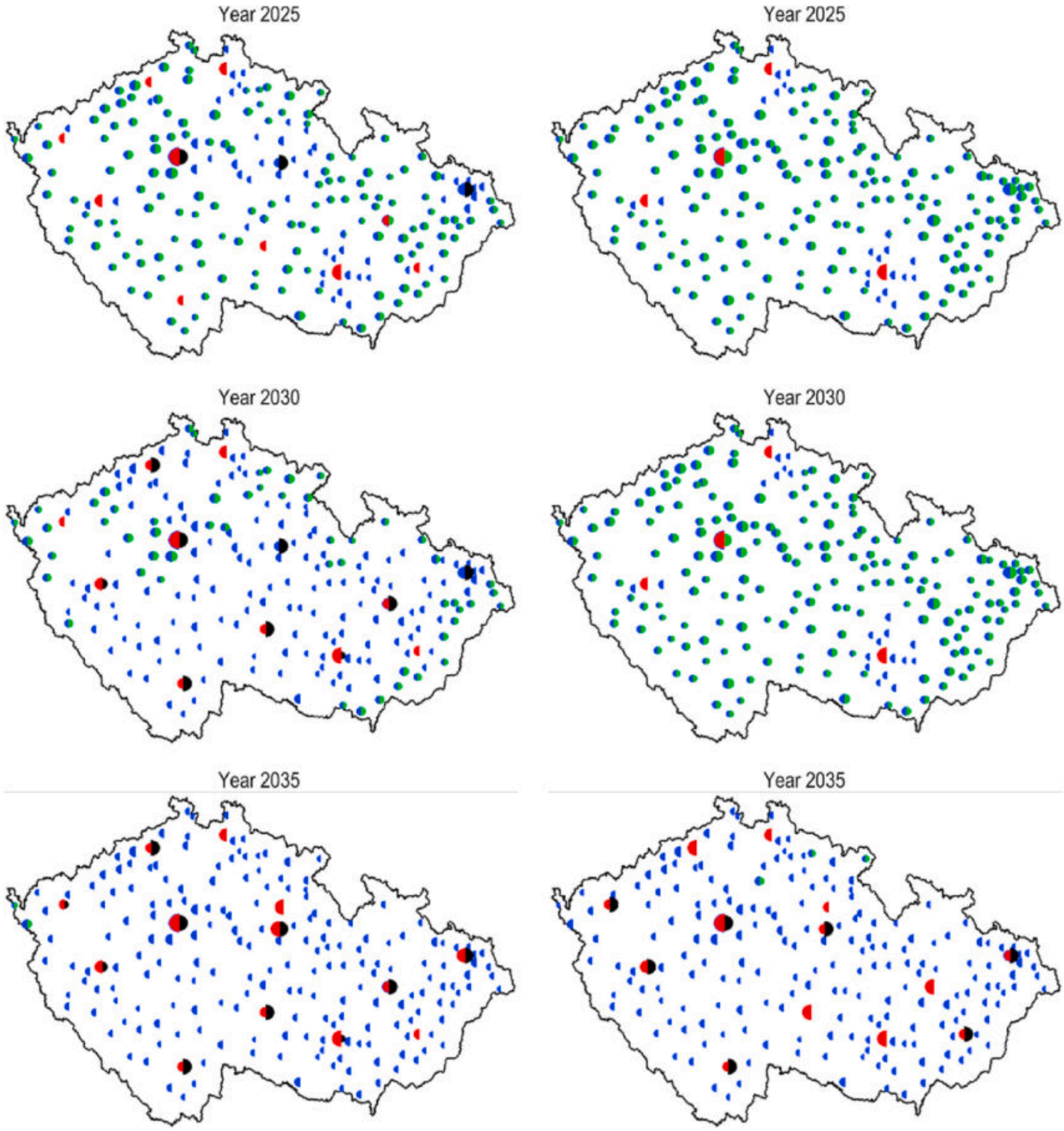


Fig. 11. Scenario 1. Solution with progressive goals on the left, the one without progressive goals on the right. The amount of generated MSW in blue, amount landfilled without pretreatment in green, amount treated in WtE plant in red, and the amount treated in MBT plant in black half-circles. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

$$ {}^{WtE}r_{t,s}^{i,o^i_{WtE}} + {}^{WtE}u_{t,s}^{i,o^i_{WtE}} = \sum_{\tau\leq t} k^i_{o^i_{WtE}} \cdot w_{\tau,s}^{i,o^i_{WtE}}, \quad \forall i, \forall t, \forall s, \tag{5} $$

$$ {}^{MBT}r_{t,s}^{i,o^i_{MBT}} + {}^{MBT}u_{t,s}^{i,o^i_{MBT}} = \sum_{\tau\leq t} k^i_{o^i_{MBT}} \cdot m_{\tau,s}^{i,o^i_{MBT}}, \forall i, \forall t, \forall s. \tag{6} $$

The penultimate set of constraints consists of the targets for the amount of landfilled MSW:

$$ \sum_j \left({}^{L}r^i_{t,s} + \kappa \cdot \sum_{o^i_{MBT}} {}^{MBT}r_{t,s}^{i,o^i_{MBT}} \right) \leq g_1 \cdot \mathrm{MSW}_{t,s}, \quad \forall i, \forall s, t = 1, \ldots, 5, \tag{7} $$

$$ \sum_j \left({}^{L}r^i_{t,s} + \kappa \cdot \sum_{o^i_{MBT}} {}^{MBT}r_{t,s}^{i,o^i_{MBT}} \right) \leq g_2 \cdot \mathrm{MSW}_{t,s}, \quad \forall i, \forall s, t = 6, \ldots, 10, \tag{8} $$

$$ \sum_j \left({}^{L}r^i_{t,s} + \kappa \cdot \sum_{o^i_{MBT}} {}^{MBT}r_{t,s}^{i,o^i_{MBT}} \right) \leq g_3 \cdot \mathrm{MSW}_{t,s}, \quad \forall i, \forall s, t = 11, \ldots, 16. \tag{9} $$

Lastly, there are the nonanticipativity constraints. These constraints guarantee that the decisions on building the facilities only depend on the information of realized uncertainties up to the present stage:

$$ w_{\tau,s}^{i,o^i_{WtE}} = w_{\tau,z}^{i,o^i_{WtE}}, \cdot \forall i, \forall \tau \text{ for which } \xi^i_{[\tau],s} = \xi^i_{[\tau],z} \tag{10} $$

$$ m_{\tau,s}^{i,o^i_{WtE}} = m_{\tau,z}^{i,o^i_{WtE}}, \cdot \forall i, \forall \tau \text{ for which } \xi^i_{[\tau],s} = \xi^i_{[\tau],z}. \tag{11} $$

It should be noted that the number of cities, scenarios, time periods, decision stages and target values that are present in Table 2 and Eq (1)–Eq (11) are the ones used in a forthcoming case study. These can be readily generalized to take any values depending on the situation at hand.

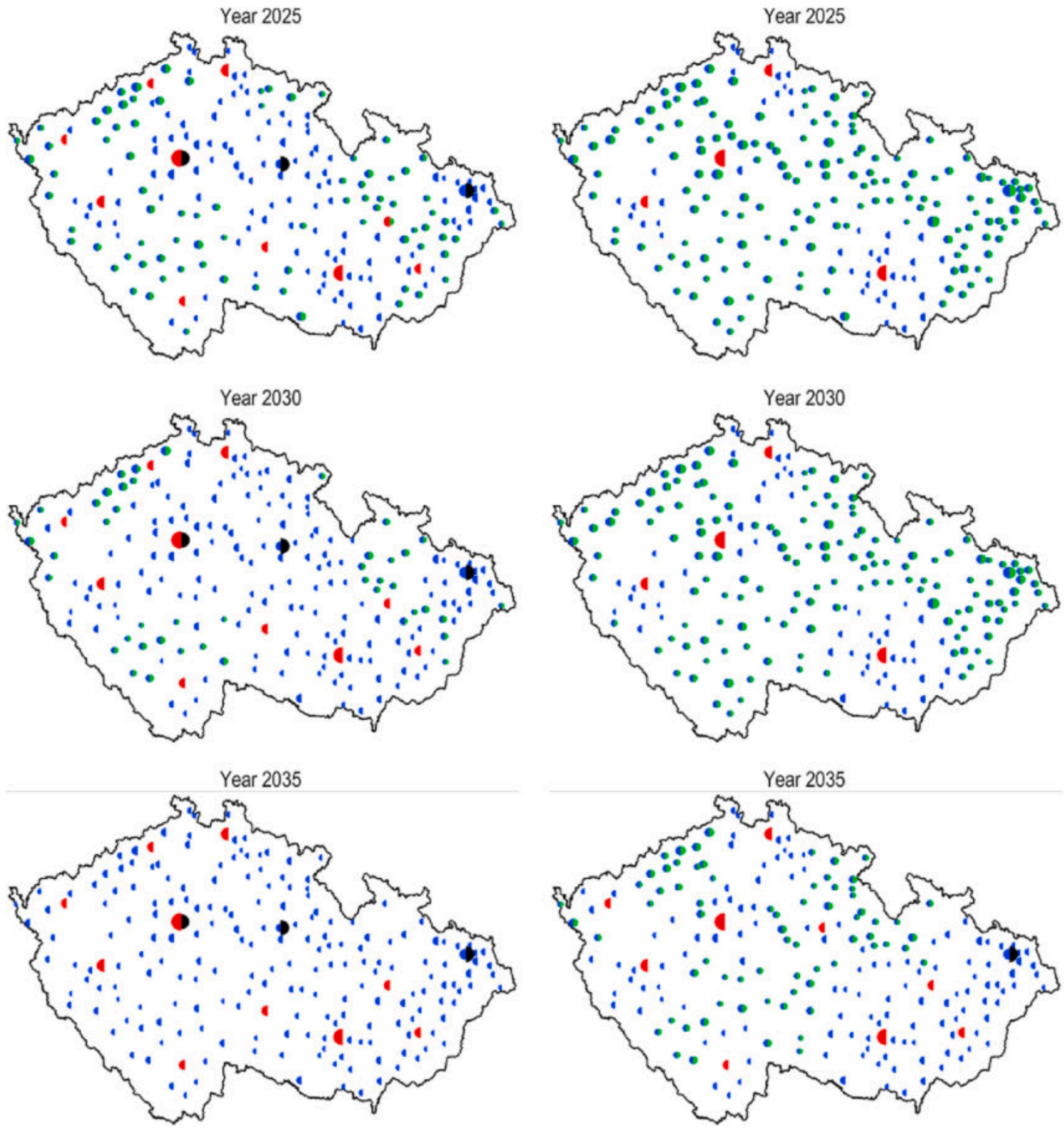


Fig. 12. Scenario 19. Solution with progressive goals on the left, the one without progressive goals on the right. The amount of generated MSW in blue, amount landfilled without pretreatment in green, amount treated in WtE plant in red, and the amount treated in MBT plant in black half-circles. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

4. Case study

To demonstrate the strengths of the presented model, it is employed in the assessment of the waste treatment situation in the Czech Republic. The granularity of the case study is the following: 206 cities, connected by a road network with 1898 arcs are considered. Out of the 206 cities, 13 were selected as the most favorable locations for possible WtE and MBT plants. These are the largest cities in their respective regions, which can benefit the most from the electricity and heat generation by the waste treatment facilities and have the largest production of MSW. In 4 of the 13 cities, there already are existing WtE plants with a combined capacity of 741 kt. It is assumed that in these four cities, no additional WtE capacity can be built (although it is possible to build a new MBT facility). There are nine options for possible sizes of the WtE and MBT plants.

The considered planning period covers 11 years, from 2025 to 2035. The reason for the gap between the current year (2020) and the first period is the following – both the WtE and MBT facilities cannot be build overnight. It is assumed that for a facility to be fully operational in a given year, the decision for its construction must be made five years prior. This necessarily means that this decision will be based not so much on the current levels of the MSW production, but on an estimate of the possible levels of MSW production in the upcoming years. The reason for omitting the years 2020–2024 in the analysis is that there are no "substantial" decisions to be made (the model could only manage the system that is currently in place). The 5-year lag between the decision on building the facility and its operation will be achieved through the nonanticipativity constraints Eq (10)–Eq (11) and is discussed further in a forthcoming subsection. In order to make the model computationally tractable (to reduce the number of binary variables), the decisions about building the facilities will be considered only in three decision stages, that corresponds to having the facilities operational in years 2025, 2030, and 2035. Additionally, the costs associated with the year 2035 are multiplied by a factor of 6 to account for the costs that are likely to occur in the years 2036–2040. This should deter the decision that results in building too much infrastructure that will not be efficiently used.

4.1. Data collection and scenario generation

According to the *Waste hierarchy*, energy recovery should be treated if the waste cannot be recovered materially. The rate of waste recycling thus affects the amount of waste for energy recovery.

Waste fractions for material recovery were determined based on the *Waste management plan of the Czech Republic for the period 2015–2024,* which was developed by the Ministry of Environment of the Czech Republic. The following waste fractions were determined as the materially recoverable: glass and glass packaging, metal and metal packaging, paper and paper packaging, plastic and plastic packaging, textiles and clothing. The mandatory waste management records identified other fractions, which are materially recovered: bio-waste and bulky waste. Fig. 4a) depicts the production of MSW fractions, which is material recoverable and its real materially recovery from the year 2009 is still growing. The spatial distribution of the material recovery of the MSW in 2017 is illustrated in Fig. 5.

Mixed municipal waste (MMW) currently accounts for a significant proportion of MSW – about 50% in the year 2017 in the Czech Republic. It is a waste fraction that can be sorted and thus creates the potential for material recovery. Fig. 6 shows the materially recoverable waste in MMW in 2017, which should be separated in the future.

However, the separated waste does not correspond directly to the materially recovered waste. Material recovery of separated waste is mainly dependent on technological and cost conditions. The recycling rate RR_f for waste fraction f, where MAT_f is materially recovered and SEP_f is separated waste f is computed as $RR_f = MAT_f/SEP_f$. The latest available data make it possible to determine the recycling rate RR_f for 2015, these values are summarized in Table 4. The expected development of the material recovery municipal solid waste (if it continues in the current fashion) achieves approximately 47% in the year 2025, as indicated in Fig. 7. But the EU target in 2025, which lies at 55%, necessitates additional steps and effort in order to be reached. The situation for the targets in the years 2030 and 2035 is quite similar, if not more severe.

Material recovery constitutes an extremely important factor as it directly affects the amount of MSW that will be treated in the considered WtE and MBT plants. At present, it is not certain in which direction the production of waste with material recovery will be taken. Three base scenarios for the material recovery are constructed to model this uncertainty:

1. Scenario: BAU – business as usual, depicted as “Forecast” in Fig. 7.
2. Scenario: middle – the EU targets with a 5-year delay
3. Scenario: on target – the “Modelled scenario” in Fig. 7.

These three base scenarios were further “branched”, as depicted in Fig. 8, to more evenly capture the possible developments, resulting in 27 individual scenarios. Alongside the material recovery, other factors went into the construction of the scenarios for the production of MSW that can be treated in the WtE or MBT facilities (denoted as $\xi^i_{t,s}$) in individual cities in the successive time periods. Additionally, demographic changes, i.e. the expected continuation of the trend of higher immigration to bigger cities in the core of the republic (such as Prague or Brno) and the population decline and ageing of the periphery were considered.

With Fig. 8 in mind, the nonanticipativity constraints Eq (10)–Eq (11) that tie certain scenarios together and enforce decisions that can be based only on the current state of knowledge about the uncertain parameters work as follows. As there is currently (the year 2020) no way of knowing which of the 27 scenarios will be the one that comes true, the decision on building the facilities must be made with all 27 scenarios in mind. In other words, for all 27 scenarios, the decision on which facilities will be operational in the year 2025 must be the same. In the year 2025, the situation changes, as one will be able to pinpoint which of the three branches (1–9, 10–18, or 19–27) is the “true one”. This affects the decisions on which facilities to open in 2030, as they will be grouped based on this branching (i.e. one decision for scenarios 1–9, the second one for 10–18, and the third one for 19–27). A similar situation repeats in the year 2030, but with even more branching, as nine possibilities tie the scenarios together.

5. Results and discussion

The optimization model was programmed in the high-performance dynamic language JULIA [71] with the JuMP package for mathematical optimization [72]), that is very well suited for large-scale scientific computing. The solution was computed by the GUROBI 8.0 solver [73]. The optimality gap parameter was set to 1%, which was decided to be sufficiently low for this application. The computations were carried out on an ordinary computer (3.2 GHz i5-4460 CPU, 16 GB RAM) and took about an hour to finish. Two distinct models were considered. The first model has progressive goals ($g_1 = 0.3, g_2 = 0.2, g_3 = 0.1$, in the years 2025, 2030, and 2035, respectively) towards the landfilling target of 10% in the year 2035, to facilitate a “smoother” transition. The second model is without these progressive goals and has only the final goal ($g_3 = 0.1$, in the year 2035). The proportion of the MBT treated waste that still will be landfilled is assumed to be $\kappa = 0.4$. The results of the computations are best summarized in Table 5 and Fig. 9 to Fig. 12

In the model with progressive goals, in the year 2020, the WtE capacity amounted to 981 kt and the MBT capacity to 600 kt (the placements were identical in all scenarios due to the nonanticipativity constraints). In 2025, in the scenarios 1–9 (that stem from the BAU base scenario) additional 850 kt of MBT capacity were built. No other facilities were deemed as needed. In 2030, additional WtE capacity was needed in 15 scenarios (1–15), and additional MBT capacity was needed in 9 scenarios (1–3, 10–15). This leaves 12 scenarios (16–27) in which the initial capacity built in 2020 was all that was necessary to achieve the progressive goals. The differences are exemplified in Fig. 11 and Fig. 12. The optimal objective value was $2.50{\cdot}10^9$ EUR.

In the model without the progressive goal, the results suggest quite the opposite strategy. As there is no pressure to decrease the amount of landfilled waste immediately, the optimal decision is to “wait until the last moment” and act according to the particular scenario path. The optimal objective value in this setting was $2.44{\cdot}10^9$ EUR, which is about 2.4% cheaper than the model with progressive goals.

There is, however, an important issue with this approach, as it requires building a large number of new facilities in the time period between 2030 and 2034 (that can be operating in 2035), in order to reach the 10% landfilling target. For instance, in scenarios 1–9, there are 16 new facilities to be built in this time interval. This would likely put a strain on whatever agency which will be given the task of building these facilities. To find a compromise between the two approaches, one could look at the facilities that are built in both. There are 9 facilities that should be built in 2025 according to the strategy with progressive goals. For the strategy without progressive goals, out of these 9 there are 7 that are built in more than half of the scenarios in 2035, and 5 that are built in more than two-thirds of the scenarios in 2035.

One of the biggest strengths of the model is that it can be used for “rolling-horizon” planning. After analyzing the compromises between possible strategies and deciding on particular facilities to open in the current year (that will become operational in the future) it is expected that the model will be recomputed again after a few years, bringing updated data and trajectories of future development.

The suggested approach has limitations in many ways. The main shortcoming may seem to be the forced link to the material recovery of the waste. Its fair value depends on the capabilities of individual territorial units. Individual regions and micro-regions are different, so their specific potential should be considered. Options for energy recovery should then only be considered for remaining waste in all municipalities. The actual implementation of the new WtE plant is time-consuming and requires the fulfillment of many legislative conditions, including environmental analysis. From the implementer's point of view, the calculation can be applied repeatedly, taking into account new or more accurate information. However, these can only be obtained or changed after binding decisions. Ideally, the options should be analyzed at the lowest possible level of territorial division, i.e. at the level of municipalities (currently around 6250 in the Czech Republic). Calculations on such level are related to the need to make predictions for small areas. However, the results for these areas can be highly variable, and these inaccuracies could affect the credibility of the outputs. Regarding the predictions, it would be beneficial to encompass the demographic development in the population across the Czech Republic. Despite all of this, the feasibility of suggested projects is also highly dependent on the willingness of local authorities and residents to support implementation, where the result of the public referendum can play a significant role.

6. Conclusion

The presented paper reviewed the current state-of-the-art within the waste management of Europe and the possible strategies on how to handle the planning of sustainable processing infrastructure with regards to the circular economy targets. It consists of crucial landfilling and recycling goals that were anchored in legislation. At the same time, the current waste treatment and material recovery were analyzed to define rates and trends used as the baseline point. Scenarios of waste production were generated from forecasts and targets to simulate three scenario trees. These were – business as usual, middle scenario considering 5-year delay and scenario on target. All scenarios were further branched to more evenly capture the possible developments.

The approach was demonstrated within the Czech Republic. One of the main contributions lies in the comparison of models with and without progressive goals. In the model with progressive goals, in the year 2020, the WtE capacity amounted to 981 kt and the MBT capacity to 600 kt. The second model suggests quite the opposite strategy. Since there were no restrictions during the time horizon, the optimal decision suggests to wait until the last moment with changes in processing infrastructure. The strength of the model is that it can be used for "rolling-horizon" planning, which means that it can be recomputed again after a few years and update the upcoming decisions with newly available data.

The future research may incorporate the decision-making regarding material recovery to meet all goals. The current approach requires a steep change from the trend. Also, the detail of the territory level will be analyzed in order to obtain more precise results. The model will identify micro-regions, where there is a potential for more effective waste treatment and management.

