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Modeling and real time optimization of a smart microgrid

Master thesis

Study programme: N2612 – Electrical Engineering and Informatics
Study branch: 3906T001 – Mechatronics

Author: **Bc. Pavel Vedel**
Supervisor: doc. Dr. Ing. Jaroslav Hlava

Liberec 2019

TECHNICKÁ UNIVERZITA V LIBERCI
Fakulta mechatroniky, informatiky
a mezioborových studií

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Diplomová práce

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Autor práce: **Bc. Pavel Vedel**
Vedoucí práce: doc. Dr. Ing. Jaroslav Hlava

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Master Thesis Assignment Form

Modeling and real time optimization of a smart microgrid

Name and Surname:	**Bc. Pavel Vedel**
Identification Number:	M18000203
Study Programme:	N2612 Electrical Engineering and Informatics
Specialisation:	Mechatronics
Assigning Department:	Institute of Mechatronics and Computer Engineering
Academic Year:	**2018/2019**

Rules for Elaboration:

1. Conduct a literature review in the field of microgrid modelling and optimization with main focus on real time economic optimization using economic model predictive control.
2. Using Matlab/Simulink/Simscape modelling environment create a simulation model of a microgrid including both controllable (e.g. generators using IC engines or gas turbines) and uncontrollable electricity generation (e.g. solar panels. wind generation) and partly controllable/shiftable electricity consumption. This microgrid is not islanded but connected to the main grid. Prices of the electricity that is sold to or bought from the main grid vary with time (real time pricing).
3. Develop a real time optimizing control that will minimize the cost of operation of this microgrid. It is recommended to use economic model predictive control for this purpose.
4. Test the operation of this real time optimizer in Matlab in connection with the simulation model built in the previous step. If the performance is satisfactory consider implementing this optimizer in an appropriate industrial programming environment like LabView.

Scope of Graphic Work:	by appropriate documentation
Scope of Report:	40–50 pages
Thesis Form:	printed/electronic
Thesis Language:	English

List of Specialised Literature:

[1] Stefano Bracco, Federico Delfino, Fabio Pampararo, Michela Robba, Mansueto Rossi, A mathematical model for the optimal operation of the University of Genoa Smart Polygeneration Microgrid: Evaluation of technical, economic and environmental performance indicators, Energy, Volume 64, 2014, pp. 912-922, ISSN 0360-5442.

[2] Seyyed Mostafa Nosratabadi, Rahmat-Allah Hooshmand, Eskandar Gholipour, A comprehensive review on microgrid and virtual power plant concepts employed for distributed energy resources scheduling in power systems, Renewable and Sustainable Energy Reviews, Volume 67, 2017, pp. 341-363, ISSN 1364-0321.

[3] Maria Lorena Tuballa, Michael Lochinvar Abundo, A review of the development of Smart Grid technologies, Renewable and Sustainable Energy Reviews, Volume 59, 2016, pp. 710-725, ISSN 1364-0321.

[4] S. Bracco, F. Delfino, R. Procopio, M. Rossi and M. Robba, "A model predictive control approach for the optimization of polygeneration microgrids and demand response strategies," 2016 IEEE 16th International Conference on Environment and Electrical Engineering (EEEIC), Florence, 2016, pp. 1-6.

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Date of Thesis Assignment:	10 October 2018
Date of Thesis Submission:	30 April 2019

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Liberec 10 October 2018

Declaration

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Abstract

An increasingly important role in the electricity system is now played by renewable generation such as solar panels, wind turbines etc. Since solar and wind generation is not controllable, new approaches are necessary to keep the production consumption balance. The relationship between current electricity generation and demand for electricity is reflected in the varying prices of the short term electricity markets. This motivates an idea that the whole electricity system can benefit if the consumer prices also become variable in the real time accordingly. Then the consumers can help to maintain the grid balance by performing their own local electricity cost minimization and shifting consumption to the times where electricity from renewables is abundant and its price is low. This thesis is focused on the consumer side of this price based control. Its objective is to develop an economic model predictive controller that minimizes the cost of operation of a microgrid with distributed electricity generation. For this purpose, a simulation model of residential community microgrid with distributed electricity generators is developed in the first part of the thesis and used as a testbed for the second part. In the second part, an economic model predictive controller based on mixed integer optimization is developed. It performs real time coordination and optimization of the microgrid operation. It includes also a prediction block for the electricity consumption and renewable generation based on ARIMA models. It was tested in Matlab/Simulink environment. Using the Matlab support for automatic code generation it can easily be ported to industrial hardware.