Author contribution

Jakub Kůdela: Conceptualization, Methodology, Software, Formal analysis, Writing - original draft, Writing - review & editing, Visualization. Veronika Smejkalová: Investigation, Resources, Data curation, Writing - original draft, Visualization. Vlastimír Nevrlý: Investigation, Resources, Data curation, Writing - review & editing, Visualization. Radovan Šomplák: Conceptualization, Supervision, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] Pires A, Martinho G, Rodrigues S, Gomes MI. Sustainable solid waste collection and management. Springer; 2019, ISBN 978-3-319-93200-2.
[2] Directive (EU. 98/EC of the European parliament and of the council of 19 november 2008 on waste and repealing certain directives (text with EEA relevance). 2008.
[3] Khan D, Kumar A, Samadder SR. Impact of socioeconomic status on municipal solid waste generation rate. Waste Manag 2016;49:15–25. https://doi.org/10.1016/j.wasman.2016.01.019.
[4] Takata M, Fukushima K, Kawai M, Nagao N, Niwa C, Yoshida T, Toda T. The choice of biological waste treatment method for urban areas in Japan—an environmental perspective. Renew Sustain Energy Rev 2013;23:556–67. https://doi.org/10.1016/j.rser.2013.02.043.
[5] Stehlík P. Contribution to advances in waste-to-energy technologies. J Clean Prod 2009;17:919–31. https://doi.org/10.1016/j.jclepro.2009.02.011.
[6] Shafiee S, Topal E. When will fossil fuel reserves be diminished? Energy Pol 2009; 37(1):181–9. https://doi.org/10.1016/j.enpol.2008.08.016.
[7] Kumar A, Samadder SR. A review on technological options of waste to energy for effective management of municipal solid waste. Waste Manag 2017;69:407–22. https://doi.org/10.1016/j.wasman.2017.08.046.
[8] Scarlat N, Motola V, Dallemand JF, Monforti-Ferrario F, Mofor L. Evaluation of energy potential of municipal solid waste from african urban areas. Renew Sustain Energy Rev 2015;50:1269–86. https://doi.org/10.1016/j.rser.2015.05.067.
[9] Psomopoulos CS, Bourka A, Themelis NJ. Waste-to-energy: a review of the status and benefits in USA. Waste Manag 2009;29(5):1718–24. https://doi.org/10.1016/j.wasman.2008.11.020.
[10] Gregson N, Crang M. Waste, resource recovery and labour: recycling economies in the EU. In: Michie J, Cooper C, editors. Why the social sciences matter. Palgrave Macmillan; 2015. 60e–76. https://doi.org/10.1057/9781137269928_5.
[11] Tomić T, Dominković DF, Pfeifer A, Schneider DR, Pedersen AS, Duić N. Waste to energy plant operation under the influence of market and legislation conditioned changes. Energy 2017;137:1119–29. https://doi.org/10.1016/j.energy.2017.04.080.
[12] Yang QZ, Yang F. Sustainability metrics for waste management. Proceedings of the ASME Design Engineering Technical Conference 2011:969–76. https://doi.org/10.1115/DETC2011-48117.
[13] Iacovidou E, Velis CA, Purnell P, Zwirner O, Brown A, Hahladakis J, Millward-Hopkins J, Williams PT. Metrics for optimizing the multi-dimensional value of resources recovered from waste in a circular economy: a critical review. J Clean Prod 2017;166:910–38. https://doi.org/10.1016/j.jclepro.2017.07.100.
[14] Gregson N, Crang M, Fuller S, Holmes H. Interrogating the circular economy: the moral economy of resource recovery in the EU. Econ Soc 2015;44:218–43. https://doi.org/10.1080/03085147.2015.1013353.
[15] Morseletto P. Targets for a circular economy. Resour Conserv Recycl 2020;153:104553. https://doi.org/10.1016/j.resconrec.2019.104553.
[16] Bocken NMP, de Pauw I, Bakker C, van der Grinten B. Product design and business model strategies for a circular economy. Journal of Industrial and Production Engineering 2016;33(5):308–20. https://doi.org/10.1080/21681015.2016.1172124.
[17] Hughes R. The EU circular economy package – life cycle thinking to life cycle law? Procedia CIRP 2017;61:10–6. https://doi.org/10.1016/j.procir.2016.12.006.
[18] Directive (EU. 851 of the European parliament and of the council of 30 may 2018 amending directive 2008/98/EC on waste. 2018 [Text with EEA relevance)].
[19] Directive (EU. 852 of the European Parliament and of the Council of 30 May 2018 amending Directive 94/62/EC on packaging and packaging waste. 2018 [(Text with EEA relevance)].
[20] Directive (EU. 850 of the European parliament and of the council of 30 may 2018 amending directive 1999/31/EC on the landfill of waste (text with EEA relevance). 2018.
[21] Eurostat. https://ec.europa.eu/eurostat/web/main/home; 2019.
[22] Malinauskaite J, Jouhara H, Czajczyńska D, Stanchev P, Katsou E, Rostkowski P, Thorne RJ, Colón J, Ponsá S, Al-Mansour F, Anguilano L, Krzyżyńska R, López IC, Vlasopoulos A, Spencer N. Municipal solid waste management and waste-to-energy in the context of a circular economy and energy recycling in Europe. Energy 2017; 141:2013–44. https://doi.org/10.1016/j.energy.2017.11.128.
[23] Luttenberger LR. Waste management challenges in transition to circular economy – case of Croatia. J Clean Prod 2020;256:120495. https://doi.org/10.1016/j.jclepro.2020.120495.
[24] Marino A, Pariso P. Comparing European countries' performances in the transition towards the Circular Economy. Sci Total Environ 2020:138142. https://doi.org/10.1016/j.scitotenv.2020.138142.

[25] European Commission. Communication from the commission to the European parliament, the council, the European economic and social committee and the committee of the regions. the role of waste-to-energy in the circular economy COM/2017/0034 Final, http://ec.europa.eu/environment/waste/waste-to-energy.pdf; 2017.
[26] Tung DV, Pinnoi A. Vehicle routing-scheduling for waste collection in Hanoi. Eur J Oper Res 2000;125(3):449–68. https://doi.org/10.1016/S0377-2217(99)00408-7.
[27] Das S, Bhattacharyya BK. Optimization of municipal solid waste collection and transportation routes. Waste Manag 2015;43:9–18. https://doi.org/10.1016/j.wasman.2015.06.033.
[28] Yousefi H, Javadzadeh Z, Noorollahi Y, Yousefi-Sahzabi A. Landfill site selection using a multi-criteria decision-making method: a case study of the Salafcheghan special economic zone, Iran. Sustainability 2018;10(4):1107. https://doi.org/10.3390/su10041107.
[29] Yadav V, Karmakar S, Dikshit A, Bhurjee A. Interval-valued facility location model: an appraisal of municipal solid waste management system. J Clean Prod 2018;171:250–63. https://doi.org/10.1016/j.jclepro.2017.09.233.
[30] Ghiani G, Laganà D, Manni E, Triki C. Capacitated location of collection sites in an urban waste management system. Waste Manag 2012;32:1291–6. https://doi.org/10.1016/j.wasman.2012.02.009.
[31] Badran M, El-Haggar S. Optimization of municipal solid waste management in Port Said-Egypt. Waste Manag 2006;26:534–45. https://doi.org/10.1016/j.wasman.2005.05.005.
[32] Cheng S, Chan CW, Huang GH. An integrated multi-criteria decision analysis and inexact mixed integer linear programming approach for solid waste management. Eng Appl Artif Intell 2003;16:543–54. https://doi.org/10.1016/S0952-1976(03)00069-1.
[33] Jin L, Fu H, Kim Y, Wang L, Li Y, Huang G. A robust inexact trapezoidal T2 fuzzy approach coupling possibility degrees for solid waste disposal allocation with integrated optimal greenhouse gas control under uncertainty. J Clean Prod 2019;221:753–67. https://doi.org/10.1016/j.jclepro.2019.02.252.
[34] Yadav V, Karmarmak S. Sustainable collection and transportation of municipal solid waste in urban centers. Sustainable Cities and Society 2020;53:101937. https://doi.org/10.1016/j.scs.2019.101937.
[35] Amponsah SK, Salhi S. The investigation of a class of capacitated arc routing problems: the collection of garbage in developing countries. Waste Manag 2004;24:711–21. https://doi.org/10.1016/j.wasman.2004.01.008.
[36] Rodrigues S, Martinho G, Pires A. Waste collection systems. Part A: a taxonomy. J Clean Prod 2016;113:374–87. https://doi.org/10.1016/j.jclepro.2015.09.143.
[37] Mohsenizadeh M, Tural MK, Kentel E. Municipal solid waste management with cost minimization and emission control objectives: a case study of Ankara. Sustainable Cities and Society 2020;52:101807. https://doi.org/10.1016/j.scs.2019.101807.
[38] Barbosa-Póvoa AP, Silva C, Carvalho A. Opportunities and challenges in sustainable supply chain: an operations research perspective. Eur J Oper Res 2018;268(2):399–431. https://doi.org/10.1016/j.ejor.2017.10.036.
[39] Ghose MK, Dikshit AK, Sharma SK. A GIS based transportation model for solid waste disposal-a case study on Asansol municipality. Waste Manag 2006;26:1287–93. https://doi.org/10.1016/j.wasman.2005.09.022.
[40] Sonesson U. Modelling of waste collection-a general approach to calculate fuel consumption and time. Waste Manag Res 2000;18:115–23. https://doi.org/10.1177/0734242X0001800203.
[41] Rafiee R, Khorasani N, Mahiny AS, Darvıshsefat AA, Danekar A, Hasan SE. Siting transfer stations for municipal solid waste using a spatial multi-criteria analysis. Environ Eng Geosci 2011;17(2):143–54. https://doi.org/10.2113/gseegeosci.17.2.143.
[42] Yadav V, Bhurjee A, Karmakar S, Dikshit A. A facility location model for municipal solid waste management system under uncertain environment. Sci Total Environ 2017;603–604:760–71. https://doi.org/10.1016/j.scitotenv.2017.02.207.
[43] Kůdela J, Šomplák R, Nevrlý V, Lipovský T, Smejkalova V, Dobrovsky L. Multi-objective strategic waste transfer station planning. J Clean Prod 2019;230:1294–304. https://doi.org/10.1016/j.jclepro.2019.05.167.
[44] Agacsapan B, Cabuk SN. Determination of suitable waste transfer station areas for sustainable territories: eskisehir case. Sustainable Cities and Society 2020;52:101829. https://doi.org/10.1016/j.scs.2019.101829.
[45] Chatzouridis C, Komilis D. A methodology to optimally site and design municipal solid waste transfer stations using binary programming. Resour Conserv Recycl 2012;60:89–98. https://doi.org/10.1016/j.resconrec.2011.12.004.
[46] Di Maria F, Sisani F, Contini S. Are EU waste-to-energy technologies effective for exploiting the energy in bio-waste? Appl Energy 2018;230:1557–72. https://doi.org/10.1016/j.apenergy.2018.09.007.
[47] Tozlu A, Ozahi E, Abusoglu A. Waste to energy technologies for municipal solid waste management in Gaziantep. Renew Sustain Energy Rev 2016;54:809–15. https://doi.org/10.1016/j.rser.2015.10.097.
[48] Baran B, Mamis MS, Alagoz BB. Utilization of energy from waste potential in Turkey as distributed secondary renewable energy source. Renew Energy 2016;90:493–500. https://doi.org/10.1016/j.renene.2015.12.070.
[49] Hu Ch, Liu X, Lu J. A bi-objective two-stage robust location model for waste-to-energy facilities under uncertainty. Decis Support Syst 2017;99:37–50. https://doi.org/10.1016/j.dss.2017.05.009.
[50] Allegrini E, Maresca A, Olsson ME, Holtze MS, Boldrin A, Astrup TF. Quantification of the resource recovery potential of municipal solid waste incineration bottom ashes. Waste Manag 2014;34(9):1627–36. https://doi.org/10.1016/j.wasman.2014.05.003.
[51] Arafat HA, Jijakli K, Ahsan A. Environmental performance and energy recovery potential of five processes for municipal solid waste treatment. J Clean Prod 2015;105:233–40. https://doi.org/10.1016/j.jclepro.2013.11.071.
[52] Cherubini F, Bargigli S, Ulgiati S. Life cycle assessment (LCA) of waste management strategies: landfilling, sorting plant and incineration. Energy 2009;34(12):2116–23. https://doi.org/10.1016/j.energy.2008.08.023.
[53] Zhao X, Li A. A multi-objective sustainable location model for biomass power plants: case of China. Energy 2016;112:1184–93. https://doi.org/10.1016/j.energy.2016.07.011.
[54] Mafakheri F, Nasiri F. Modeling of biomass-to-energy supply chain operations: applications, challenges and research directions. Energy Pol 2014;67:116–26. https://doi.org/10.1016/j.enpol.2013.11.071.
[55] Boonmee Ch, Arimura M, Asada T. Location and allocation optimization for integrated decisions on post-disaster waste supply chain management: on-site and off-site separation for recyclable materials. International Journal of Disaster Risk Reduction 2018;31:902–17. https://doi.org/10.1016/j.ijdrr.2018.07.003.
[56] López PR, Galán SG, Reyes NR, Jurado F. A method for particle swarm optimization and its application in location of biomass power plants. Int J Green Energy 2008;5(3):199–211. https://doi.org/10.1080/15435070802107165.
[57] Cebi S, Ilbahar E, Atasoy A. A fuzzy information axiom based method to determine the optimal location for a biomass power plant: a case study in Aegean Region of Turkey. Energy 2016;116(1):894–907. https://doi.org/10.1016/j.energy.2016.10.024.
[58] Kim BI, Kim S, Sahoo S. Waste collection vehicle routing problem with time windows. Comput Oper Res 2006;33:3624–42. https://doi.org/10.1016/j.cor.2005.02.045.
[59] Benjamin AM, Beasley J. Metaheuristics for the waste collection vehicle routing problem with time windows, driver rest period and multiple disposal facilities. Comput Oper Res 2010;37(12):2270–80. https://doi.org/10.1016/j.cor.2010.03.019.
[60] Azadeh A, Ahmadzadeh K, Eslami H. Location optimization of municipal solid waste considering health, safety, environmental, and economic factors. J Environ Plann Manag 2018;62:1185–204. https://doi.org/10.1080/09640568.2018.1482200.
[61] Achillas C, Vlachokostas C, Moussiopoulos N, Banias G, Kafetzopoulos G, Karagiannidis A. Social acceptance for the development of a waste-to-energy plant in an urban area. Resour Conserv Recycl 2011;55(9–10):857–63. https://doi.org/10.1016/j.resconrec.2011.04.012.
[62] Randazzo L, Cusumano A, Oliveri G, Di Stefano P, Renda P, Perricone M, et al. Landfill site selection for municipal solid waste by using AHP method in GIS environment: waste management decision-support in Sicily (Italy). Detritus 2018;2:78–88. https://doi.org/10.31025/2611-4135/2018.13656.
[63] Gambella C, Maggioni F, Vigo D. A stochastic programming model for a tactical solid waste management problem. Eur J Oper Res 2018;273(2):684–94. https://doi.org/10.1016/j.ejor.2018.08.005.
[64] Li YP, Huang GH, Nie SL. A mathematical model for identifying an optimal waste management policy under uncertainty. Appl Math Model 2012;36:2658–73. https://doi.org/10.1016/j.apm.2011.09.049.
[65] Hrabec D, Kůdela J, Šomplák R, Nevrlý V, Popela P. Circular economy implementation in waste management network design problem: a case study. Cent Eur J Oper Res 2019:1–18. https://doi.org/10.1007/s10100-019-00626-z.
[66] Li YP, Huang GH, Nie SL. A two-stage fuzzy robust integer programming approach for capacity planning of environmental management systems. Eur J Oper Res 2008;189:399–420. https://doi.org/10.1016/j.ejor.2007.05.014.
[67] Li YP, Huang GH, Yang ZF, Chen X. Inexact fuzzy-stochastic constraint-softened programming – a case study for waste management. Waste Manag 2009;29:2165–77. https://doi.org/10.1016/j.wasman.2008.12.011.
[68] Yadav V, Karmakar S, Dikshit AK, Vanjari S. A feasibility study for the locations of waste transfer stations in urban centers: a case study on the city of Nashik, India. J Clean Prod 2016;126:191–205. https://doi.org/10.1016/j.jclepro.2016.03.017.
[69] Birge JR, Louveaux F. Introduction to stochastic programming. New York, USA: Springer; 1997, ISBN 978-0-3879-8217-5.
[70] King AJ, Wallace SW. Modeling with stochastic programming. Springer; 2012, ISBN 978-0-387-87817-1.
[71] Bezanson J, Edelman A, Karpinski S, Shah VB. Julia: a fresh approach to numerical computing. SIAM Rev 2017;59:65–98. https://doi.org/10.1137/141000671.
[72] Dunning I, Huchette J, Lubin M. JuMP: a modeling language for mathematical optimization. SIAM Rev 2017;59:295–302.
[73] GUROBI. Gurobi optimizer 7.5. http://www.gurobi.com/. [Accessed 26 March 2019].

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Bulky waste for energy recovery: Analysis of spatial distribution

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The data regarding the current potential of unrecyclable waste and its spatial distribution play an essential role in the planning process. As per the circular economy strategies, especially the bulky waste streams suitable for energy recovery are to be identified. The public databases, however, collect data from a variety of sources (production and handling reports), which implies the presence of errors. This paper therefore proposes a multi-objective approach to identification and elimination of such errors to improve the accuracy of the assessment of potential energy recovery. The discussed model tracks the flow of waste from producers to processing nodes and minimises the deviation from the original data. Economic aspects are considered as well by preferring the shortest transport distance. The combination of data reconciliation and network flow enhances performance, as objective functions are solved separately, and only then the normalised individual optima are used in the multi-objective function. The model was tested using a Czech Republic regional-level dataset from 2015. A new perspective on the current state of waste management was provided, and valuable information for future planning was revealed, which can be useful for modelling of flows of other commodities.

1. Introduction

Social development results in a higher use of primary resources. This is associated with the consumption of goods and higher waste production [1]. For environmental and economic reasons, the pressure is currently being put on the reuse of goods and recycling of waste. This causes the gradual transformation of the linear waste management (i.e., the feedstock creates the product, which then creates the waste) to the so-called circular economy [2]. This is a comprehensive system that optimises consumption and management not only of natural resources, but also of wastes whose world production is still growing [7]. Its detailed description, approaches, and aims were identified and implemented by the EU in Circular Economy Package (Directive (EU) 2018/849 [3], 2018/850 [4], 2018/851 [5] and 2018/852 [6]). The present paper aims to uncover the hidden potential of bulky waste as a secondary material or energy source.

The role of thermal treatment with energy utilisation is often suppressed in the circular economy scheme due to the belief that the already minimised residual streams are not suitable for material recovery. However, not all wastes can be recycled and in the future, other ways of waste handling (such as energy recovery [8]) have to be considered. Expected reduced amounts of waste suitable for incineration increase the pressure on proper Waste-to-Energy (WtE) planning. Since the availability of waste presents a serious risk to the future WtE operation (see Ref. [9] for details), all suitable input streams to WtE including their spatial distribution should be properly investigated using the latest data as well as the forecasted values. Only then a sustainable system can be designed and successfully operated.

Bulky waste represents one of the streams which could primarily be affected by the circular thinking, where products might be designed to facilitate their end-of-life recycling. A proper assessment of the current methods of bulky waste treatment and the share of such treatment are needed. The respective waste treatment options are therefore reviewed in Section 1.1, and the potential for improvement in bulky waste reuse is specified. The current approaches to facilities planning, based on the data with spatial distribution, are then mentioned in Section 1.2.

1.1. Bulky waste as an energy source

A waste type-related analysis estimating the corresponding environmental impacts is available in Ref. [10]. According to the

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Abbreviations

C	Corrected data
E1, E2	Amount of waste exported
EU	European Union
I1, I2	Amount of waste imported
K	Known data
LHV	Lower heating value
MMW	Mixed municipal waste
MSW	Municipal solid waste
p	Production
t	Treatment
U	Unknown data
WtE	Waste-to-Energy
x_1, x_2	Realistic value of transported waste

waste specific properties, a suitable disposal grid is to be designed. According to Ref. [11], economic and environmental assessments of the involved facilities must be performed to identify the opportunities in terms of process integration. For example, municipal solid waste (MSW) incineration was assessed from environmental point of view and its global impact was also investigated [12]. Nevertheless, the supply chain review [13] or future possible pinch analysis applications [14] suggest that the ongoing dynamic changes in waste management make the sophisticated models indispensable. The current research direction comes in line with optimisation applied in the public sector, consumer goods, waste management, chemical processes, and biomass to energy. Most of the recent papers on waste treatment options deal with the MSW as a whole [15] or with mixed municipal waste (MMW) and its material or energy recovery [16], while these two terms are often confused. Nonetheless, other waste streams must be identified and studied in terms of their potential utilisation to fulfil the targets in waste management.

The shift from landfilling to WtE, together with its sustainability, are studied mainly in terms of MSW [17] or industrial wastes. As shown in Fig. 1, however, bulky waste has a huge potential when it comes to the its treatment. This applies not only to the Czech Republic, but also to many other countries [18]. What is more, the potential of bulky waste, which contains a significant percentage of high calorific value components, will increase with newly eco-designed products [19].

The term "bulky waste" refers to large and usually heavy items such as furniture or electrical appliances. According to the Controlled Waste Regulation 1992 (Schedule 2), the definition of bulky waste is as follows: "(1) any article of waste which exceeds 25 kg in weight or (2) any article of waste which does not fit or cannot be fitted into a cylindrical container of 750 mm in diameter and 1 m in length" [20]. Because of the dimensions, collection of bulky waste as part of the automated waste collection system is problematic. Still, according to Czech Statistical Office [21], bulky waste represents roughly 9% of MSW, that is, a non-negligible portion. Information on the two bulky waste disposal options available in the United Kingdom and on the issues related to the disposal of bulky items can be found in Ref. [22], while in case of Austria this is available in Ref. [23]. Estimation of the amount of bulky waste collected in Hong Kong, the way it was treated, and the corresponding environmental impact were analysed in Ref. [18]. This paper suggested that there was a considerable difference between the official and the real bulky waste flow (nearly 320% more) because of incomplete records.

According to Ref. [24], wood and rattan wastes have a large recovery potential, but due to a small amount of waste in official statistics, they are not used. Even though a lot of bulky waste is suitable for reuse, only a small portion of it can actually be reused. A considerable potential for reuse of bulky waste is mentioned by Reeve [25]. Similarly, only 27.5% of furniture and white goods is unsuitable for repair or reuse [26] with the respective percentages being as follows:

- furniture, reusable in its current condition 20%
- furniture, potentially repairable 25%
- white goods, potentially repairable 7.5%
- white goods & other metals, recyclable 20%
- unrecoverable items not suitable for repair or reuse 27.5%

Increased reuse of bulky waste would have a positive impact on the environment and it would also bring social benefits. In view of the waste hierarchy, the second most appropriate waste treatment

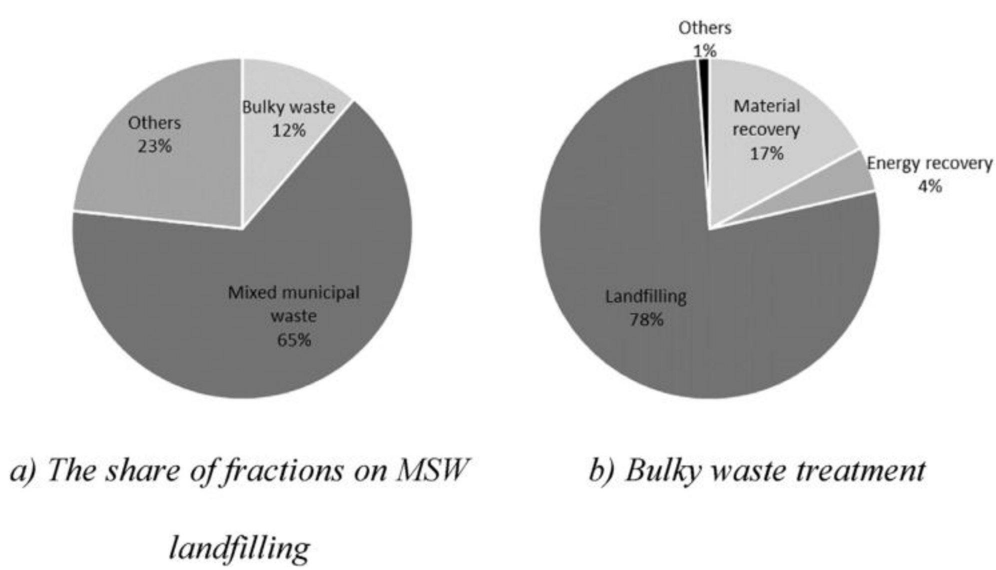


Fig. 1. Landfilling and bulky waste treatment in the Czech Republic in 2015.

method after material recovery is energy recovery. A recent study [27] therefore focused on the preparation of solid recovered fuels and mentioned also the average values obtained during elemental analysis of bulky waste. This study also listed the higher heating values and lower heating values (LHV) of fractions of this type of waste, which were expressed on the dry and wet bases. Apparently, plastic fractions have the highest heating values (LHV of roughly 40 MJ wet kg^{-1}), followed by foams (ca 25 MJ wet kg^{-1}), textiles (ca 20 MJ wet kg^{-1}), and wood (ca 16 MJ wet kg^{-1}). This shows the potential of bulky waste for energy generation.

1.2. Planning in waste management

For adequate planning of waste management systems, parameters of the waste streams should be identified as accurately as possible. The forecast of spatial distributions of waste production and composition is a crucial step, because various factors may influence their development. For the estimation of the number of MSW fractions, population size and age, expected lifespan in the cities, and the total amount of MSW were considered by Ghinea et al. [28]. Several tools for the analysis and forecasting of time series were proposed for the study of MSW generation [29]. Hazardous waste forecasting and the corresponding mathematical model were developed to address the prediction problem with spatially distributed and uncertain data [30]. This model was based on regression analysis and data reconciliation.

Recent research focused on future planning and process integration or optimisation; however, the existing material flows, waste treatment options, and waste production with regard to the accuracy and credibility of input parameters were not justified or examined. The evaluation of a specific region requires up-to-date information on the transportation and treatment. Nevertheless, due to data aggregation, it is difficult to obtain high-quality inputs even though the legislations of countries with well-developed waste management systems force waste producers to submit their waste production and processing data.

In general, the records are kept in a large database, which is available in whole or in part to the public. The challenge here is to process the data in such a way that additional information is obtained for the design and optimisation of the waste management system. For efficient waste management planning, the information on the composition and waste treatment are not sufficient. It is necessary to add the data on waste flows, i.e., from where to where the wastes are transported. For example [31], identified the flows of construction and demolition wastes in China.

For many reasons, public databases on waste management contain inaccuracies and inconsistencies. These can be significant, while in many cases large amounts of data are completely missing. The following errors can typically be encountered:

- inconsistent registration methodology at the regional level;
- systematic errors in data recording and formatting;
- loss of information within the waste flow between waste management entities;
- duplicate data;
- missing data (errors caused by data aggregation).

These errors necessitate the identification of the actual material flows, while the lack of information on waste flows between individual entities involved in waste management represents a crucial problem. A material flow analysis was conducted e.g. for mined landfills and the respective energy consumption was calculated with the emphasis on logistics [32]. Another study analysed the flow of municipal waste for the Maltese Islands [33]. Carbon footprint was then assessed for both the current and the future situation through the estimation of waste flow. Material flow analysis was also used in multi-criteria decision-making [34] for the case when it was not possible to determine how waste from a specific producer was treated. The problem of unknown flows may be caused by e.g. different reporting methodologies. This greatly complicates future planning of waste management, as well as reporting and possible support from legislation applying to smaller regions. The processing chain of waste from wind turbines was identified through material flow analysis in Ref. [35] and the treatable percentage was given.

The mentioned studies deal mostly with aggregated flows due and material flows are evetually resolved within a certain process. Flow problems are addressed, but these are not concerned with information on specific streams between the producers and treatment facilities. However, none of the studies discusses in a complex manner the material flows in terms of their geographical distribution, available transport routes, and the links between the waste producers and the processing facilities.

1.3. Novel approach

The majority of published papers focus on predicting the future situation, while the current state of waste management – especially in case of bulky waste – is not properly analysed in any of them. There are no error identification techniques available. Systematic error balancing was therefore studied with regard to individual databases in Ref. [36]. The mentioned approach, combined with the economic aspect and presented as a network flow problem, was discussed in Ref. [37]. This problem is illustrated in the following example, which relates to the practice of reporting waste data (such reporting systems can be found in many countries and for various commodities).

Because waste is not always treated locally, mainly due to its production rate and available treatment capacities, it may be necessary to transport it between nodes (see Fig. 2). In Fig. 2a, the input data (production rates, treatment capacities) are shown and their mass balance has to be facilitated via transport. Fig. 2b and c show just two solutions out of the infinitely many feasible ones.

The set of feasible solutions may be further reduced by the application of additional constraints. For example, a minimum transport distance may be considered (see Section 2.2) or additional information on the flows along the edges and treatment options in the nodes may be available (see Section 2.1). This enables the identification of the existing network flows between producers and treatment facilities.

The presented approach concerns the analysis of waste flows and thus obtaining more data for other applications and future planning (establishing of new or extending of existing energy recovery facilities). The case study presented in Section 3 focuses on waste flows and treatment data reconciliation for identification of bulky waste potential for energy recovery. Czech Republic was selected as the region of interest to demonstrate the practical impacts of the presented methods. The flows from the producers to the processing nodes were modelled to discover the following:

- where the waste from a particular producer was processed;
- how the waste was treated in the target node and whether this was done in accordance with the waste treatment hierarchy (material recovery, energy utilisation, disposal).

Knowledge of these facts is key to identifying the potential of waste, analyzing the current state of treatment, and suggesting future plans (see Section 3).

The model introduced in this paper the network flow model principle where the material balance in nodes is guaranteed. It

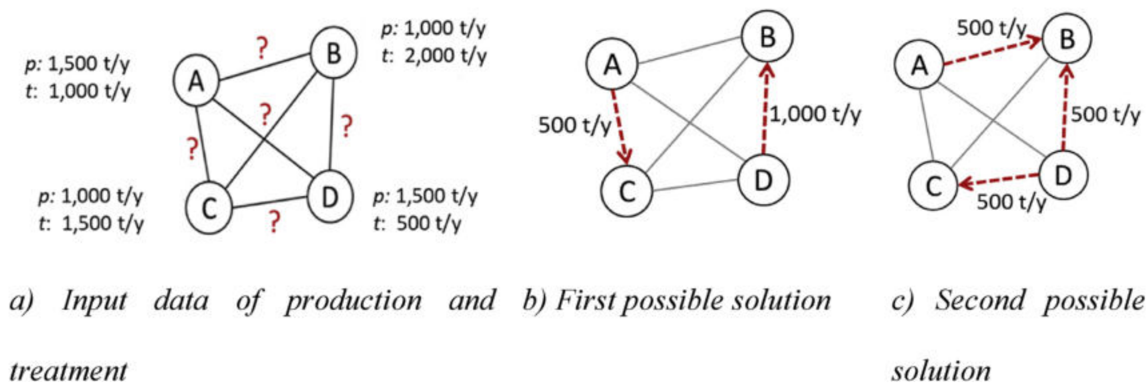


Fig. 2. The available sources and sinks with two possible solutions; *p* denotes production rate and *t* treatment capacity.

combines the identification of errors in the reported data (stored in a publicly accessible database) with minimisation of the total transported distance. The paper extends the ideas in Ref. [36], which focuses on the error identification, and [37], where uncertainties were considered in the waste network flows. The combination of both these approaches makes it possible to reveal the previously mentioned key information.

2. Methods

2.1. Mathematical model identifying errors

Credibility of input data plays the key role in network flow models. The data must also be balanced and verified to obtain credible results. Several approaches to data reconciliation are used in the industry [38]. Papers were published on data reconciliation used together with the fuzzy set theory and the underlying physics phenomena to form the constraints [39]. Another proposed application was nonlinear data reconciliation for material flows using the weighted least squares approach [40]. However, in most cases this concerned the identification of measurement errors or isolated systematic errors. For example, in Ref. [36] the effect of a large number of systematic errors in the data, which significantly restricted the applicability of common data reconciliation methods, was investigated. Other solutions are therefore needed to assess the current state and how waste management targets are being met.

The paper presents a mathematical model for elimination of errors in a large database of waste production and waste treatment data. This database is an essential source of information in waste management for subsequent analyses and planning. The data are collected from the entities (both producers and operators of treatment facilities) which, by law, are subject to annual reporting. However, the data are reported at different levels of detail starting with the whole country and continuing with regions and municipalities. They also come from different sources and thus the error rate increases.

Locations where waste is produced or processed represent nodes and the transport routes between them edges. The available data consist of production rates (p) and processing capacities (t) in the nodes, and flows through the edges. The producer and processing facilities for individual portions of the waste, however, are unknown due to the effects described in Ref. [41]. Errors may be present in the database in both the edge and the node data (causing the total production and processed amount being different).

The data in the utilised database are more suitable for the discussed purpose because the edge flows are recorded by two entities (the first entity hands the waste over to the second one, which receives it). This makes it easier to detect errors. The waste is transported from the source through the transfer node to the target facility. The exported amount E1 should be equal to the imported amount I1, and the same applies to E2 and I2. In practice, though, this often is not the case. Fig. 3 shows the case where E1, I1 and E2, I2 do not correspond.

The actual values x_1 and x_2 (further in the model denoted as $x_{j,o}$, where o is the producer and j the edge) in Fig. 3 are unknown due to the presence of errors. Such errors, be them random or systematic (which originate from reporting a value multiple times by different entities), limit the planning of future infrastructure.

The problem of how to handle the errors in the database is considered in this study as a waste flow data reconciliation task. Emphasis is placed on the node mass balances and the requirement on the minimum change from the input data. The total amount of waste that is imported into a node (I in Fig. 3) and produced there (p in Fig. 2) is equal to the amount of waste that is processed there (t in Fig. 2) or exported from this node (E in Fig. 3). Data quality is assessed and considered in a weighted procedure (see the terms in the objective function Eq (1)). If the amount of waste E1 is close to I1, then the weight is higher and there is no reason to assume that the values are incorrect. In any case, the issue described in this paper requires an additional viewpoint to preserve relations from the real operations.

2.2. Mathematical model using distances

The waste management chain consists of waste transfer, possible change in its properties, and final processing. Transport cost can be approximated using the respective distance due to its being proportional to fuel consumption. Environmental protection, especially nowadays when industrial production is increasing, is also a relevant factor. The relationship between transport distance, waste separation, and the corresponding economic perspective was addressed in Ref. [42]. A similar idea was transformed into a larger and more general scheme in Ref. [37].

An approach to determine the reverse logistics flow was proposed in Ref. [37]. The model objective was to optimise the flow of

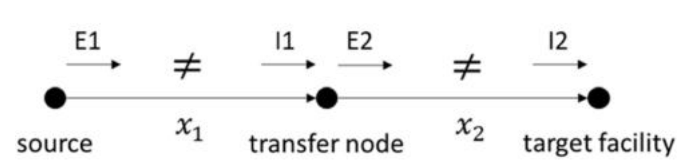


Fig. 3. Schematic chain of flows in the database.

non-utilisable products from producers to facilities. This could include uncertainties due to incomplete or unknown data, and decisions were made on the basis of distance. This criterion had economic background, where closer treatment facilities were preferred due to the lesser cost incurred. Also, scenario-based modelling was employed to allow for more distant facilities to simulate competition and more environmentally friendly options.

2.3. Complex approach

The previous sections deal with two mathematical models – the balance model (Section 2.1) and the model using distances to determine the actual waste flows (Section 2.2). The aim of the present paper is combine both models into a single, complex one. This approach provides a more realistic distribution of reconstructed waste flows because financial-based decisions of the producers are taken into consideration. The presented optimisation model maintains the balance in the nodes and detects the errors in the database with the aggregate waste production and treatment data. At the same time, the waste transport distance is minimised. The hierarchy of possible treatment options is considered according to the legislation, that is, the Directive 2008/98/EC on waste [43].

The proposed model (see Appendix A) evaluates and estimates the current state of waste handling and, due to the network structure, it is possible to find the corresponding waste flows. The resulting data must preserve the continuity of flow in the network. Fig. 4 shows a block schematic of the method.

This makes it possible to identify the processing methods for each producer and waste type. Corrective tools can then be proposed and micro-regions which fail to meet the global character of waste management, can be effectively motivated. The proposed approach verifies the historical data and the way they were handled to meet the generally valid balances. This is motivated by the following applications:

- analysis of the current state;
- necessary data for prognoses;
- identification of targets of the European Union;
- identification of wastes suitable for energy recovery (see Section 3 further).

To illustrate how balances are carried out for the nodes, and for simplicity's sake, only two treatment types (energy recovery and disposal) will be considered here. The vertical axis, i.e., the amount of waste produced and treated, is arbitrarily scaled and does not correspond to a real node. The graph (Fig. 5) is also separated into two parts: production and treatment. The overall production (p) can be processed via energy recovery or disposal (marked by different colours), and in the node where it was produced or in a different node to which it was exported (marked by different hatching styles). The combination of colour and hatching style then symbolises the selected treatment in the respective node and export from the node, respectively. Because the treatment capacity of the node is lower than waste production therein, a portion of the waste had to be exported. This is indicated by the differences in column heights. Also, columns are marked using K, U, or C according to the available data. Known data (K) were fixed, unknown data (U) were unavailable in the input database and therefore they were calculated by the model. Corrected data (C; namely the production in the node p_i and the transported amount $x_j^{\pm}$) were taken from the database, but they contained errors and had to be corrected. These were rectified while the relationships between all the node-related values had to be maintained.

To summarise, the goals were:

- Evaluate the methods by which the waste produced in the node was treated (column 3).
- Determine where the waste was treated, i.e., whether this was done directly in the production node or a certain portion was exported (column 5).
- In the case of import, find how the imported waste was treated (column 9).

3. Case study

3.1. Introductory information and input data

The approach discussed in Section 2 (i.e., the model described in Appendix A) has been applied to the regional-level(14 regions, see Fig. 6) bulky waste data from 2015 available for the Czech Republic.

The goal was to identify the regional distribution of production, treatment, and transport of bulky waste. Since several treatment methods were analysed, the obtained results were also used to define, on the regional basis, the potential of bulky waste for energy recovery. The amounts of waste which are currently landfilled were taken into account together with the amounts currently treated in WtE plants.

The input data came from the national database on waste management (waste management information system) [44], which has been operated by the Ministry of the Environment of the Czech Republic. The network describing the regional administrative division consisted of 14 nodes and, apart from production (p), the

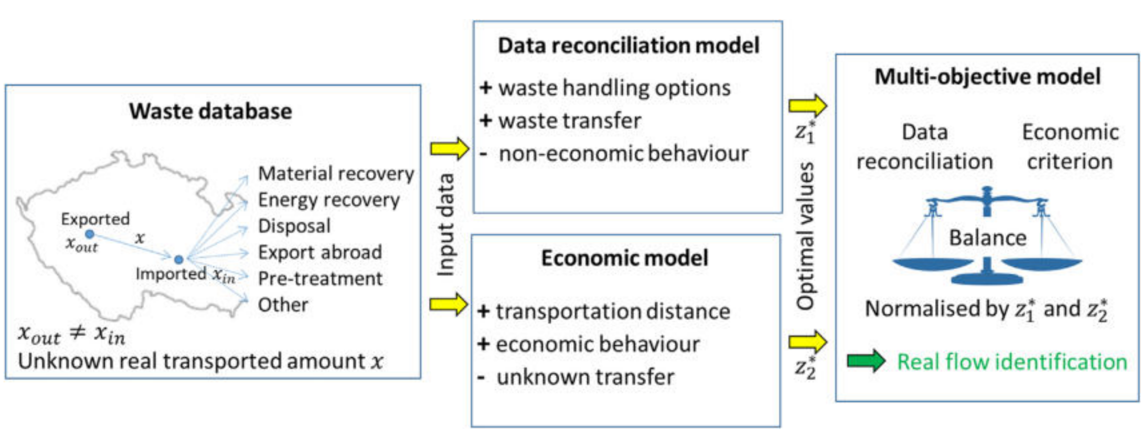


Fig. 4. Database repair – block schematic of flow identification.

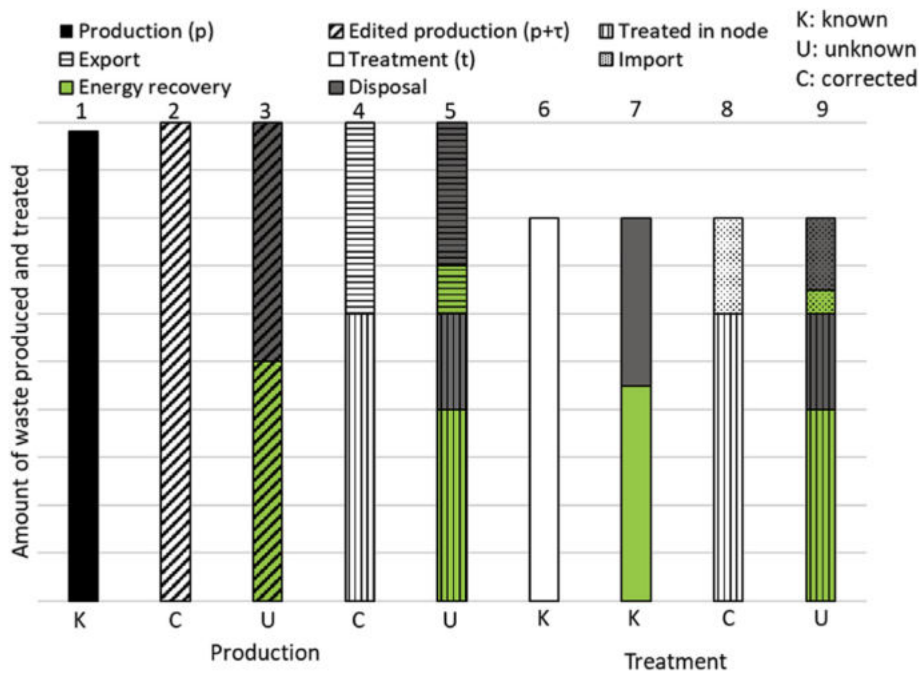


Fig. 5. Node balance.

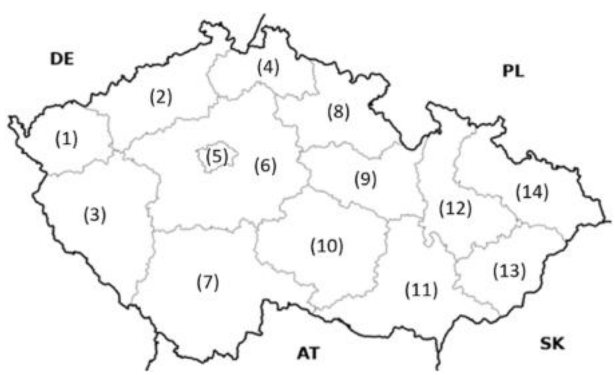


Fig. 6. 14 regions of the Czech Republic.

following treatment methods were considered:

- material recovery,
- energy recovery,
- national export abroad,
- pre-treatment,
- disposal,
- other way of processing.

Bulky waste represents a relatively large portion of MSW and its regional production p and treated amounts t are shown in Fig. 7. It can be seen that transports between regions are necessary. Considering geographical locations of the City of Prague (Region 5) and Central Bohemia (Region 6) and their productions and processing capacities, a significant transfer of waste between these two nodes can be expected.

It is beneficial to track the transfer of bulky waste between nodes. Compared to the example from Fig. 5, more treatment options make this task much more complicated. One should distinguish between:

- treated amounts by specific method l in region i ($t_{i,l}$),
- treated amounts in region i from the producer o by method l ($t^{O}_{i,o,l}$).

The flow in the network was reconstructed using the algorithm described in Appendix A. The lowest possible change from the original data was required. In addition, emphasis was placed on mass balances in the nodes (inherent due to the way the model was constructed). The value of parameter β was set to 0.5, which corresponded to no preferences in the weighted objective function.

3.2. Production and treatment balances

The results provide valuable information on the current handling of bulky waste, but they can be applied to other commodities of waste as well. The transport of waste from a producer through intermediate nodes to the respective processor can be tracked. The obtained data can serve as a basic dataset for future waste management planning. Fig. 8 shows the results with the amounts of treated bulky waste being split by treatment method for all considered regions.