Key words: Smart grid, Economic MPC, ARIMA models, Real time pricing.

Abstrakt

Výroba elektřiny z obnovitelných zdrojů jako jsou solární panely či větrné turbíny hraje v současné době stále významnější roli. Jelikož solární ani větrná výroba nejsou řiditelné, udržení rovnováhy mezi výrobou a spotřebou vyžaduje nové přístupy. Vztah mezi aktuální výrobou elektřiny a poptávkou po ní se odráží v proměnných cenách krátkodobých trhů s elektřinou. To motivuje myšlenku, že pro celek elektrizační soustavy by bylo prospěšné, pokud by se odpovídajícím způsobem měnily v reálném čase i spotřebitelské ceny elektřiny. Spotřebitelé pak pomohou zachovat rovnováhu celé elektrizační soustavy tím, že si budou lokálně minimalizovat své vlastní náklady na spotřebovanou elektřinu a posunou spotřebu do doby, kdy je k dispozici velké množství levné elektřiny z obnovitelných zdrojů. Tato práce je zaměřena na spotřebitelskou stranu tohoto řízení pomocí ceny. Jejím cílem je vyvinout systém založený na ekonomickém prediktivním řízení, který minimalizuje cenu provozu mikrosítě s decentralizovanými generátory elektřiny. K tomuto účelu je nejprve v první části práce vytvořen simulační model rezidenční mikrosítě s decentralizovanou výrobou elektřiny. Ve druhé části je tento model využit jako platforma pro testování. V této druhé části je vyvinut ekonomický prediktivní řídicí systém používající smíšenou celočíselnou optimalizaci. Tento systém v reálném čase koordinuje a optimalizuje provoz celé mikrosítě. Obsahuje také blok pro predikci spotřeby elektřiny a výroby z obnovitelných zdrojů založený na ARIMA modelech. Byl testován v prostředí Matlab/Simulink. S využitím možností Matlabu pro automatické generování kódu může být snadno přenesen na průmyslový hardware.

Klíčová slova: Inteligentní elektrizační sítě, Ekonomické MPC, ARIMA modely, ceny elektřiny proměnné v reálném čase.

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Rád bych poděkoval všem, kteří přispěli ke vzniku tohoto dílka.

Contents

List of Abbreviations

ACO	Ant Colony Optimization
ADF	Augmented Dickey Fuller
ANN	Artificial Neural Networks
ARIMA	AutoRegressive Integrated Moving Average
CBC	Coin-or Branch and Cut
CIGRE	Conseil International des Grands Réseaux Électriques i.e. International Council on Large Electric Systems
DAM	Day-Ahead Market
EMS	Energy Management System
FL	Fuzzy logic
GS	Gauss Seidel
HHV	the Higher Heating Value
HJB	Hamilton-Jacobi-Bellman equations
IEA	International Energy Agency
ILP	Integer Linear Programming
LFP	Lithium-Iron-Phosphate
LV	Low Voltage
MAPE	Mean Absolute Percentage Error
MG	MicroGrid
MILP	Mixed Integer Linear Programming
MLD	Mixed-Logical Dynamics
MLM	Maximum Likelihood Method
MPC	Model Predictive Control
MQP	Mixed Quadratic Program
MSPC	Modified Simple Power Consumption Model
OP	Original Parameter
PSS	Probability of Self-Sufficiency
RR	Round Robin
SA	Simulated Annealing
SDS	Sustainable Development Scenario
SO	System Operators
SOC	State Of Charge
SOFC	Solid-Oxide Fuel Cells
STLF	Short Term Load Forecast
TOU	Time-Of-Use
UC	Unit Commitment