The obtained data also include waste transfers among the regions. For example, in the City of Prague only a portion of the produced waste (ca. 19.8 kt) was treated, and around 48.5 kt were exported to the Central Bohemian Region. As a consequence, the rest of the treated waste was imported, even though the production in this region is higher than the treatment capacity (see the supplementary material). Ca. 0.7 kt were imported from the Karlovy Vary Region, ca. 0.2 kt from the Hradec Králové Region, ca. 0.6 kt from the Plzeň Region, and ca. 16.4 kt from the Central Bohemian Region. It is worth mentioning here, however, that a WtE plant is operated in the City of Prague (i.e., some waste from Central Bohemia was imported to the City of Prague due to a preferable treatment option, which is not available in the region of origin). Such transfers seem to conflict with the mathematical model using distances, but are the consequence of the distance between the City of Prague and Central Bohemian Region being artificially set to zero

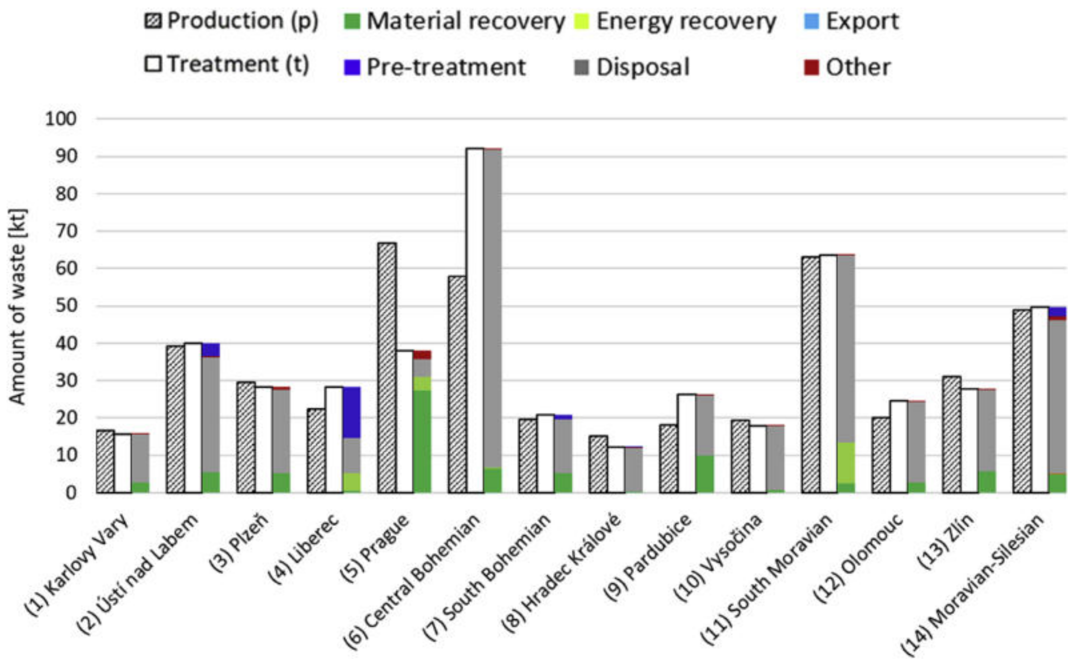


Fig. 7. Bulky waste production (p) and treatment (t) in the regions (input data).

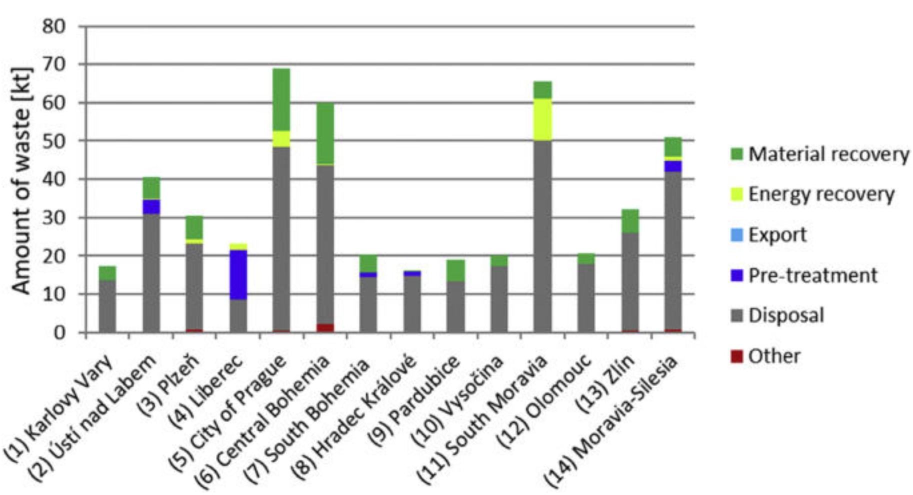


Fig. 8. Results for treatment of bulky waste produced in the specific regions.

because of their geographical arrangement.

Fig. 9 shows the waste treatment methods used in the regions of the Czech Republic. The most common method is disposal (landfilling or incineration without energy recovery; shown in grey). It represents more than 70% in almost all the regions, while ca. 360 kt in total were disposed of using this method in the Czech Republic in 2015.

The second most common treatment method is material recovery (80 kt in total). There were only 3 regions where WtE plants were operated in 2015 (the City of Prague, South Moravia, and Liberec regions). Most of the waste that was used for energy recovery (20 kt) was therefore produced in these regions.

3.3. Transport

The locations where the waste was transported to, were also obtained using the model. To provide comprehensive results, the Pardubice Region was selected for detailed investigation. Fig. 7 shows that the production of bulky waste in the Pardubice Region was lower than the treated amount with the difference being approx. 8 kt. The map in Fig. 10 shows the three regions (except for the Pardubice Region itself) where waste was produced and subsequently transported to the Pardubice Region for final treatment. Specifically, these were the Hradec Králové Region, the Vysočina Region, and the South Moravia Region, which are all adjacent or close to the Pardubice Region. The transport distances were therefore relatively short.

Although not all these regions are the exporting ones (see Fig. 9), transport between them was revealed, which was not apparent from a simple production–treatment balance, $((p + \tau) - t)$. Even the region where the production is lower than the processed amount, $((p + \tau) < t)$, can export waste. This feature is captured by the presented approach.

Most of the waste (18.8 kt, i.e., 71.9%) which was treated in the

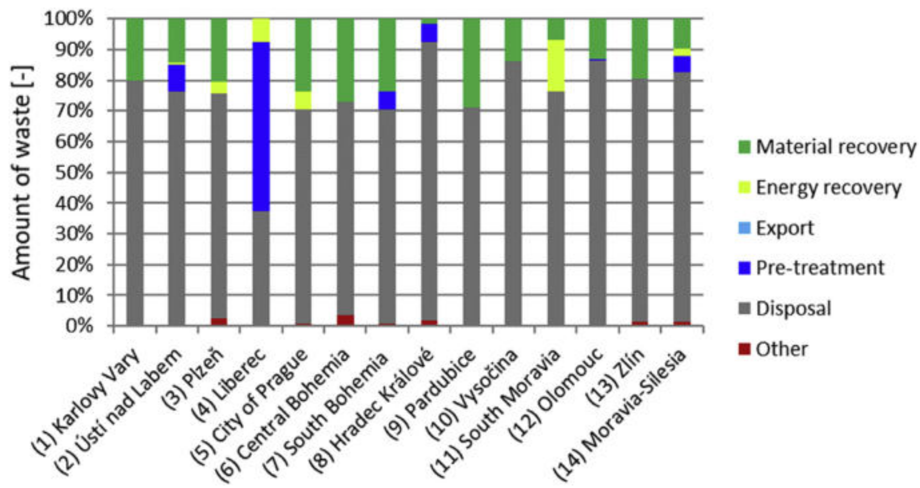


Fig. 9. Utilisation of bulky waste treatment options produced in individual regions.

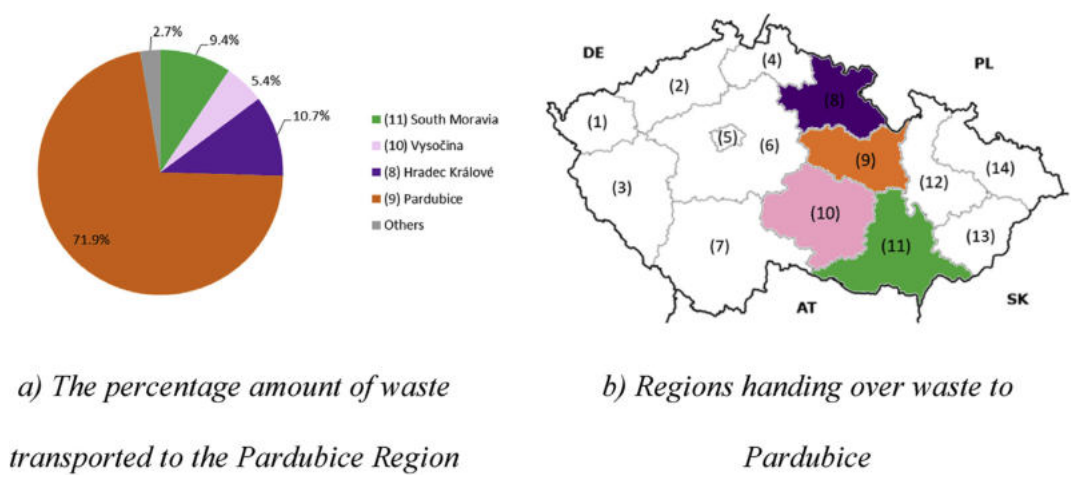


Fig. 10. Pardubice Region – sinks for produced waste.

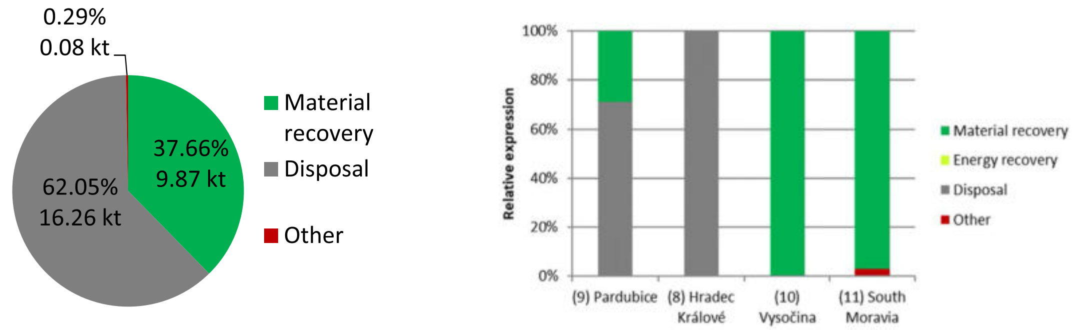
Pardubice Region (coloured orange in the map) originated in the same region. This corresponded to the assumption that waste should be transported the shortest distance possible. The actual transported amounts of waste to the Pardubice Region were 2.8 kt from the Hradec Králové Region, 2.5 kt from the South Moravia Region, and 1.4 kt from the Vysočina Region. Other regions accounted for negligible amounts of waste (0.002–0.4 kt, 0.7 kt in total) imported to the Pardubice Region.

Fig. 11b shows the treatment methods for waste produced in other regions, but treated in the Pardubice Region. The following methods were used there: material recovery (9.9 kt in total), disposal (16.3 kt in total), and other (0.08 kt in total), see Fig. 11a. The waste produced in the Pardubice Region was either disposed of in this region (13.4 kt) or materially recovered (5.4 kt). The waste imported to the Pardubice Region was mostly recovered to produce secondary raw materials (4.5 kt), while almost all the rest was disposed of (2.8 kt). Only a very small amount of waste (0.1 kt) was processed in a different way.

Eastern Bohemia, that is, the Pardubice and Hradec Králové regions, is an area where a future WtE plant is considered. For example, a plant in Pardubice was discussed a few years ago in Ref. [45]. The total heat demand, which is important for efficient operation of such a plant, is about 3500 TJ/year [46]. One of the largest power plants of the Czech Republic is operated in Opatovice nad Labem; only 10 km from Hradec Králové (ca. 93,000. inhabitants) and 15 km from Pardubice (ca. 90,000 inhabitants). The heat produced in the WtE plant could be transported to both cities and the surrounding area via the existing district heating network. This could mean even better utilisation of waste because a portion of the disposed waste could be used to generate energy (waste from the Pardubice Region and the Hradec Králové Region is mainly disposed of as shown in Fig. 11).

The waste transferred to the Pardubice Region is reported to be used in accordance with waste hierarchy (materially recovered). It is not desirable to transport a large amount of waste to treat it by a less preferred method (pre-treatment, disposal, other). However, the mathematical model must respect the input data and thus it sometimes suggests to transport waste to farther treatment facilities. In any case, the results are quite similar for all regions and meet all the objectives (economic and environmental). Transport of waste to different regions is realised mainly for material and energy recovery. In some cases, waste is transported to be treated using other methods. It can be assumed that the model is well designed, but to validate it, data at a higher level of detail (i.e., from individual micro-regions or even individual producers/treatment facilities) would be needed.

The largest amount of waste transported to the Pardubice Region came from the Hradec Králové Region, which leads to the



a) Overall treatment options in the Pardubice Region

b) Treatment options in the Pardubice Region of the waste produced in the specific regions

Fig. 11. The Pardubice Region – transport and processing of waste.

analysis of the waste produced there. Fig. 12 shows that a large amount of the waste produced in the Hradec Králové Region was not transported anywhere, but processed directly in the region. Focusing on the exported waste only, most of it was transferred to the Pardubice Region. The remainder was sent to the Liberec Region, and a small amount to the City of Prague.

Fig. 13 shows how the waste produced in the Hradec Králové Region was processed in the target regions. All the waste transported to the City of Prague was processed by "other" methods. The waste which was sent to the Liberec Region was entirely pretreated. It is likely that, in the end, it was used for energy recovery because there is a WtE plant in Liberec. Otherwise, the waste was disposed of.

With reference to Figs. 12 and 13, it is obvious that bulky waste produced in the Hradec Králové Region was not used in line with the waste management hierarchy. Only 0.2 kt were used for production of secondary raw materials, 1.0 kt was pre-treated (one can assume that it was used for energy recovery), 0.3 kt were processed in other way, and 14.5 kt were disposed of. This means that nearly 91% of the waste was disposed of.

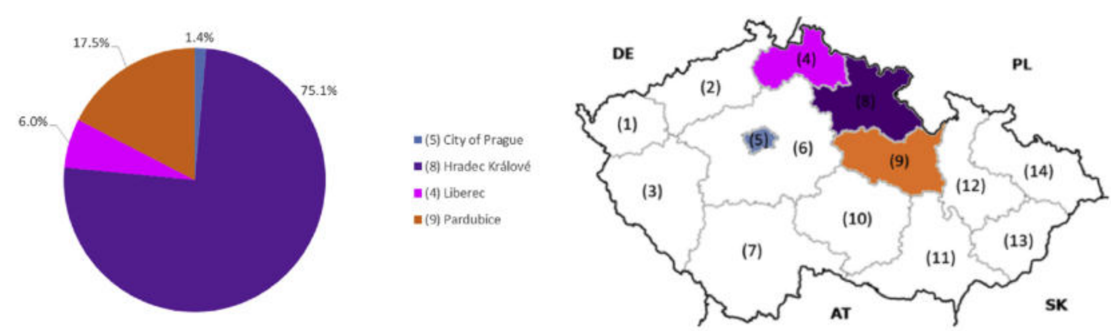
3.4. Bulky waste potential for energy recovery

The results discussed in the previous sections were used to identify the potential of bulky waste for energy recovery. These are summarised in Table 1, which compares the situation from 2015 with the future potential in terms of both the amount of waste and energy content.

Average value of LHV for bulky waste (approx. 20 GJ/t) was taken from Ref. [27]. Considering the total capacity of 650 kt/y of all the WtE plants operating in the Czech Republic, the overall potential for energy recovery from bulky waste was 2,494,710 GJ in 2015. The produced heat would then depend on the actual production efficiency. An analysis of utilisation of such heat in the district heating system and by the industry was done by Putna et al. [47] for the purposes of modelling of heat demand. Compared to the modelling of individual regions, this identified a large energy potential, which meant that there were suitable conditions for building new facilities or increasing the capacities of the existing ones.

4. Conclusions

A complex approach to waste data reconciliation through error elimination and network flow analysis is presented. It takes into account two aspects: detection of errors in input data obtained



a) The percentage amount of waste transported from the Hradec Králové Region

b) Regions taking over waste from Hradec Králové Region

Fig. 12. Transport of waste from the Hradec Králové Region.

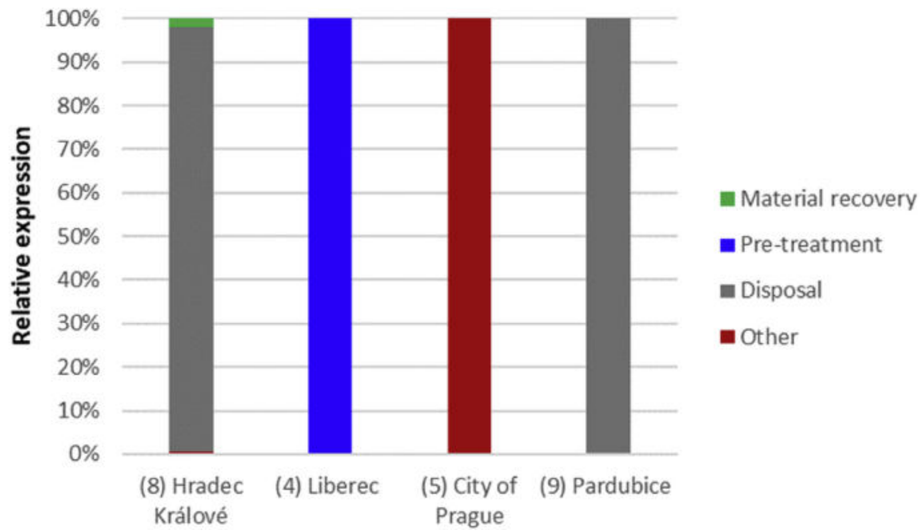


Fig. 13. The percentage amounts of the waste produced in the Hradec Králové Region according to methods of treatment in various regions.

Table 1
Results of potential increase in energy recovery from bulky waste.

Region	Energy recovery in 2015 [t]	Additional Potential in 2015 [t]	Unrealised potential in 2015 [GJ]
City of Prague	4221	52,321	962,000
South Bohemia Region	0	14,285	285,700
South Moravia Region	10,861	60,818	999,140
Karlovy Vary Region	0	13,668	273,360
Vysočina Region	0	17,266	345,320
Hradec Králové Region	0	14,547	290,940
Liberec Region	1722	10,342	172,400
Moravia-Silesia Region	1172	42,380	824,160
Olomouc Region	0	17,929	358,580
Pardubice Region	0	13,425	268,500
Plzeň Region	1135	23,556	448,420
Central Bohemia Region	91	41,821	834,600
Ústí nad Labem Region	365	31,246	617,620
Zlín Region	7	25,472	509,300
Total	**19,574**	**379,076**	**7,190,040**

from the waste reporting database and transport distance, which keeps the results economically feasible. The weights used in the multi-objective function are set according to data credibility, while the segregated nature of the model makes it possible to identify the potential of waste for energy recovery. The presented model therefore takes an incomplete dataset, which also is inconsistent, contains errors, and for which waste treatment methods are not known, and transforms it into a complete dataset with known information on waste flow between producers and treatment facilities, treatment method used, etc.

The model was tested on the Czech Republic waste database data from 2015. Bulky waste management was considered at the regional level and the energy potential was calculated and compared to the current situation. It was found that only 19.6 kt of bulky waste was used for energy recovery in contrast to the remaining 379.1 kt processed otherwise, i.e., the unrealised potential was 7190 TJ. A completely new perspective on the current state of waste management was created, and valuable information for the next waste management planning was provided. Future research should be focused on testing of the model using data corresponding to a lower territorial level (micro-regions). Still, this would bring multiple challenges [48]. Another research direction could be the improvement in the way uncertainties are handled.

Acknowledgements

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.energy.2019.05.175.

Appendix B. Mathematical model

The model is built in a form of a multi-objective optimisation problem and, in its present state, is tailored to the specifics of the waste management data reporting system of the Czech Republic. Mandatory reporting applies to all entities handling waste and transported waste is recorded twice – by the sender (scenario (−)) and by the receiver (scenario (+)). Both these record types provide significant information to the model because there are no details about the quality of individual data. The model also minimises transport distances to simulate the economic behaviour of the producers.

Sets			
$i,o\in I$	Nodes	$l\in L$	Waste treatment options
$j\in J$	Edges	$j\in J(i)$	Edges of cycle for node i
Parameters			
$x_j^{\pm}$	Amount of waste transferred on edge$j$ according to the scenario + or − (carry to/take away)	β	The weight of the objective function
$A_{i,j}^{\pm}$	Incidence matrix for the scenario + or −	M	Upper bound-related big constant
p_i	Waste production in the node i	$\delta_{i,o}$	Binary indicator $\begin{cases} 1 & if\ i = o \\ 0 & if\ i \neq o \end{cases}$
$t_{i,l}$	Waste treatment type l in the node i	z_1^*, z_2^*	Optimal objective function values
w_j	The weight of the edge j, $w_j\in(0;1)$	a	The threshold for the zero penalization
d_j	Length of the edge j	W	Weight of penalization
Variables		**Positive variables**	
z_1, z_2, z_3	Objective functions	$\varepsilon_j^{\pm\pm}$	The positive or negative part of the error ε_j^+ or ε_j^-
τ_i	Error in the production in the node i	$t_{i,o,l}^O$, $t_{i,o,l}^{O,dir}$, $t_{i,o,l}^{O,cyc}$	Treatment of the waste in the node i from the producer o type l; divided into direct and cycled treated amount
y_i	Penalization	$x_{j,o}$, $x_{j,o}^{out}$	Amount of shipped waste from the producer o on the edge j; divided into cycled and direct outflows
$\varepsilon_j^{\pm}$	Error on the edge j according to the scenario + or -	$y_i^{\pm}$	The positive or negative part of the penalization y_i

The proposed model consists of three objective functions Eq (1) – Eq (3). The used equations, as well as the nomenclature, are summarised below.

$$z_1 = \sum_{j\in J}\left(\varepsilon_j^{-+} + \varepsilon_j^{--} + \varepsilon_j^{++} + \varepsilon_j^{+-}\right)w_j + W\sum_{i\in I}\left(y_i^+ + y_i^-\right) \tag{1}$$

$$z_2 = \sum_{j\in J}\sum_{i\in I} d_j x_{j,i} + W\sum_{i\in I}\left(y_i^+ + y_i^-\right) \tag{2}$$

$$z_3 = \frac{\beta z_1}{z_1^*} + \frac{(1-\beta)z_2}{z_2^*} \tag{3}$$

s.t.

$$\sum_{j\in J\setminus J(i)} A_{i,j}^+ x_{j,o} + \delta_{i,o}(p_i + \tau_i) \quad \forall i,o\in I \tag{4}$$

$$t_{i,l} = \sum_{o\in I} t_{i,o,l}^O \quad \forall i\in I, \forall l\in L \tag{5}$$

$$p_o + \tau_o = \sum_{i\in I}\sum_{l\in L} t_{i,o,l}^O \quad \forall o\in I \tag{6}$$

$$\sum_{j\in J} A_{i,j}^+ x_{j,o} + \delta_{i,o}(p_i + \tau_i) = \sum_{j\in J} A_{i,j}^- x_{j,o} + \sum_{l\in L} t_{i,o,l}^O \quad \forall i,o\in I \tag{7}$$

$$x_j^+ + \varepsilon_j^+ = \sum_{i\in I}\sum_{o\in I} A_{i,j}^- x_{j,o} \quad \forall j\in J \tag{8}$$

$$x_j^- + \varepsilon_j^- = x_j^+ + \varepsilon_j^+ \quad \forall j\in J \tag{9}$$

$$x_j^- + \varepsilon_j^- \geq 0 \quad \forall j\in J \tag{10}$$

$$p_i + \tau_i \geq 0 \quad \forall i\in I \tag{11}$$

$$\varepsilon_j^- = \varepsilon_j^{-+} - \varepsilon_j^{--} \quad \forall j\in J \tag{12}$$

$$\varepsilon_j^+ = \varepsilon_j^{++} - \varepsilon_j^{+-} \quad \forall j\in J \tag{13}$$

$$y_i = \tau_i - a p_i \quad \forall i\in I \tag{14}$$

$$y_i = y_i^+ - y_i^- \quad \forall i\in I, \tag{15}$$

$$x_{i,o}^{dir} + \sum_{j\in J(i)} x_{j,o} - t_{i,o}^{O,cyc} = \sum_{j\in J\setminus J(i)} A_{i,j}^- x_{j,o} \quad \forall i,o\in I \tag{16}$$

$$\sum_{l\in L} t_{i,o,l}^O = t_{i,o}^{O,cyc} + t_{i,o}^{O,dir} \quad \forall i,o\in I \tag{17}$$

The computation is done in two phases. Optimisation problems involving just the objective function Eq (1) or Eq (2) and constraints Eq (4) – Eq (17) are solved first. The obtained optima are normalised using z_1^* and z_2^*. The entire problem including all three objective functions is solved afterwards.

Objective function Eq (1) minimises the weighted total error in the database to ensure the balance in each node. The first summation deals with errors on the edges for scenarios (+) and (−), the weight w_j determines data quality based on both scenarios (see Eq (18)). If the sending and receiving nodes recorded a similar value (scenarios (+) and (−) are similar), then it can be assumed that the data are correct. In such a case the weight w_j is higher.

$$w_j = \begin{cases} M, & x_j^-, x_j^+ = 0 \\ \dfrac{x_j^- + x_j^+}{2\left|x_j^- - x_j^+\right|}, & otherwise \end{cases} \quad \forall j\in J \tag{18}$$

The second summation in the objective function Eq (1) takes into account penalization in the nodes.

The second objective function Eq (2) minimises the total transport distance, which simulates economic behaviour of the producers. Eq (3) combines the two different factors, which are minimised in the Eq (1) and Eq (2) and normalised by z_1^* and z_2^* from the initial separate computations. The priorities of z_1 (Eq (1)) and z_2 (Eq (2)) in z_3 (Eq (3)) are given by the parameter β.

The first constraint Eq (4) ensures the validity of the balance in each node for edges of cycle for node i. Eq (5) defines the total amount of the treated waste in the node i as a sum of the treated amounts from all producers. Eq (6) says that all waste produced by producer o is treated somewhere by one or more methods l. The data on production p_i and treatment $t_{i,l}$ are known in the node i. The total production ($\sum_{i\in I} p_i$) and treatment ($\sum_{i\in I,\, l\in L} t_{i,l}$) are not equal due to export/import issues or errors. If an error is present, it is expected only on the production side due to the way the data are recorded, and so the production p_i is corrected by error τ_i when applicable. This production adjustment is included in the objective function in the form of the penalty function Eq (14). Also, equality between corrected production $(p_i + \tau_i)$ and overall treatment in the specific node i ($\sum_{l\in L} t_{i,l}$)is not ensured because of export and import of waste. This means that the waste transported from a different node can be treated in the node i by a method l. Eq (7) keeps the flow balance for each producer o. The sum of waste shipped to the node i and produced there (if $i = o$) equals to the sum of waste shipped away and processed in the node i. This is achieved through the identification of errors in production data $\tau_i$and transport data $\varepsilon_j^{\pm}$. In the Eq (8), the flow reported in the database is connected with the edge flows (total amounts of the waste match – exported and imported). The equality of both scenarios (+) and (−) is assured by Eq (9), thus the amount of waste that was transported along the edge j is taken over in the appropriate node. Eq (10) and Eq (11) are the constraints for non-negative waste flows on each edge j and waste productions in each node i. Splitting of errors into their positive and negative parts is reflected in Eq (12) and Eq (13). The penalty y_i is calculated according to Eq (14) and splitting of the penalty into its positive and negative parts is in Eq (15). Eq16 and 17 distribute the flows of a producer into the outflows and treated amounts in the respective node while considering cycle edges.

Selection of the threshold for zero penalty a was described in Ref. [36]. Penalization y_i is a part of the objective function Eq (1) because the recorded data can contain errors on case of both the edges $j$and nodes i. The production and processing of waste is recorded in the nodes. Errors are more likely to be expected on the producers' side who are subject to the annual reporting obligation. Data inconsistency can be solved by integrating the penalty into optimisation problems, specifically into all the objective functions. The idea behind the penalty function is shown in Figure A1.

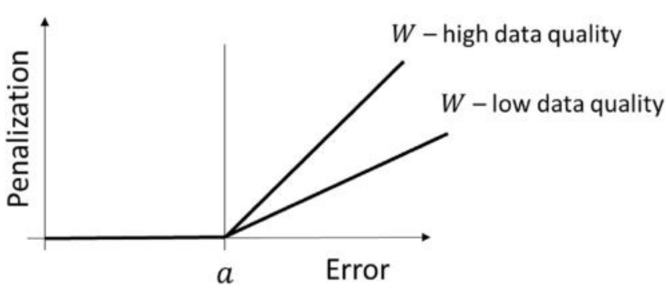

Fig. A1. Penalty function.

The actual threshold for zero penalty a in Eq (14) was set according to Eq (19), which corresponds to the ratio of an average change of production and the average production to maintain the processing–treatment balance. The parameter a actually determines the error ratio for each producer (assuming that each producer contributes to the overall error equally).

$$a = \frac{\sum_{i\in I}\left(\sum_{l\in L} t_{i,l} - p\right)}{\sum_{i\in I} p_i} \tag{19}$$

The calculation of the penalization weight W is done as shown in Eq (20). Essentially, it is the average of edge weights for which the deviation of input parameters is non-negligible.

$$W = \frac{1}{|J|_{j:w_j \neq M}} \sum_{j\in J: w_j \neq M} w_j \tag{20}$$

References

[1] Hoornweg D, Bhada-Tata P. What a Waste: A Global Review of Solid Waste Management. Urban development series knowledge papers; 2012. p. 15.
[2] Korhonen J, Honkasalo A, Seppälä J. Circular economy: The concept and its limitations. Ecol Econ 2018;43:37–46. https://doi.org/10.1016/j.ecolecon.2017.06.041.
[3] Directive (EU) 2018/849 of the European Parliament and of the Council of 30 May 2018 amending Directives 2000/53/EC on end-of-life vehicles, 2006/66/EC on batteries and accumulators and waste batteries and accumulators, and 2012/19/EU on waste electrical and electronic equipment, 93–99.
[4] Directive (EU) 2018/850 of the European Parliament and of the Council of 30 may 2018 amending directive 1999/31/EC on the landfill of waste (Text with EEA relevance), 100–108.
[5] Directive (EU) 2018/851 of the European Parliament and of the Council of 30 may 2018 amending directive 2008/98/EC on waste, 109–140.
[6] Directive (EU) 2018/852 of the European Parliament and of the Council of 30 may 2018 amending directive 94/62/EC on packaging and packaging waste, 141–154.
[7] Tanmoy K, Bhagat RM, Bhattacharyya P. Municipal solid waste generation, composition, and management: The world scenario. Crit Rev Environ Sci Technol 2012;42(15):1509–630. https://doi.org/10.1080/10643389.2011.569871.
[8] Malinauskaite J, Jouhara H, Czajczyńska D, Stanchev P, Katsou E, Rostkowski P, Thorne RJ, Colón J, Ponsá S, Al-Mansour F, Anguilano L, Krzyżyńska R, López IC, Vlasopoulos A, Spencer N. Municipal solid waste management and waste-to-energy in the context of a circular economy and energy recycling in Europe. Energy 2017;141:2013–44. https://doi.org/10.1016/j.energy.2017.11.128.
[9] Ferdan T, Šomplák R, Zavíralová L, Pavlas M, Frýba L. A waste-to-energy project: A complex approach towards the assessment of investment risks. Appl Therm Eng 2015;89:1127–36. https://doi.org/10.1016/j.applthermaleng.2015.04.005.
[10] Bogacka M, Pikoń K, Landrat M. Environmental impact of PV cell waste scenario. Waste Manag 2017;70:198–203. https://doi.org/10.1016/j.wasman.2017.09.007.
[11] Varbanov PS, Klemeš JJ, Wang X. Methods optimisation, Process Integration and modelling for energy saving and pollution reduction. Energy 2018;146:1–3. https://doi.org/10.1016/j.energy.2018.01.122.
[12] Tabasová A, Kropáč J, Kermes V, Nemet A, Stehlík P. Waste-to-energy technologies: Impact on environment. Energy 2012;44(1):146–55. https://doi.org/10.1016/j.energy.2012.01.014.
[13] Eskandarpour M, Dejax P, Miemczyk J, Péton O. Sustainable supply chain network design: An optimization-oriented review. Omega 2015;54:11–32. https://doi.org/10.1016/j.omega.2015.01.006.
[14] Klemeš JJ, Varbanov PS, Walmsley TG, Jia X. New directions in the implementation of pinch methodology (PM). Renew Sustain Energy Rev 2018;98:439–68. https://doi.org/10.1016/j.rser.2018.09.030.
[15] Lee CKM, Yeung CL, Xiong ZR, Chung SH. A mathematical model for municipal solid waste management – a case study in Hong Kong. Waste Manag 2016;58:430–41. https://doi.org/10.1016/j.wasman.2016.06.017.
[16] Fiorentino G, Ripa M, Protano G, Hornsby C, Ulgiati S. Life cycle assessment of mixed municipal solid waste: Multi-input versus multi-output perspective. Waste Manag 2015;46:599–611. https://doi.org/10.1016/j.wasman.2015.07.048.
[17] Tomić T, Dominković DF, Pfeifer A, Schneider DR, Pedersen AS, Duić N. Waste to energy plant operation under the influence of market and legislation conditioned changes. Energy 2017;137:1119–29. https://doi.org/10.1016/j.energy.2017.04.080.
[18] Chung S-S, Lau K-YW, Zhang C. Measuring bulky waste arisings in Hong Kong. Waste Manag 2010;30:737–43. https://doi.org/10.1016/j.wasman.2010.01.009.
[19] MacDonald EF, She J. Seven cognitive concepts for successful eco-design. J Clean Prod 2015;92:23–36. https://doi.org/10.1016/j.jclepro.2014.12.096.
[20] TSO. The Controlled waste Regulations 1992. The Stationery Office Limited, ISBN 0110235886, London, UK.
[21] Czech Statistical Office. Generation, recovery and disposal of waste. Prague: Environment; 2016. October 2016, Publication Code: 280020-16, 1, Available at: https://www.czso.cz/documents/10180/49151919/28002016.pdf.
[22] Curran A, Williams ID, Heaven S. Management of household bulky waste in England. Resour Conserv Recycl 2007;51(1):78–92. https://doi.org/10.1016/j.resconrec.2006.08.003.
[23] Ramusch R, Pertl A, Scherhaufer S, Schmied E, Obersteiner G. Modelling informally collected quantities of bulky waste and reusable items in Austria. Waste Manag 2015;44:3–14. https://doi.org/10.1016/j.wasman.2015.07.015.
[24] EPD. Monitoring of Solid Waste in Hong Kong: Waste Statistics for 2007. Hong Kong: Environmental Infrastructure Division; 2008.
[25] Reeve S. Local Authority Good Practice in the Re-use and Recycling of

Household Collection Bulky Item Waste Stream: Literature Review. Report for Defra. Bristol: Network Recycling; 2004.
[26] Cole C, Osmani M, Wheatley A, Quddus M. Bulky household waste management in a UK local authority area: Current practice, challenges and improvement opportunities. In: Proceedings of Fourteenth International waste management and landfill Symposium, S. Margherita Di Pula; 2013. Cagliari, Italy; September 2013.
[27] Garcés D, Díaz E, Sastre H, Ordóñez S, González-LaFuente JM. Evaluation of the potential of different high calorific waste fractions for the preparation of solid recovered fuels. Waste Manag 2016;47:164–73. https://doi.org/10.1016/j.wasman.2015.08.029.
[28] Ghinea C, Drăgoi EN, Comăniță E-D, Gavrilescu M, Câmpean T, Curteanu S, Gavrilescu M. Forecasting municipal solid waste generation using prognostic tools and regression analysis. J Environ Manag 2016;182:80–93. https://doi.org/10.1016/j.jenvman.2016.07.026.
[29] Navarro-Esbrí J, Diamadopoulos E, Ginestar D. Time series analysis and forecasting techniques for municipal solid waste management. Resour Conserv Recycl 2002;35(3):201–14. https://doi.org/10.1016/S0921-3449(02)00002-2.
[30] Pavlas M, Šomplák R, Smejkalová V, Nevrlý V, Szásziová L, Kůdela J, Popela P. Spatially distributed production data for supply chain models - forecasting with hazardous waste. J Clean Prod 2017;161:1317–28. https://doi.org/10.1016/j.jclepro.2017.06.107.
[31] Zheng L, Wu H, Zhang H, Duan H, Wang J, Jiang W, Dong B, Liu G, Zuo J, Song Q. Characterizing the generation and flows of construction and demolition waste in China. Constr Build Mater 2017;136:405–13. https://doi.org/10.1016/j.conbuildmat.2017.01.055.
[32] Hölzle I. Analysing material flows of landfill mining in a regional context. J Clean Prod 2019;207:317–28. https://doi.org/10.1016/j.jclepro.2018.10.002.
[33] Camilleri-Fenech M, Oliver-Solà J, Farreny R, Gabarrell X. Where do islands put their waste? – a material flow and carbon footprint analysis of municipal waste management in the Maltese Islands. J Clean Prod 2018;195:1609–19. https://doi.org/10.1016/j.jclepro.2017.07.057.
[34] Makarichi L, Techato K-a, Jutidamrongphan W. Material flow analysis as a support tool for multi-criteria analysis in solid waste management decision-making. Resour Conserv Recycl 2018;139:351–65. https://doi.org/10.1016/j.resconrec.2018.07.024.
[35] Tazi N, Kim J, Bouzidi Y, Chatelet E, Liu G. Waste and material flow analysis in the end-of-life wind energy system. Resour Conserv Recycl 2019;145:199–207. https://doi.org/10.1016/j.resconrec.2019.02.039.
[36] Šomplák R, Nevrlý V, Smejkalová V, Pavlas M, Kůdela J. Verification of information in large databases by mathematical programming in waste management. Chem Eng Trans 2017;61:985–90. https://doi.org/10.3303/CET1761162.
[37] Šomplák R, Nevrlý V, Málek M, Pavlas M, Klemeš JJ. Network flow based model applied to sources, sinks and optimal transport of combustible waste. Chem Eng Trans 2017;61:991–6. https://doi.org/10.3303/CET1761162.
[38] Jiang X, Liu P, Li Z. Data reconciliation and gross error detection for operational data in power plants. Energy 2014;75:14–23. https://doi.org/10.1016/j.energy.2014.03.024.
[39] Džubur N, Sunanta O, Laner D. A fuzzy set-based approach to data reconciliation in material flow modeling. Appl Math Model 2017;43:464–80. https://doi.org/10.1016/j.apm.2016.11.020.
[40] Cencic O. Nonlinear data reconciliation in material flow analysis with software STAN. Sustain Environ Res 2016;26(6):291–8. https://doi.org/10.1016/j.serj.2016.06.002.
[41] Šomplák R, Pavlas M, Nevrlý V, Touš M, Popela P. Contribution to Global Warming Potential by waste producers: Identification by reverse logistic modelling. J Clean Prod 2019;208:1294–303. https://doi.org/10.1016/j.jclepro.2018.10.165.
[42] Struk M. Distance and incentives matter: The separation of recyclable municipal waste. Resour Conserv Recycl 2017;122:155–62. https://doi.org/10.1016/j.resconrec.2017.01.023.
[43] Directive (EU) 2008/98/EC of the European Parliament and of the council on waste and repealing certain directives. Off. J. Eur. Union, L312, pp. 3–30.
[44] Ministry of the environment of the Czech Republic. Public waste management information system. available from: https://isoh.mzp.cz/VISOH/Main/ZpravyZp.
[45] Malek SA. Waste-to-Energy in Eastern and South Eastern Europe. In: Karagiannidis A, editor. Waste to Energy: Opportunities and Challenges for Developing and Transition Economies. London: Springer; 2012. https://doi.org/10.1007/978-1-4471-2306-4_11.
[46] Elektrárny Opatovice, a.s. Annual report 2017. In Czech: Výroční zpráva. https://www.eop.cz/vyrocni-zpravy. [Accessed 24 October 2018].
[47] Putna O, Janošťák F, Šomplák R, Pavlas M. Demand modelling in district heating systems within the conceptual design of a waste-to-energy plant. Energy 2018;163:1125–39. https://doi.org/10.1016/j.energy.2018.08.059.
[48] Kůdela J, Popela P. Warm-start cuts for generalized benders decomposition. Kybernetika 2017;53(6):1012–25. https://doi.org/10.14736/kyb-2017-6-1012.

Příloha 10: Modelling of waste separation scenarios at the municipal level to meet state targets

Modelling of Waste Separation Scenarios at the Municipal Level to Meet State Targets

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Abstract

Efforts to save the environment and primary resources have led to the release of a Circular Economy Package by EU. One of the basic principles is to turn waste into raw material and use the potential hidden in waste. The fulfilment of recycling targets at the state level is the result of the activity of lower territorial units. For the required waste recycling, it is necessary to achieve adequate waste separation already in households and companies. The presented approach divides state goals (changes) into lower territorial units regarding the current state (potential for change). The uniqueness of the presented approach is mainly in the use of the properties of the hierarchical data structure, the coherence of the process at the national and regional levels needs to be ensured. Potential for increasing waste separation is identified, it is assumed that all municipalities contribute to increasing the separation efficiency until the separation potential is fulfilled. The scenario is modelled for multiple waste fractions simultaneously, considers the transfer of waste from the unseparated residue to the separated waste and the separation of a new waste fraction. The results will be useful in waste management planning at the state level and will help to effectively target the necessary measures. The scenario modelling is presented on waste production in the Czech Republic. The separation efficiency from mixed municipal waste is estimated on 72 % based on business-as-usual scenario in summary for all waste fractions considered. According to the modelled scenarios, the separation can be increased to 73%, 77% and 87 %. Based on the business-as-usual scenario, the intervention is recommended to target the western part of the country in particular.

Keywords
Waste separation; material recovery, territorial hierarchy; Circular Economy Package; mixed municipal waste; bulky waste

1. Introduction

In waste management (WM) there is a strong emphasis on the protection of the environment and the primary resources saving. To support this, one of the important movements is the legislation change in Europe. The Circular Economy Package (CEP) was released in 2018 in order to support the change from linear to the circular economy. This EU legislation then should be incorporated on the national level for each EU member state. Directive (EU) 2018/851 sets the minimum percentage of recycled or reused municipal solid waste (MSW) to 55% in 2025, 60% in 2030 and 65% in 2035. Directive (EU) 2018/852 then gives details about minimum recycling and reuse for individual types of packaging waste. The maximum landfill of MSW is set to 10% in 2035 by Directive (EU) 2018/850. Most of the countries currently do not comply with new EU directives (Smejkalova et al., 2020b). Moreover, each country has different starting position to meet the CEP requirement. Therefore, significant changes in WM of individual countries are necessary (Tomić and Schneider, 2020). The main applicable measures focus on support of recycling and landfill restrictions. There are several ways to accelerate this change, e.g., waste prevention, waste separation, new technologies for recycling or new materials to support easier recycling (Avsec and Kaučič, 2018). WM in municipalities is very variable depending on the local conditions (sociological, economic, etc.), see (Rosecký et al., 2021). The detailed granularity of the area and information about diverse levels of WM may be advantageous when planning the changes in the WM when it is appropriate to focus on the areas with high potential for improvement (Lavee et al., 2020). Changes in WM are implemented based on compiled WM plans. These plans in most cases use the information on current and expected future waste production. The EU's goals are set at the national level. In order to achieve these goals, it is necessary to take action in lower territorial units (regions, municipalities). Increasing recycling is a key objective of the EU which is conditioned by sufficient waste separation. Intervention in the existing WM system should be targeted at areas with potential for improvement. When modelling waste separation, it is necessary to consider the current separation, composition of unseparated residues (UR), waste prevention, production of new waste streams, etc. This paper aims to compile an analytical approach that identifies the potential for increasing waste separation at the municipal level. Taking into account WM in all municipalities then gives the character of a national level. Its application will make it possible to target interventions to increase separation in municipalities that have the potential for change. It is therefore about supporting the achievement of the EU's goal at the national level.