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1 Modern energy system and literature review in the field of microgrid optimization

1.1 Reasons of transition to renewable energy

World energy system is developed and evolved during the time. Energy demand is growing and, thus, growing the energy supply. However, uncontrollable usage of traditional (primary) energy sources leads to the world's ecological problems. Greenhouse gas emissions (carbon dioxide CO_2, methane CH_4, nitrogen oxides NO_x, chlorofluorohydrocarbons (freons)), depletion of energy sources and global warming – all of them will negatively influence the life on the Earth in the long-term outlook.

By the aforementioned reasons, the agreement of synergies of all world powers for containment climate changes was developed in Paris in 2015. The main figures of the agreement are the following:

- Holding the global average temperature well below 2 °C above pre-industrial levels and to make an effort to limit the increase of temperature to 1.5 °C above pre-industrial level.
- In order to reach the long-term global temperature goal, all sides strive for achieving the peak of greenhouse gas emissions in order to then achieve well-balanced level between anthropogenic emissions from sources and absorption by absorbents of greenhouse gases in the second half of 21 century.

Thus, it is possible to achieve the requirements of the agreement, if the consumption of fossil fuel would be significantly reduced and the complex transition to renewable energy would be started.

It is necessarily to introduce the sufficient number of solar panels, wind turbines and hydro turbines to cover all consumers' needs; petroleum cars should be replaced with electro cars; space heating should be done with the help of heat pumps.

Since it is much more difficult to store electricity than fossil fuel, the huge production share of stochastic electricity requires intellectual energy supply system – so called SmartGrid. Such system balances energy consumption and production all the time.

SmartGrid requires flexible energy producers and consumers, which can actively help the energy system. Such paradigm means active usage of heat and electricity storages, replenishment of capacity of the storages during the periods of cheap electricity and smart discharging during the periods of expensive electrical energy.

Additional advantages include higher system reliability, cheaper price of energy supply (by saving fuel and delayed investments in additional generation capacities) and reducing the impact on the environment.

Figure 1.1 shows the Sustainable Development Scenario (SDS), which is provided by International Energy Agency [1]. The Figure depicts an integrated approach to achieve internationally agreed objectives on climate change, air quality and universal access to modern energy.