2. Waste production forecasts and projections

Adequate detailed plans must be used for changes in WM. These plans are based on forecasts and projections of the expected development of the waste characteristics. First, it is appropriate to introduce terminology and explain the difference between forecast and projection. The forecast, in the concept of this work, represents the most probable scenario of future development. It is based on historical data and does not include (with the necessary exceptions) the expert aspect, e.g., a change in trend due to expected changes of influencing factors, etc. The forecast will be referred to as a business-as-usual scenario (BAU). In contrast, the projection is based on some defined scenario of future development. However, the projection reflects expertly set boundary conditions so that it reflects the historical course as much as possible. Thus, it is as consistent as possible with the forecast of future development (BAU). The literature provides several different approaches for forecasting in WM, as is summarized in literature review (Goel et al., 2017). In general, it is possible to distinguish two main groups of approaches – time series analysis and regression models (including machine learning). Time series analysis methods use the historical trend in data in order to describe future development (Denafas et al., 2014). Regression analysis methods need to incorporate also links to socio-economic factors (Mazzanti and Zoboli, 2008). However, in this case, good quality forecast of these influencing factors is needed. The regression model and time series analysis were applied by Ghinea et al. (2016). The results presented by Ghinea et al. (2016) showed that regression model can describe the impact of independent variables on waste production, the time series analysis was recommended for the forecast of the absolute waste production. The procedure for selecting a suitable method for forecasting the development of waste production should be determined based on the nature of available historical data. Waste production forecasts are the starting point for assessing whether a set trend is in line with legislation targets. With a few exceptions, it is obviously necessary to intervene in the current situation (Smejkalová et al., 2022).

Projections in WM are created when the system is interfered by external influences and thus the historical trend changes. These effects (legislative, technological progress, etc.) cannot be forecasted. Therefore, the modelling of projections, i.e. scenarios of future development in relation to specific conditions chosen by the author, is often approached. Scenarios are compared to the BAU scenario in order to simulate and evaluate the impact of various scenarios. Therefore, the authorities take measures to improve the way of waste treatment and meet the set interventions (legislative, financial etc.). It is possible to model scenarios for each intervention, scenarios should have the following properties:

- connection in the territorial hierarchy,
- connection of waste fractions (e.g. reduction of mixed municipal waste – MMW production due to higher separation),
- limitation by potential for change (e.g. composition of MMW),
- all territories contribute to the scenario if the potential allows,
- the development of the territory is monotonous in terms of fulfilling the potential.

The modelled scenarios reflect expert opinion and are usually created for several variants from pessimistic through neutral to optimistic. It is essential to model the scenarios regarding the territorial hierarchy and the current state of WM in each territory. The results then show the different potential between regions and thus provide feedback to the authorities. They can then target the interventions effectively and support the fulfilment of the given scenario and thus the national target in WM.

2.1. Projections – literature review

Scenarios in WM may be created by using impact of some influencing factors and their expected development. An example is the model for estimating waste production in various scenarios of economic and demographic development, including the tourism impact in the coastal area (Bramati, 2016). Another commonly used technique is the incorporation of expert knowledge about the problem. In the study (Estay-Ossandon et al., 2018b) 12 experts provide an opinion on current and future waste production and treatment. The experts' estimates were then incorporated into the model for creating projections in WM. This approach makes it possible to take into account expected changes (legislative, technological, social, etc.) which cannot yet be observed in historical data. Regarding the methodology itself, methods of projections like System Dynamics and Scenario Analysis (Estay-Ossandon et al., 2018a) were used for MSW production and treatment model. The results showed that by maintaining the BAU it will be impossible to meet the set targets about MSW treatment. All scenarios were set in accordance with the EU Directive and national targets. The impact of these interventions on MSW production is described and simultaneously the socio-economic influence is incorporate in some scenarios. The results of study (Estay-Ossandon et al., 2018a) will allow better targeting of changes in the WM system in a given locality (Balearic Islands). The strength of policy measures to reduce the amount of MSW produced is evaluated through scenarios for Swedish case by Sjöström et al. (2010). The models combine MSW from households and from firms, whose production has grown in recent years at the same time as the country's prosperous economy. The goal is to set a scenario that separates MSW production from the country's economic growth, so that waste production does not increase with further economic growth, as has been the case in the past. The mentioned studies deal with scenarios in an aggregated form for the national level and are not further distributed to the regional level. This is a significant shortcoming, especially in large countries, where there is high inter-regional variability. Then it is not possible to target effective measures with regard to the potential and character of the site.

Data from on-site surveys were used by (Long et al., 2012) for scenario modelling principles of municipal plastic waste production. The aim of mentioned model is to set priorities for plastic waste treatment in cities based on regional characteristics. Two scenarios were presented: natural trend scenario without intervention and integrated control scenario (control on the population, environmental policy, economy and waste plastic recovery). Also, according to Hatik et al. (2017) it is useful to analyse waste production and composition on the detailed level (regional or communal) and create adapted local scenarios for optimisation of overall WM. Using principal component analysis, groups of localities with similar characteristics were compiled and then the scenario for each of these groups was modelled. In this way, the number of required scenarios and thus the complexity of the calculation has been reduced. In addition, Hatik et al. (2017) recommends this method of grouping territories for cooperation between authorities. It is appropriate to link approaches focused on the state level (aggregated territorial unit) and approaches focused on individual regions. This will create a compact tool for planning and implementing interventions tailored to individual regions, linked to national targets.

2.1.1. Projections for different levels of the territory

The achieve of WM targets is modelled through scenarios. As the review above showed, the scenarios are modelled both at the national and local levels depending on the issues addressed. Due to the territorial hierarchy, it is also appropriate to use the possibility of disintegrating national targets, which can be divided into individual regions according to their potential for change. The data scaling from the national level (NUTS 1) down to more regional type of levels (NUTS 2, NUTS 3 etc.) is widely used in miscellaneous areas, for example, energetics (Müller et al., 2019), the impact of Brexit on the industrial sectors employment (Brautzsch and Holtemöller, 2021) or distribution of knowledge production function (Vadia and Blankart, 2021).

Study (Müller et al., 2019) provided an open-source dataset of gross floor area and energy demand for space heating and hot water in for European countries. The methodology was based on a top-down approach, starting from a consistent dataset at the national level (NUTS 1), breaking this down to the NUTS 3 level and further to the hectare level by means of a series of regional indicators (population, building stock characteristics, value added per sectors). Another example is the study (Brautzsch and Holtemöller, 2021), which used the World Input–Output Database to explore which industries in which countries will be affected the most by a decline of British imports from EU member. For the EU countries the regional breakdown on the NUTS 2 level (and for Germany additionally on the NUTS 3 level) was performed by simple equation using the distribution of employment by industry in each region. More complex approach was presented by Chen et al. (2018), which developed an index of EU regions and countries exposure to the negative trade-related consequences of Brexit. Input data were regionalized using value added and regional income and demand. These regionalized national coefficients were used as a prior information for the subsequent optimization model.

The technique for data scaling is very connected to the nature of dataset available. Sometimes very simple techniques are sufficient to use. For example, study (Vadia and Blankart, 2021) explored the distribution of knowledge production function of cardiovascular research and funding in Europe within Regional Innovation Systems (RIS). In other words, how public funding contributes to a region’s knowledge output. To identify distinguished regions in the RIS, the 2016 version of the NUTS 3 classification was used. The study (Naqvi, 2021) provided the tracker of data on daily COVID-19 cases at the sub-national level for 26 European countries. National level data sources were identified and processed to form a homogenized panel at the NUTS 3 or NUTS 2 level. For most countries this was done by using official regions-to-NUTS correspondence tables.

Sometimes the focus is not intended primarily to the scaling down to lower units, but the conversion of data due to administrative changes. An example may be study (Rizzati et al., 2022), which focused on future residential electricity demand in Italy at the local level based on population, land use, socio-economic and climate scenarios for the year 2050. Data for the historical electricity consumption were available on the province level. The majority of the provinces corresponded to NUTS 3 division. Several provinces were newly established during the period of interest, so the conversion for those to NUTS 3 was done by using the population data. The paper quantifies the effect of socio-economic and geographical variables on residential area and electricity demand. Rizzati et al. (2022) mentioned different takeaways about the policy implications of the modelled scenarios such as reaction on expansion of residential land or decarbonising the energy mix. Territorial similarity is also used in WM to estimate waste production and composition, which is essential information when planning WM. It is not usually feasible to perform detailed analysis in all relevant localities (regions, municipalities). Using stratification, sufficiently representative areas are selected, where the analysis are carried out and then there is a generalization to other territorial units of a similar character (Guérin et al., 2018). In this case, the task arises at the hierarchical level in the opposite direction, where the information for higher levels (regional, national) is generalized on the basis of information from a lower level. The aim is to obtain the most accurate estimate of the actual composition of the waste using a limited number of analysis (Miezah et al., 2015).

In the area of WM, targets are set at the national level (e.g. CEP) and the intention is to distribute these national plans to lower territorial units. For territorial units where there is great potential for change, greater change can be expected (e.g. increasing waste sorting), it is therefore necessary to identify the potential for change. The benefit of scenario solutions is especially in cases where there are links between data. Data on waste production for lower territorial units has higher variability than aggregated data. Aggregated data was used to smooth lower-level estimates of links between waste fractions, the approach was presented within TIRSMZP719 project. All territorial units show a shift towards meeting the scenario if the potential allows. Simultaneously, individual territories do not overtake in the sense of fulfilling the potential, so the monotony is maintained. In general, it is appropriate to deviate as little as possible from the BAU scenario while meeting the requirements of the scenario.

2.2. Novelty of the contribution

The approach presented in this paper works with scenarios at multiple levels of territorial hierarchy. The setting of input conditions at the national level is distributed below to the level of municipalities based on their potential for change. The presented approach follows the logical conditions for dividing the scenario into lower levels:

- All territories of the system contribute to the national target.
- The methodology includes the advantages for scenario modelling on national level (aggregated level) and regional level (regarding WM characteristics).
- Monotony is maintained in terms of potential fulfilment (municipalities do not overtake when changing from BAU to scenario). However, the order changes in absolute quantity. The approach reflects the differences in production and composition in territorial units and thus supports the rationality of the scenario.
- New waste streams are reflected which in practice arise due to a change in the system (Smejkalová et al., 2020a) or technological changes (Wang et al., 2021).
- The waste prevention is included. This aspect will affect the overall production of waste and its composition, thus affecting the potential.
- The production of waste from municipal and industrial producers is included.
- All aspects are interconnected into one analytical model. The approach is compiled generally for any number of UR and separated waste fractions and also for a territorial breakdown.
- The case study for the Czech Republic is performed. The data set from the period 2010–2018 was used for 6178 municipalities and for selected types of MSW, which show potential for material recovery.
- The results identified specific municipalities where it is appropriate to target support for increasing MSW separation.

Compared to the previous studies, the presented approach is unique in its complexity. Especially, by including the territorial hierarchy and the links between the waste fractions. This approach includes a compact tool to support WM planning with a link to increasing the material recovery of waste. By including interventions in WM according to the modelled scenarios, environmental protection can be supported according to the WM hierarchy (Directive 2008/98/EC).

3. Analytical approach

The projection is based on the need to increase the waste separation, which is a necessary prerequisite for a higher level of material recovery of MSW. The increase in MSW separation is made possible by diverting the waste from the UR. This is primarily MMW and some other waste (bulky waste (BW), street sweep etc.). A possible increase in separation is considered in the approach for waste fractions f. It is possible to include the production of new waste stream h. The new waste stream is a waste that was not previously part of MSW (for example, due to composting on gardens). Separated waste as a whole is marked as SEP. There is a possibility to distinguish the waste producer p (municipalities and industry). The approach for this type of projection consists of two main steps. In the first phase the scenario will be set at the national level so that the required target is achieved, sec. 3.1. In the next phase, the national targets are divided into regional level 3.2. The marking of parameters in the mathematical notation follows the rule of indices, which is shown in the fig. 1 for parameter SR (separation rate). Some parameters do not include all indices. For example, the national level has the upper NUTS index marked as N1, the lower index j for the territory no longer occurs, e.g. $SR^{BAU,N1}_{\bar{\tau},p,u,f}$. If the parameter does not include all indexes, they are usually removed from the last one, e.g. $prev^{SC,N1}_{\bar{\tau},p}$. The exception is the amount of SEP fraction f ($K^{SC,N1}_{\bar{\tau},p,f}$ resp. $K^{SC,N2}_{\bar{\tau},p,f,j}$), where there is no index u for UR (tab. 3 resp. tab. 4) and amount of UR fraction u ($L^{SC,N2}_{\bar{\tau},p,u,j}$), where there is no index f for waste fraction (tab. 4).

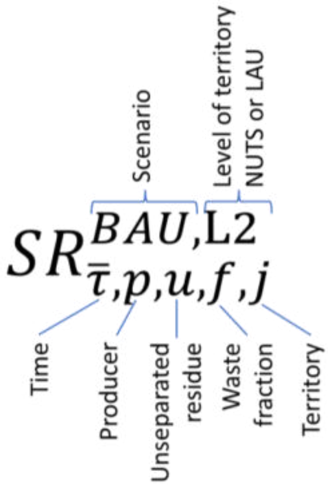


Fig. 1: Indices in the mathematical notation

3.1. Setting the scenario at the national level

The amount of SEP in the scenario is increased by diverting the separable fractions f from set UR or production of new waste stream h. Furthermore, it is possible to reflect in the scenario a reduction in MSW production due to waste production prevention. The user therefore has the option to choose the SR from UR, new waste stream h production and the percentage MSW production prevention. The starting point for compiling the scenario is the BAU scenario (Smejkalová et al., 2022). Scenario modelling is influenced by the link between UR generation and SEP, the links between UR produced and SEP are analysed, which will allow to better estimate the potential for increasing separation. An optimization-based model to the description of these links was introduced in the TIRSMZP719 project. The result is a value $\delta_{p,u,f}$ which indicates what percentage of newly separated waste fraction f comes from individual UR u. These links $\delta_{p,u,f}$ are included in the setting of the scenario at the national level.

Input parameters for setting the scenario are available in tab. 1 including description and data source, $\iota \in T$ indicates the last year with historical data and $\bar{\tau} \in T$ indicated the year of modelling scenario.

Tab. 1: Input values for setting the scenario in year $\bar{\tau}$ at the national level

Nomenclature	Description, [unit]	Data source
$k^{BAU,N1}_{\bar{\tau},p,u,f}$	Forecasted SEP of fraction f in the year $\bar{\tau}$, from producer p, which originates in a specific u, [t].	BAU.
$\bar{k}^{BAU,N1}_{\bar{\tau},p,u,f}$	Change in production from the last year with data $\bar{\iota}$ to the period of the year $\bar{\tau}$, [t].	$\bar{k}^{BAU,N1}_{\bar{\tau},p,u,f} = k^{BAU,N1}_{\bar{\tau},p,u,f} - k^{BAU,N1}_{\bar{\iota},p,u,f}$.
$\delta^{BAU,N1}_{p,u,f}$	Coefficient of transfer from UR u to SEP for fraction f, [–].	Results of the model described by TIRSMZP719.
$L^{BAU,N1}_{\bar{\tau},p,u}$	Forecasted amount of individual UR u, [t].	BAU.
$\bar{l}^{BAU,N1}_{\bar{\tau},p,u,f}$	Percentage of fraction f in u, [%].	Analyzes of UR composition.
$l^{BAU,N1}_{\bar{\tau},p,u,f}$	Amount of fraction f in u, [t].	The amount of f in u is not directly part of the BAU. The value of $\delta_{p,u,f}$ indicates the extent to which the increase in separation until year $\bar{\tau}$ was due to

		separation from u. Thus, the potential of this faction in the u is affected. $$l_{\bar{\tau},p,u,f}^{BAU,N1} = L_{\bar{\tau},p,u}^{BAU,N1}\bar{l}_{\bar{\tau},p,u,f}^{BAU,N1} - \delta_{p,u,f}^{BAU,N1}\bar{k}_{\bar{\tau},p,u,f}^{BAU,N1}.$$
$SR_{\bar{\tau},p,u,f}^{BAU,N1}$	SR of fraction f from u, [%].	$$SR_{\bar{\tau},p,u,f}^{BAU,N1} = \frac{k_{\bar{\tau},p,u,f}^{BAU,N1}}{k_{\bar{\tau},p,u,f}^{BAU,N1} + l_{\bar{\tau},p,u,f}^{BAU,N1}}.$$

The optional parameters are listed in the tab. 2, it is possible to specify the MSW generation prevention, SR of individual fractions and production of new waste fraction. Marking values in a modelled scenario will use the SC superscript (scenario).

Tab. 2: Optional parameters for scenario setting

Nomenclature	Description [unit]
$prev_{\bar{\tau},p}^{SC,N1}$	Reduction of MSW production due to prevention, [%].
$SR_{\bar{\tau},p,u,f}^{SC,N1}$	SR of fraction f from u for scenario, [%].
$N_{\bar{\tau},p,h}^{SC,N1}$	Total production of new waste fraction h (both SEP and redidue in UR), [t].
$\bar{\delta}_{p,u,h}^{BAU,N1}$	Coefficient of transfer of new waste fraction h from UR u to SEP for new waste fraction h or the opposite direction (plus or minus value), [–].

The output of the scenario setting at the national level are the values given in tab. 3. In the next step (sec. 3.2), the scenario is divided into lower levels of territory.

Tab. 3: Outputs of the modelled scenario on the N1 territory level

Nomenclature	Description [unit]	Calculation
$k_{\bar{\tau},p,u,f}^{SC,N1}$	Amount of separated fraction f, originating from u, [t].	$$k_{\bar{\tau},p,u,f}^{SC,N1} = \left(1 - prev_{\bar{\tau},p}^{SC,N1}\right)\left(k_{\bar{\tau},p,u,f}^{BAU,N1} + l_{\bar{\tau},p,u,f}^{BAU,N1}\right)SR_{\bar{\tau},p,u,f}^{SC,N1}.$$
$K_{\bar{\tau},p,f}^{SC,N1}$	The total amount of separated fraction f, [t].	The value is given as a sum of SEP waste in scenario over set $u \in U$. $$K_{\bar{\tau},p,f}^{SC,N1} = \sum_{u\in U} k_{\bar{\tau},p,u,f}^{SC,N1}.$$
$n_{\bar{\tau},p,u,h}^{SC,N1}$	Amount of separated fraction h, [t].	$$n_{\bar{\tau},p,u,h}^{SC,N1} = \bar{\delta}_{p,u,h}^{BAU,N1} N_{\bar{\tau},p,u,h}^{SC,N1}.$$
$l_{\bar{\tau},p,u,f}^{SC,N1}$	Amount of fraction f in u, [t].	$$l_{\bar{\tau},p,u,f}^{SC,N1} = \left(k_{\bar{\tau},p,u,f}^{BAU,N1} + l_{\bar{\tau},p,u,f}^{BAU,N1}\right)\left(1 - SR_{\bar{\tau},p,u,f}^{SC,N1}\right)\left(1 - prev_{\bar{\tau},p}^{SC,N1}\right).$$
$L_{\bar{\tau},p,u}^{SC,N1}$	UR generation, [t].	$$L_{\bar{\tau},p,u}^{SC,N1} = L_{\bar{\tau},p,u}^{BAU,N1}\left(1 - prev_{\bar{\tau},p}^{SC,N1}\right) - \left(\sum_{f\in F} l_{\bar{\tau},p,u,f}^{BAU,N1}\left(1 - prev_{\bar{\tau},p}^{SC,N1}\right) - \sum_{f\in F} l_{\bar{\tau},p,u,f}^{SC,N1}\right).$$
$\bar{l}_{\bar{\tau},p,u,f}^{SC,N1}$	Amount of new fraction h in UR u, [t].	$$\bar{l}_{\bar{\tau},p,u,f}^{SC,N1} = \left(1 - \bar{\delta}_{p,u,h}^{BAU,N1}\right)N_{\bar{\tau},p,u,h}^{SC,N1}.$$

In the way given in tab. 1 – tab. 3, the scenario at the national level in the target year $\bar{\tau}$ is calculated. The waste production $k_{\bar{\tau},p,u,f}^{SC,N1}$ for the whole time series over the years τ up to the target year $\bar{\tau}$ is given by the formula (1). Index τ_0 indicates the first forecasted year. The overall SEP generation of fraction f, regardless of its origin u is given by (2).

$$k_{\tau,p,u,f}^{SC,N1} = k_{\bar{\tau},p,u,f}^{BAU,N1} + \frac{k_{\bar{\tau},p,u,f}^{SC,N1} - k_{\tau_0,p,u,f}^{BAU,N1}}{k_{\bar{\tau},p,u,f}^{BAU,N1} - k_{\tau_0,p,u,f}^{BAU,N1}} \left(k_{\tau,p,u,f}^{BAU,N1} - k_{\tau_0,p,u,f}^{BAU,N1}\right) \qquad \forall \tau \in T, \forall p \in P, \forall u \in U, \forall f \in F \qquad (1)$$

$$K_{\bar{\tau},f}^{SC,N1} = \sum_{p \in P} \sum_{u \in U} k_{\tau,p,u,f}^{SC,N1} \qquad \forall f \in F \qquad (2)$$

3.2. Division of the targets into lower territorial units

This part of the text proposes an approach that meaningfully estimates the potential of individual lower territorial units for increase waste separation. The presented approach for scenario modelling is based on assumptions that has been mentioned in sec. 2. The aim of the chosen scenario is to set the production of selected waste fraction, so that the sum over all municipalities corresponds to the national level described in sec. 3.1. Increased production of this fraction f has a logically positive effect on SR. An important aspect for real results is the well-estimated separation potential in the form of maximum SR ($\max SR_{p,u,f,j}^{BAU,L2}$).