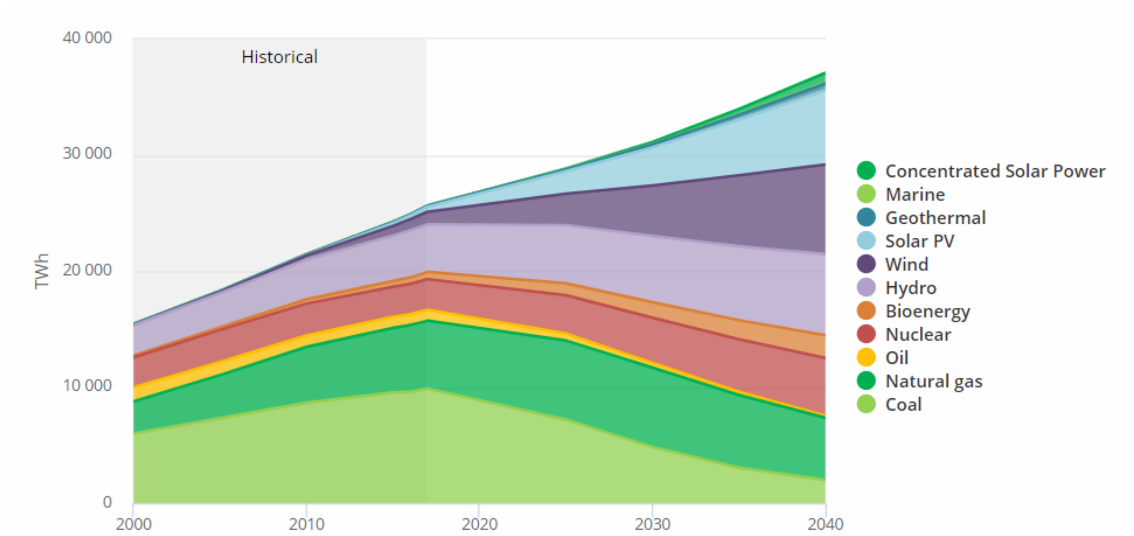

Figure 1.1: Sustainable Development Scenario predicted till the year of 2040

1.2 Energy system

Industrial, commercial and residential customers need different types of energy services that are provided by different infrastructures.

So far different infrastructures are considered and work almost independently. In SmartGrid all of the systems should by combined for achieving synergy between conversion and storage of various forms of energy. Electricity can be transmitted to the long distances with relatively small loses. Chemical energy carries, such as natural gas, can be stored with the help of relatively simple and inexpensive technologies. Combining infrastructures enables power exchange between them.

When one considers the energy sources with discontinuous primary energy such as wind or solar energy it is important to save the energy. Storage provides redundancy in supply, higher reliability and large degree of freedom for optimization.

1.3 The power system

We will briefly describe the markets of the modern power system. Electricity is considered as an absolute necessity in the modern society and it is consumed at the same moment when it is generated. It cannot be stored in significant quantities by economical mean. If electricity is not stored it should be then delivered immediately [2]. Thus, power system consists of an electrical grid, which transports electricity between producers and consumers. The grid is splits into several layers:

The upper layer is a high voltage transmission system. Typical producers, such as power plans and renewable energy sources are connected to that layer. Their generated power is transmitted to the end consumers throughout low voltage distributed grids. Retailer provides the electrical energy to its consumers according to the contract. The consumers can easily change their retailers of electricity through the retail market. Most electricity markets in Europe are liberalized in such way and have some common features.

Electricity market is usually divided into several parts: transmission, distribution, retail trade and generation. Markets facilitate competition in generation and retail, while transmission remains a monopoly, which is controlled by non-commercial organizations known as System Operators (SO).

Electricity is transmitted through wires almost instantly. A unit of electricity (a kWh), delivered to a consumer, cannot be traced back to the producer of electricity that literally produces it. Such feature makes special demands to the metering and billing system for electricity and motivates the needs for markets. Production and consumption must be balanced at any moment, each minute, daily and nightly during the whole year. Traditional price mechanisms cannot handle the fast dynamics in real time. Electricity prices always must be either ahead of real time or after real time.

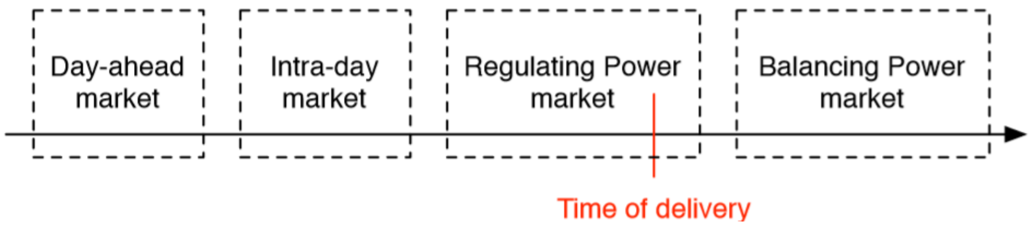

Figure 1.2: Market time scale [3]

Nowadays, trading of electrical energy is organized in pools or exchanges, where producers and consumers submit prices for energy delivery both to the grid and from the grid.

Energy consumption is volatile with a good predictable characteristic during the day, night, and week as well as in seasonable and annual time scales. Several markets are available depending on the time scale. Daily arrangements are made on a Day-Ahead Market (DAM), which is often called as a forward market in USA or spot market in Europe.

Adjusting of energy needs is made in intra-day markets and in a real time or regulation markets [4]. Figure 1.2 illustrates the wide time scale of these energy markets.