The aim of the presented approach is to divide the necessary increase in waste separation to the municipalities based on the potential that individual territories have for improving separation. The potential for higher separation is evaluated by $\overline{SR}_{\bar{\tau},p,u,f,j}^{BAU,L2}$, which means the percentage fulfilling of the specified $\max SR_{p,u,f,j}^{BAU,L2}$ ($\overline{SR}_{\bar{\tau},p,u,f,j}^{\mathrm{BAU},L2} = SR_{\bar{\tau},p,u,f,j}^{BAU,L2}/\max SR_{p,u,f,j}^{BAU,L2}$). As mentioned above, an increase in waste separation is primarily required in municipalities, which according to the BAU scenario have lower $\overline{SR}_{\bar{\tau},p,u,f,j}^{\mathrm{BAU},L2}$. These municipalities therefore have significant potential for improvement. A linear dependence is assumed for the increase in $\overline{SR}_{\bar{\tau},p,u,f,j}^{\mathrm{BAU},L2}$, see fig. 2. The scenario for the limit increase of SR, i.e. the maximum possible separation that can be achieved with respect to $\max SR_{p,u,f,j}^{BAU,L2}$, is shown in red. However, the aim of this task is to model the specific percentage increase of SR (denoted $\Delta\overline{SR}_{\bar{\tau},p,u,f,j}^{\mathrm{SC},L2}$) in individual municipalities j. The value $\Delta\overline{SR}_{\bar{\tau},p,u,f,j}^{\mathrm{SC},L2}$ gives the difference of $\overline{SR}_{\bar{\tau},p,u,f,j}^{\mathrm{BAU},L2}$ according to the BAU scenario and the modelled scenario for fraction f originates in u and territory j. The modelled scenario is shown in fig. 2, marked in black color. For the sake of clarity, two fictitious municipalities are illustrated in fig. 2, denoted by the indices j = 1 and j = 2. According to the BAU scenario (green line), the municipality j = 1 has a lower fulfilling of separation potential $\overline{SR}_{\bar{\tau},p,u,f,j}^{\mathrm{BAU},L2}$ of the modelled waste fraction f than the municipality j = 2. This fact is captured by the location of the $\overline{SR}_{\bar{\tau},p,u,f,j}^{\mathrm{BAU},L2}$ of these two municipalities on the horizontal axis. Based on the linear dependence, the necessary increase $\Delta\overline{SR}_{\bar{\tau},p,u,f,j}^{\mathrm{BAU},L2}$ for these municipalities denoted $\Delta\overline{SR}_{\bar{\tau},p,u,f,1}^{\mathrm{BAU},L2}$ and $\Delta\overline{SR}_{\bar{\tau},p,u,f,2}^{\mathrm{BAU},L2}$, is determined. The resulting fulfilling of separation potential according to the scenario is then determined by the sum $\overline{SR}_{\bar{\tau},p,u,f,j}^{\mathrm{BAU},L2} + \Delta\overline{SR}_{\bar{\tau},p,u,f,j}^{\mathrm{SC},L2}$. Individual municipalities j do not have the opportunity to overtake others in terms of fulfilling the $\max SR_{p,u,f,j}^{BAU,L2}$ ($\overline{SR}_{\bar{\tau},p,u,f,j}^{\mathrm{BAU},L2}$). However, they may overtake in the $SR_{\bar{\tau},p,u,f,j}^{BAU,L2}$, because each municipality may have a different $\max SR_{p,u,f,j}^{BAU,L2}$.

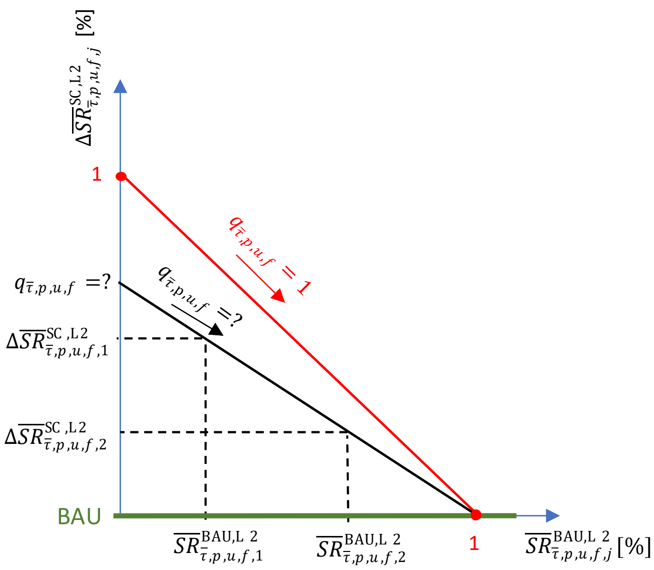
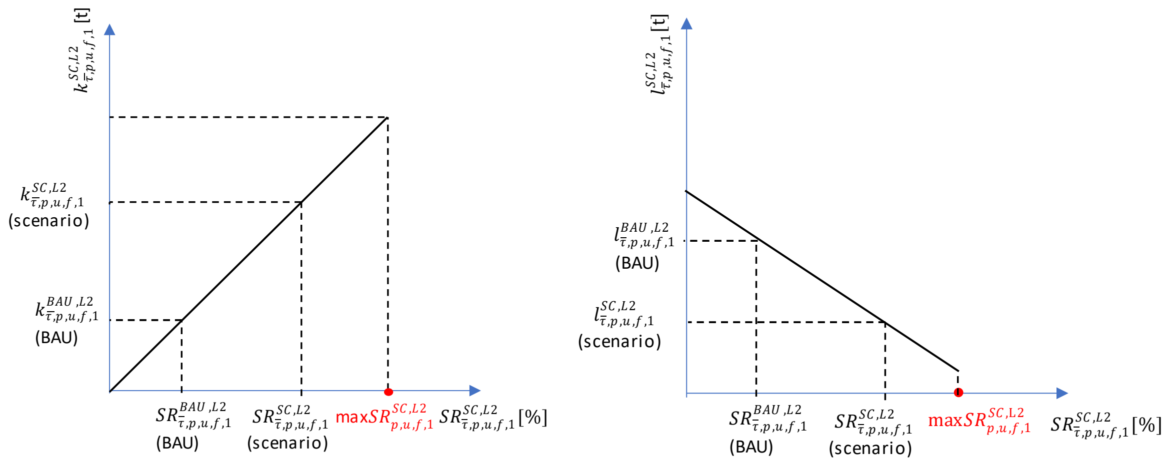


Fig. 2: Schematic description of the approach

Within the modelled scenario, the amount of the monitored fraction f in the UR u and its separated amount will change. The schematic representation for the difference between the BAU scenario and the modelled scenario is in fig. 3a) and fig. 3b), for a fictitious municipality with index j = 1. Specifically, fig. 3a) shows the dependence of the $SR^{SC,L2}_{\bar{\tau},p,u,f,1}$ on SEP ($k^{SC,L1}_{\bar{\tau},p,u,f,j}$) of fraction f, this is also a linear dependence limited by $\max SR^{BAU,L2}_{p,u,f,j}$. Fig. 3 b), there is a representation of the influence of the scenario solution on the amount of f in u. When increasing the $SR^{SC,L2}_{\bar{\tau},p,u,f,1}$ in the municipality j = 1 the amount of fraction f in u ($l^{SC,L2}_{\bar{\tau},p,u,f,1}$) will decrease. The line in fig. 3b) marks the linear dependence of the $l^{SC,L2}_{\bar{\tau},p,u,f,1}$ on amount $SR^{SC,L2}_{\bar{\tau},p,u,f,j}$. The red point on the horizontal axis in fig. 3b) indicates the $\max SR^{SC,L2}_{p,u,f,j}$. Because of the fact, that $\max SR^{SC,L2}_{p,u,f,j}$ cannot reach 100 % in real data, the fraction f still remains present in the u even with this $\max SR^{SC,L2}_{p,u,f,j}$.



a) Change in the amount of SEP for fraction f *b) Change in the amount of fraction f in UR*

Fig. 3: The effects of the increase in the SR on the composition of the waste

The aim of the model is to determine the parameters $q_{\bar{\tau},p,u,f}$ (see fig. 2) of the linear dependence (3).

$$\Delta\overline{SR}^{SC,L2}_{\bar{\tau},p,u,f,j} = q_{\bar{\tau},p,u,f}\left(1 - \overline{SR}^{SC,L2}_{\bar{\tau},p,u,f,j}\right) \qquad \forall p \in P, \forall u \in U, \forall f \in F, \forall j \in J \qquad (3)$$

The necessary requirement for the problem statement is that fraction f separation in all municipalities corresponds to national separation, see (4).

$$\sum_{j\in J}\left(\overline{SR}^{BAU,L2}_{\bar{\tau},p,u,f,j} + \Delta\overline{SR}^{SC,L2}_{\bar{\tau},p,u,f,j}\right)\max SR^{BAU,L2}_{p,u,f,j}\left(k^{BAU,L2}_{\bar{\tau},p,u,f,j} + l^{BAU,L2}_{\bar{\tau},p,u,f,j}\right) = k^{SC,N1}_{\bar{\tau},p,u,f} \qquad \forall p \in P, \forall u \in U, \forall f \in F \qquad (4)$$

On the left side of equation (4), the new SR within the modelled scenario is multiplied by the total production of the fraction f, i.e., ($k^{SC,L2}_{\bar{\tau},p,u,f,j} + l^{SC,L2}_{\bar{\tau},p,u,f,j}$). After summation, this amount must be equal to the sum of the national generation in scenario $k^{SC,N1}_{\bar{\tau},u,f}$. After adjustment, the unknown parameter $q_{\bar{\tau},p,u,f,}$ is determined by (5). The outputs of the scenario on municipal level (LAU 2) is given in Tab. 4.

$$q_{\bar{\tau},p,u,f} = \frac{k^{SC,N1}_{\bar{\tau},p,u,f} - \sum_{j\in J}\left(\overline{SR}^{BAU,L2}_{\bar{\tau},p,u,f,j}\max SR^{BAU,L2}_{p,u,f,j}\right)\left(k^{BAU,L2}_{\bar{\tau},p,u,f,j} + l^{BAU,L2}_{\bar{\tau},p,u,f,j}\right)}{\sum_{j\in J}\left(1 - \overline{SR}^{BAU,L2}_{\bar{\tau},p,u,f,j}\right)\max SR^{BAU,L2}_{p,u,f,j}\left(k^{BAU,L2}_{\bar{\tau},p,u,f,j} + l^{BAU,L2}_{\bar{\tau}p,,u,f,j}\right)} \qquad \forall p \in P, \forall u \in U, \forall f \in F \qquad (5)$$

Tab. 4: Outputs of the scenario on the L2 territory level

Nomenclature	Description [unit]	Calculation
$SR^{SC,\mathrm{L2}}_{\bar{\tau},p,u,f,j}$	SR in scenario of fraction f, originating from u, [%].	$SR^{SC,\mathrm{L2}}_{\bar{\tau},p,u,f,j} = \max SR^{BAU,\mathrm{L2}}_{p,u,f,j}\left(\overline{SR}^{BAU,\mathrm{L2}}_{\bar{\tau},p,u,f,j} + \Delta\overline{SR}^{\mathrm{SC,L2}}_{\bar{\tau},p,u,f,j}\right).$
$k^{SC,L2}_{\bar{\tau},p,u,f,j}$	The separated fraction f, originating from u, [t].	$k^{SC,L2}_{\bar{\tau},p,u,f,j} = SR^{SC,\mathrm{L2}}_{\bar{\tau},p,u,f,j}\left(1 - prev^{SC,N1}_{\bar{\tau},p}\right)\left(k^{BAU,L2}_{\bar{\tau},p,u,f,j} + l^{BAU,L2}_{\bar{\tau},p,u,f,j}\right).$
$K^{SC,L2}_{\bar{\tau},p,f,j}$	Total amount of separated fraction f, [t].	$K^{SC,L2}_{\bar{\tau},p,f,j} = \sum_{u \in U} k^{SC,L2}_{\bar{\tau},p,u,f,j}.$
$l^{SC,L2}_{\bar{\tau},p,u,f,j}$	Amount of fraction f in UR u, [t].	$l^{SC,L2}_{\bar{\tau},p,u,f,j} = \left(1 - SR^{SC,L2}_{\bar{\tau},p,u,f,j}\right)\left(1 - prev^{SC,N1}_{\bar{\tau},p}\right)\left(k^{BAU,L2}_{\bar{\tau},p,u,f,j} + l^{BAU,L2}_{\bar{\tau},p,u,f,j}\right).$
$L^{SC,L2}_{\bar{\tau},p,u,j}$	Generation of UR u, [t].	$L^{SC,L2}_{\bar{\tau},p,u,j} = L^{BAU,L2}_{\bar{\tau},p,u,j}\left(1 - prev^{SC,N1}_{\bar{\tau},p}\right) - \left(\left(1 - prev^{SC,N1}_{\bar{\tau},p}\right)\sum_{f \in F}\left(l^{BAU,L2}_{\bar{\tau},p,u,f,j} - l^{SC,L2}_{\bar{\tau},p,u,f,j}\right)\right).$
$n^{SC,L2}_{\bar{\tau},p,u,h}$	Amount of separated fraction h, [t].	$n^{SC,L2}_{\bar{\tau},p,u,h} = n^{SC,N1}_{\bar{\tau},p,u,h}\frac{\sum_{f \in F} k^{SC,L2}_{\bar{\tau},p,u,f,j}}{\sum_{f \in F} k^{SC,N1}_{\bar{\tau},p,u,f,j}}.$

4. Case study

This section presents a case study for waste production in the Czech Republic in 2035. This is a key period in terms of EU legislation, see sec. 1. In the Czech Republic, 46% of MSW is still landfilled in 2020 and 41% of MSW is destined for material recovery (VISOH, 2022). In order to meet the EU targets, it is therefore necessary to streamline material recovery, a prerequisite for the material recovery is waste separation. The SR according to BAU in 2035 is estimated on 44 % with the forecast of MSW production 6,823 kt. The SR is increased within scenarios. The legislation of the Czech Republic supports the separation of waste as follows (Act No. 541/2020 Coll.):

- Separation of new waste fractions: textile from 2025.
- Increasing the landfill fee: annual increase until 2029.
- The obligation of municipalities to achieve minimum separation: 60% in 2025 and next 5% each five years up to 2035.
- Bulky waste sorting: at least metals, plastics and wood from 2023.
- The obligation to separate MSW in companies: paper, plastics, glass, metal, bio-waste from 2021.
- Landfill restrictions for some waste fractions: wastes from electrical equipment, batteries, tires and MSW with a calorific value higher than 6.5 MJ / kg in the dry matter.
- Prohibition of landfilling of usable waste: from 2030.
- And others.

These legislation interventions beyond the BAU are likely to lead to a higher waste separation. However, it can be expected to get more waste polluted or otherwise inappropriate to material recovery in SEP. So, it is necessary to take into account the fact that not all SEP is material recovered. After sorting the waste on the sorting lines, the non-recyclable residue in the form of return streams is intended for energy recovery or, in the worst case, landfilling (Pluskal et al., 2021).

It is worth noting that no increase in the production of a new waste stream was considered for the creation of the scenarios in the case study. It is assumed that it is fully described in the BAU scenario of the forecast. Only the transfer from UR and the impact of waste prevention are modelled. In this study, three scenarios (SC1, SC2, SC3) of waste separation at the national level for the Czech Republic are compiled and subsequently they are divided into the level of municipalities. The increase in SEP production is made possible by the separation from UR fractions, in this study for the Czech Republic MMW and BW are considered as UR. Waste fractions f are commonly separated waste fractions: paper (PAP), plastic (PLA), glass (GLA), textiles (TEX), metals (MET), biowaste from gardens (BIO-G), biowaste from kitchens (BIO-K), wood (WOO). Waste production is divided according to the producer p into waste from municipalities and industry.

The potential for increasing separation in 2035 ($l_{\bar{\tau},p,u,f}^{BAU,N1}$) is determined from the current composition of UR and an estimate of the transfer between UR and SEP ($\delta_{p,u,f}^{BAU,N1}$), values are given in Tab. 5. For this study, the UR composition (EKO-KOM, 2019) and transfer between UR and SEP TIRSMZP719 are considered the same for all municipalities. This is a significant simplification of the model, where in the case of complete input data, information should be available for each municipality. However, there are currently insufficient data sets to determine the composition of MMW at the municipality level. It is assumed that PLA, MET and WOO can be separated from BW, and no significant representation in BW is expected for the other fractions (f) considered. The composition of BW is taken from a study (Sekito et al., 2003), it is a case study from Japan. The authors do not anticipate significant differences in the composition of BW depending on the geography, as can be expected, for example, for bio-waste. Studies from the EU, such as Denmark, are also available (Larsen et al., 2012). However, the Danish study only lists components of BW suitable for material recovery, so it is not the overall composition of BW. Furthermore, a transfer from BW to SEP is not expected in the historical data, so there is no value for transfer Tab. 5. The maximal SR is not limited in this study, so $maxSR_{p,u,f,j}^{SC,L2} = 1$. In the further research, it would be beneficial to supplement the input data especially with the composition of UR and the related potential of separation at the level of municipalities.

Tab. 5: Input information for determining the potential in BAU scenario

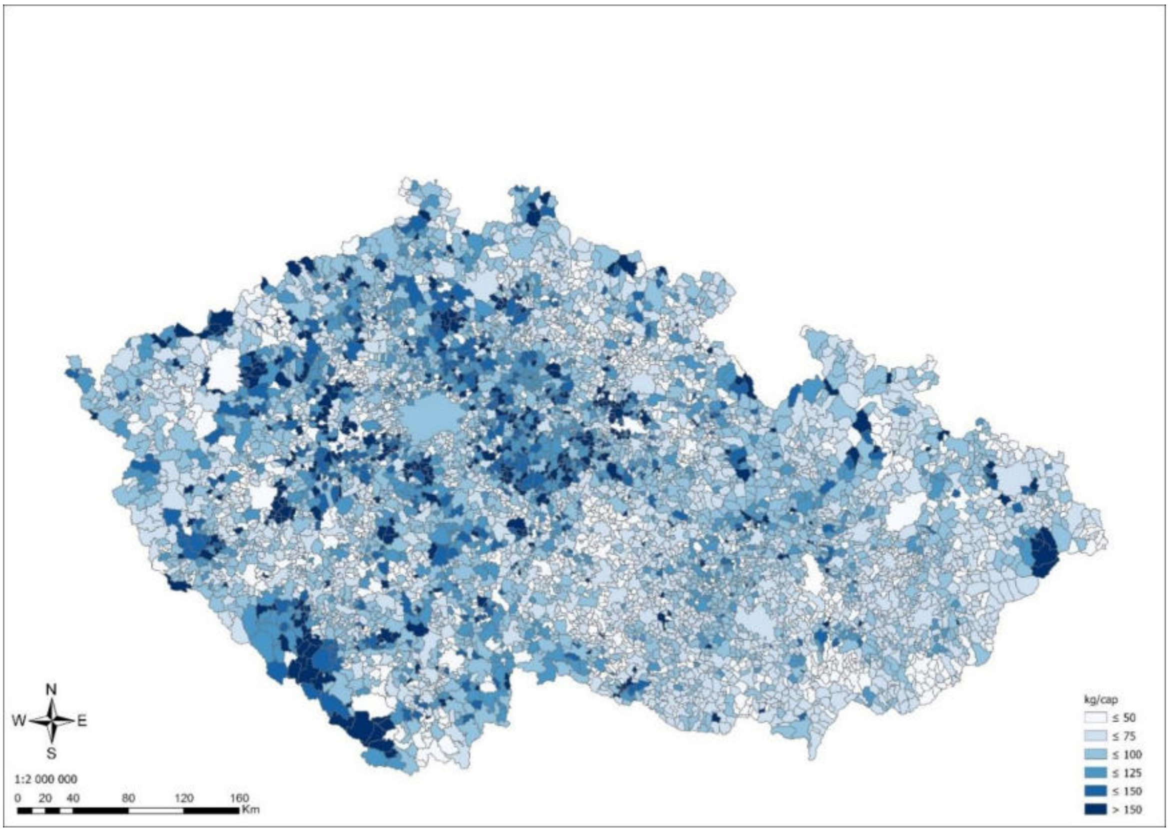
	MMW		BW
	Composition [%] (EKO-KOM, 2019)	Transfer [-] (Šompák et al., 2022)	Composition [%] (Sekito et al., 2003)
PAP	8.7%	0.86	–
PLA	10.1%	0.94	20.9%
GLA	4.0%	0.87	–
TEX	2.1%	0.99	–
MET	2.5%	0.04	20.3%
BIO-G	15.3%	0.20	–
BIO-K	10.3%	1.00	–
WOO	1.0%	0.20*	42.4%
Others	46.0%		16.4%**

Remarks:

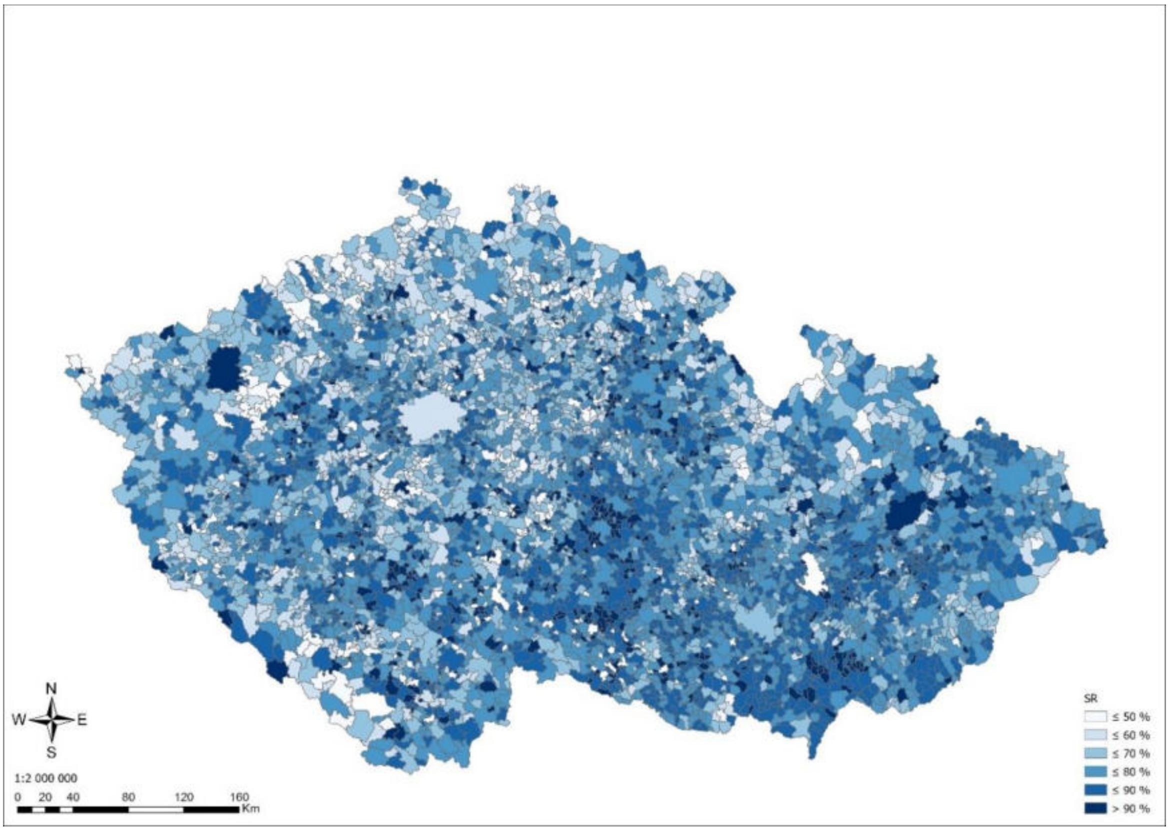
** WOO was not addressed in the paper TIRSMZP719. Therefore, an estimate was made of the same value as BIO-G. In both cases, it is waste that has the character of garden waste.*

*** The composition of the BW lists only those fractions that will be separated according to the legislation. The Others item therefore includes all other fractions (PAP, GLA, TEX, etc.).*

The evaluation of the potential in the BAU scenario in the municipalities is shown on the maps (Fig. 4) for MMW produced by municipalities. The low value of the SR (Fig. 4a)) means great potential for improvement. Low SR is often in the connection with high amount of SEP in MMW (Fig. 4b)). The intervention is effective to target municipalities that have a large amount of SEP in MMW and simultaneously low SR. These municipalities are able to contribute more to the national goal. The maps for municipalities shows the better level of BAU for east part of the Czech Republic. The most significant potential seems to be south-west part (South Bohemian region), north-west part (Ústí nad Labem region) and area around the capital city Prague (Central Bohemian region). In the case of industry waste, the potential will be highly dependent on the type of industry operated in the locality. Historical data do not consider a transfer from BW to SEP, so the potential according to BAU is the same for all municipalities.



a) SR



b) Amount of separable waste in MMW

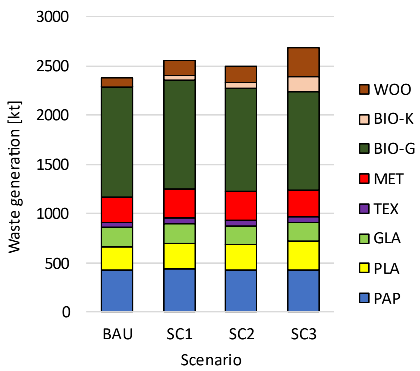
Fig. 4: Map of separation potential from MMW produced by municipalities, Czech Republic, municipality level, year 2035

The potential for change is given by composition of UR in BAU. Optional parameters are the rate of waste prevention, SR from MMW and SR from BW. In consultation with waste management experts who participate in the creation of Czech legislation (Act No. 541/2020 Coll.), three scenarios were formulated: realistic (SC1), positive (SC2), optimistic (SC3), see Tab. 6.

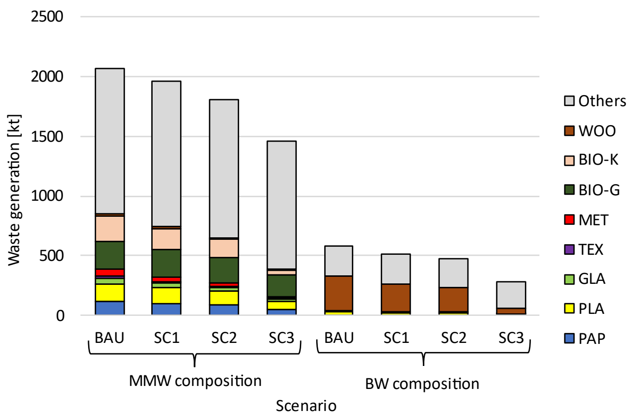
Tab. 6: Setting of modelled scenarios, Czech Republic, year 2035

Producer		Municipalities				Industry			
Scenario		BAU	SC1	SC2	SC3	BAU	SC1	SC2	SC3
Prevention [%]		0%	0%	5%	12%	0%	0%	5%	12%
SR from MMW [%]	PAP	78%	82%	84%	90%	89%	91%	91%	95%
	PLA	62%	65%	67%	80%	13%	20%	25%	80%
	GLA	79%	84%	86%	90%	43%	46%	48%	90%
	TEX	65%	75%	80%	90%	50%	50%	52%	55%
	MET	82%	88%	93%	95%	41%	43%	50%	85%
	BIO-G	84%	83%	83%	85%	74%	74%	74%	85%
	BIO-K	2%	20%	27%	80%	53%	60%	65%	80%
	WOO	83%	85%	86%	87%	82%	84%	86%	87%
SR from BW [%]	PLA	0%	20%	25%	80%	0%	20%	25%	80%
	MET	0%	20%	25%	80%	0%	20%	25%	80%
	WOO	0%	20%	25%	80%	0%	20%	25%	80%

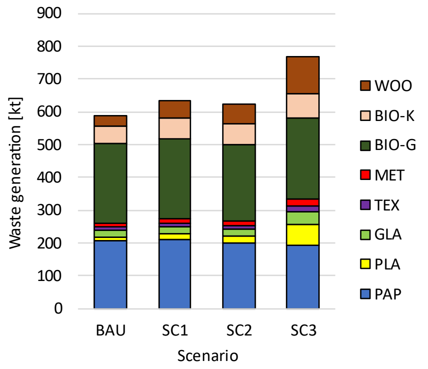
With the input values given in Tab. 5 and Tab. 6 were according to the procedure of sec. 3 calculated scenarios first at the state level and then for municipalities in the Czech Republic. Graphically, the composition of SEP and UR is indicated in Fig. 5 for producer municipalities. The first column in Fig. 5 always indicates the BAU and the modelled scenarios follow. In the modelled scenarios, there is a higher production of SEP fractions, although their total production is corrected in SC2 and SC3 by preventing of MSW production. According to BAU, there is already more than half of non-separable waste ("Others") in MMW, this waste cannot be transferred from UR by separation. The scenarios show that some fractions have a greater potential for higher separation than others. It can be mentioned BIO-K in MMW, which in the case of MMW from municipalities occupies a significant part of MMW and according to the model it can be successfully separated. In the scenarios, separable components from MMW and BW are eliminated. This reduces the potential for further separation and most UR is represented by “Others”.



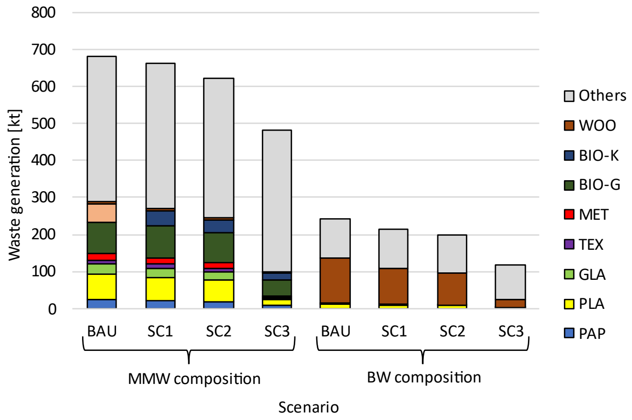
a) Separated waste from municipalities



b) Unseparated residue from municipalities



c) Separated waste from industry



d) Unseparated residue from industry

Fig. 5: The results of the scenario modelling, Czech Republic, year 2035

According to BAU specified in the project TIRSMZP719, production of 6,823 kt MSW; 2,753 kt MMW and 822 kt BW (total from municipalities and industry) is expected in 2035. Under the scenarios, the production of these UR representatives is reduced, according to the optimistic SC 3 to 6,004 kt MSW; 1,903 kt MMW and 399 kt BW. The SR of MSW for SC 3 is 58 %. The SR from MMW is estimated on 72 % based on BAU in summary for all waste fractions considered. According to the modelled scenarios (SC1, SC2, SC3), the separation can be increased to 73%, 77% and 87 %. The MMW is the main UR but not the only one. All UR fractions would need to be included for the overall assessment of the SR of MSW. Moreover, the SR is not the same as the recycling rate, so these values cannot be directly compared with the targets included in the CEP (sec. 1). Real waste treatment is affected by a number of decision uncertainties (Soltani et al., 2017).

The following Fig. 6 shows the change in the SR for MMW and produced by municipalities in individual scenarios. The value for the national level is marked as NUTS 1. It is obvious that all territories are moving even higher SR. However, primarily the increase in SR is realised in municipalities with low SR according to BAU, as they have the greatest potential for improvement. A significant difference in the distribution of histograms can be seen between producers (municipalities and industry). This is probably due to the fact that the nature of industrial waste varies greatly from one municipality to another and is influenced, among other things, by industry field. The composition of waste produced by municipalities is not so variable, the difference is especially in SR. In the case of industrial waste, it is therefore even more important to set up interventions adequate to the given locality.

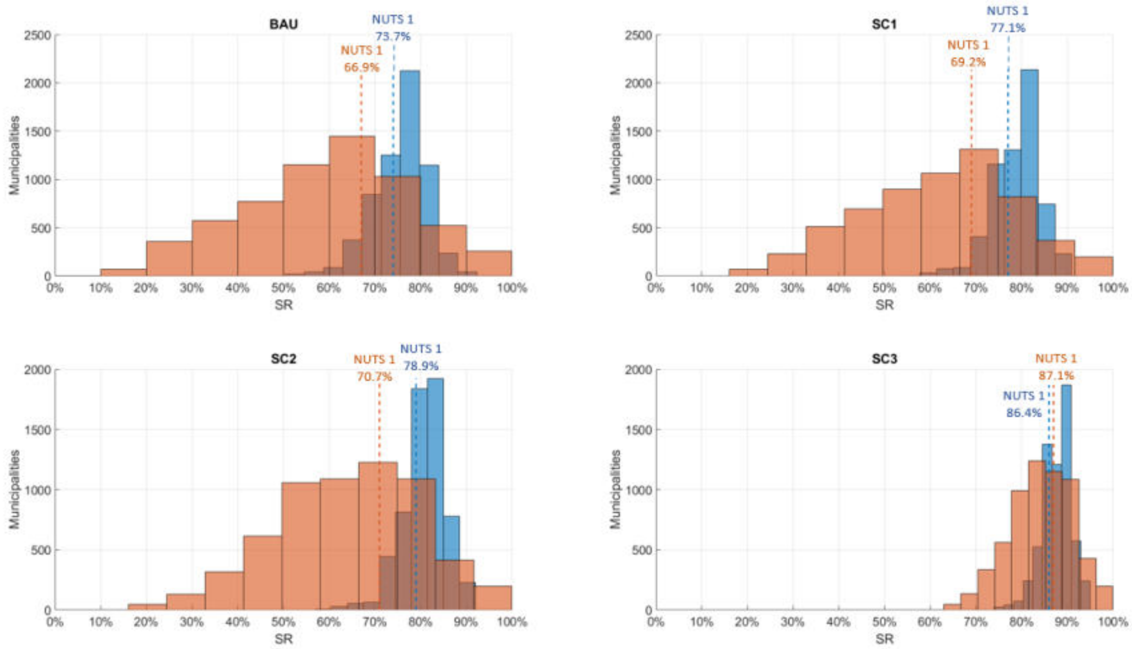


Fig. 6: Separation rate in municipalities, year 2035, municipality producer (blue) and industry producer (brown)

5. Conclusion

The BAU evaluation identified specific municipalities where it is appropriate to target support for increasing MSW separation. The modelled scenarios make it possible to target specific interventions in WM in order to achieve the set goal at the national level. It can be recommended that the greatest effect can be achieved by targeting interventions especially in the western part of the Czech Republic (Bohemia). According to the results, eastern part of the Czech Republic (Moravia) has a more advanced waste separation according to BAU. The SR in the given municipality and at the same time the size of the producer is decisive, because a larger producer can contribute more effectively to the fulfilment of national goals by targeting WM. The presented study is the basis for decisions in WM planning. The results show that current legislation may not be sufficient to meet the objectives of the CEP. The presented approach allows repeated modelling of future developments and serves as a sophisticated support for planning in WM. Authorities have several options to promote waste separation (collection network density, awareness, financial motivation, etc.). The next step would therefore be to analyse the impact of individual changes on waste separation.

The quality of the scenario is significantly affected by the estimation of potential in municipalities. It is therefore essential to have an adequate estimate of the composition of the UR and the rate of transfer between waste fractions. In general, these parameters depend on local conditions, and it is therefore appropriate to evaluate them individually for each municipality. There has been a simplification in the case study of this paper, due to lack of data, the same composition and transfer was considered for each municipality. The main future research should be aimed at improving input data.

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Reference

Act No. 541/220 Coll. Waste law. In Czech.

Avsec S., Kaučič B., 2018. Eco-efficient decision support model of solid waste recycling, Environmental Engineering and Management Journal, 17 (5), 1149-1159. doi: 10.30638/eemj.2018.114

Beigl P., Lebersorger S., Salhofer S., 2008. Modelling municipal solid waste generation: A review, Waste Management, 28 (1), 200-214. doi: 10.1016/j.wasman.2006.12.011.

Bramati M.C, 2016. Waste production and regional growth of marine activities an econometric model, Marine Pollution Bulletin, 112 (1–2), 151-165. doi:10.1016/j.marpolbul.2016.08.025.

Brautzsch H.U., Holtemöller O., 2021. International trade barriers and regional employment: the case of a no-deal Brexit. Economic Structures 10 (11). doi 10.1186/s40008-021-00241-9

Chen W., Los B., McCann P., Ortega-Argilés R., Thissen M., van Oort F., 2018. The continental divide? Economic exposure to Brexit in regions and countries on both sides of The Channel. Regional Science 97(1), 25– 54. doi 10.1111/pirs.12334

Denafas G., Ruzgas T., Martuzevičius D., Shmarin S., Hoffmann M., Mykhaylenko V., Ogorodnik S., Romanov M., Neguliaeva E., Chusov A., Turkadze T., Bochoidze I., Ludwig C., 2014, Seasonal variation of municipal solid waste generation and composition in four East European cities, Resources, Conservation and Recycling, 89, 22-30. doi: 10.1016/j.resconrec.2014.06.001

Directive (EU) 2018/850 of the European Parliament and of the Council of 30 May 2018 amending Directive 1999/31/EC on the landfill of waste (Text with EEA relevance)

Directive (EU) 2018/851 of the European Parliament and of the Council of 30 May 2018 amending Directive 2008/98/EC on waste (Text with EEA relevance).

Directive (EU) 2018/852 of the European Parliament and of the Council of 30 May 2018 amending Directive 94/62/EC on packaging and packaging waste (Text with EEA relevance).

Directive 2008/98/EC of the European Parliament and of the Council of 19 November 2008 on waste and repealing certain Directives (Text with EEA relevance)

EKO-KOM, 2019. Composition of mixed municipal waste from Czech households. https://www.ekokom.cz/skladba-smesneho-komunalniho-odpadu-z-domacnosti-cr/. In Czech.

Estay-Ossandon Ch., Mena-Nieto A., 2018a. Modelling the driving forces of the municipal solid waste generation in touristic islands. A case study of the Balearic Islands (2000–2030), Waste Management, 75, 70-81. doi:10.1016/j.wasman.2017.12.029.

Estay-Ossandon Ch., Mena-Nieto A., Harsch N., 2018b. Using a fuzzy TOPSIS-based scenario analysis to improve municipal solid waste planning and forecasting: A case study of Canary archipelago (1999–2030), Journal of Cleaner Production, 176, 1198-1212. doi:1016/j.jclepro.2017.10.324.

Ghinea C., Drăgoi E.N., Comăniţă E.-D., Gavrilescu M., Câmpean T., Curteanu S., Gavrilescu M., 2016. Forecasting municipal solid waste generation using prognostic tools and regression analysis, Journal of Environmental Management, 182, 80-93. doi: 10.1016/j.jenvman.2016.07.026.

Goel S., Ranjan V.P., Bardhan B., Hazra T., 2017. Forecasting solid waste generation rates. Modelling Trends in Solid and Hazardous Waste Management, 20, 35-64. doi:10.1007/978-981-10-2410-8_3.

Guérin J.É., Paré M.C., Lavoie S., Bourgeois N., 2018. The importance of characterizing residual household waste at the local level: a case study of Saguenay, Quebec (Canada). Waste Management, 77, 341-349. doi: 10.1016/j.wasman.2018.04.019.

Hatik C., Gatina J.-C., 2017, Waste production classification and analysis: A PCA-induced methodology, Energy Procedia, 136, 488-494. doi:10.1016/j.egypro.2017.10.308.

Larsen A.W., Petersen C., Chrostensen H., 2012. Bulky waste quantities and treatment methods in Denmark. Waste Management and Research, 30(2), 147-154. doi: 10.1177/0734242X11417973.

Lavee D., Khatib M., 2020. Benchmarking in municipal solid waste recycling, Waste Management, 30/11, 2204-2208. doi: 10.1016/j.wasman.2010.03.032.

Long F., Song B., Wang Q., Xia X., Xue L., 2012, Scenarios simulation on municipal plastic waste generation of different functional areas of Beijing, Journal of Material Cycles and Waste Management, 14 (3), 250-258. doi: 10.1007/s10163-012-0066-9.

Mazzanti M., Zoboli R., 2008. Waste generation, waste disposal and policy effectiveness, Evidence on decoupling from the European Union. Resources, Conservation and Recycling, 52 (10), 1221-1234. doi: 10.1016/j.resconrec.2008.07.003

Miezah K., Obiri-Danso K., Kádár Z., Fei-Baffoe B., Mensah M.Y., 2015. Waste Management, 46, 15-27. doi: 10.1016/j.wasman.2015.09.009

Müller A., Hummel M., Kranzl L., Fallahnejad M., Büchele R., 2019. Open Source Data for Gross Floor Area and Heat Demand Density on the Hectare Level for EU 28. Energies 12(24), 4789. doi 10.3390/en12244789

Naqvi A., 2021. COVID-19 European regional tracker. Sci Data 8, 181. doi 10.1038/s41597-021-00950-7

Pluskal J., Šomplák R., Nevrlý V., Smejkalová V., Pavlas M., 2021. Strategic decisions leading to sustainable waste management: Separation, sorting and recycling possibilities. Journal of Cleaner Production, 278, 123359. doi: 10.1016/j.jclepro.2020.123359

Rizzati M., De Cian E., Guastella G., Mistry M., N., Pareglio S., 2022. Residential electricity demand projections for Italy: A spatial downscaling approach. Energy Policy, 160,112639. doi 10.1016/j.enpol.2021.112639.

Rosecký M., Šomplák R., Slavík J., Kalina J., Bulková G., Bednář J., 2021, Predictive modelling as a tool for effective municipal waste management policy at different territorial levels, Journal of Environmental Management, 291, 112584. doi: 10.1016/j.jenvman.2021.112584.

Sekito T., Tanaka N., Matsuto T., 2003. Study on composition and particle characteristics of shredded municipal waste for the improvement of separation efficiency in a municipal bulky waste processing facility. Waste Management and Research, 21, 299-308.

Sjöström M., Östblom G., 2010. Decoupling waste generation from economic growth — A CGE analysis of the Swedish case, Ecological Economics, 69 (7), 1545-1552. doi:10.1016/j.ecolecon.2010.02.014.

Smejkalová V., Šomplák R., Nevrlý V., Burcin B., Kučera T., 2020a. Trend forecasting for waste generation with structural break. Journal of Cleaner Production, 266, 121814. doi: 10.1016/j.jclepro.2020.121814.

Smejkalová V., Šomplák R., Pluskal J., Rybová K., 2022. Hierarchical optimisation model for waste management forecasting in EU. Optimisation and Engineering. In press.

Smejkalová V., Šomplák R., Rybová K., Nevrlý V., Rosecký M., Burcin B., Kučera T., 2020b. Waste Production and Treatment Modelling for EU Member States, Chemical Engineering Transactions, 81, 691-696. doi: 10.3303/CET2081116.

Soltani A., Sadiq R., Hewage K., 2017. The impact of decision uncertainty on municipal solid waste management. Journal of Environmental Management, 197, 305-315. doi: 10.1016/j.jenvman.2017.03.079.

TIRSMZP719. Prognosis of waste production and determination of the composition of municipal waste. Technology Agency of the Czech Republic, solution period: 1.1.2019–31.12.2021. Available from: https://starfos.tacr.cz/en/project/TIRSMZP719

Tomić T., Schneider D.R., 2020. Circular economy in waste management – Socio-economic effect of changes in waste management system structure, Journal of Environmental Management, 267, 110564. doi: 10.1016/j.jenvman.2020.110564.

Vadia R., Blankart K., 2021. Regional Innovation Systems of Medical Technology: A knowledge production function of cardiovascular research and funding in Europe. REGION, 8(2), 57–81. https://doi.org/10.18335/region.v8i2.352.

VISOH, 2022. Public information on production and waste management. Ministry of the Environment. In Czech.

Wang F., Yu L., Wu A., 2021. Forecasting the electronic waste quantity with a decomposition ensemble approach. Waste Management, 120, 828–838. doi: 10.1016/j.wasman.2020.11.006.