1.4 The future power system

Due to the appearance of fluctuating energy generation from the renewable sources, such as wind and solar power, the future of the energy system needs flexible consumers and producers. In the modern energy systems energy load is fairly predictable, and the large plants mainly provide the necessary adjustable power to deal quickly with imbalance. The smart grid introduces a main shift of paradigm in the power system from production according to demand to letting demand follow production [5, 6]. Therefore, it is obvious and even economically effective [7] to include the rising electrification of the demand side as a flexible and controllable actuator. The future Smart Grid requires new strategy of control, which combines flexible demand and effectively balances production and consumption of energy. Research advances within predictive control and forecasting opens opportunity for demand response based on control as a crucial variant to raise the flexibility of the power system. The control tasks for successful realization of demand response are to identify the reliable control strategies, connect these strategies with markets and manipulate the power balance of all flexible units [3].

1.5 Limitations in the problem of energy management

In real life the optimal energy control system for MicroGrid (MG) depends on some limitations.

The limits of energy generation are maximal and minimal borders of output power. System must work within these limitations for safe and cost-effective work. All types of loads, such as residential, commercial and industrial, consume the energy according to their operating limits. It is known as a consumption or load limit. Battery storage devices, such as hydrogen and ultra-capacitors, have speed limit for charging and discharging. These storage elements have the limit of discharging as well. Excessive speed of charging and discharging influences the lifetime and efficiency of these elements. All of these operational limits are known as storage limits.

Operational constrains are used for non-spinning, spinning reserves, ramping limits, starting and stopping rates of generating elements. In some countries, such as USA, there are prices of selling and buying energy from the grid in case of its surplus or deficit. For instance, electrical prices in real time depend on the online load. When the load exceeds defined limit the price of energy continuously increases. Such scheme reduces peak load on power units.

Microgrids depend mainly on renewable sources of energy for decreasing carbon emission. Solar, wind and fuel cells energy is integrated into microgrid. Wind and solar energy are undefined and have certain output limits. Fuel cell has also some operational limits. These working conditions are taken as constrains while solving the formulation of optimization related to energy management for microgrids that utilize renewable resources [3].

1.6 Optimization types used in energy management problem

Different optimization techniques have been used by researchers to solve the problem of energy management in microgrids. In Figure 1.3 one can see the various methods, which are used to solve the problem of energy management. Each method is utilized in different microgrid strategies, where each is tuned to reach specified goal. Some of the methods are discussed further. The main aim of these tables is to show the range of solving tasks when microgrid is used.

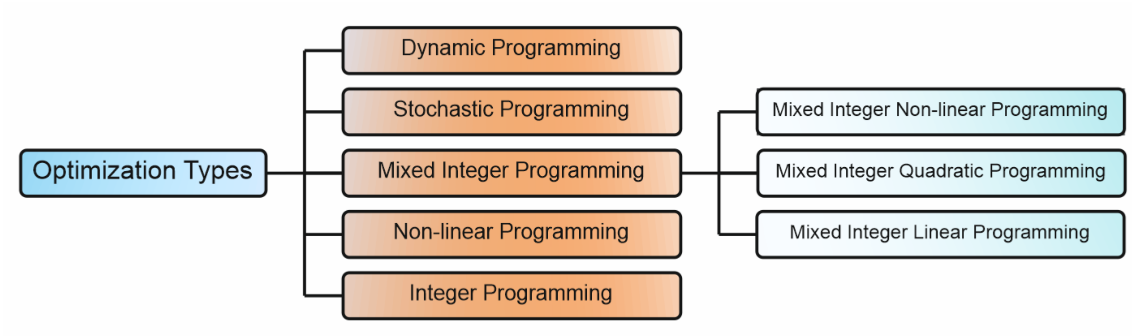

Figure 1.3: Optimization types

Table 1.1: Critical analysis MG EMSs based on linear programming methods

Ref.	**Main stream**	**Innovation, features or approach**
[8]	Reducing demand fluctuations and improving economic balance	Annual decrease of demand fluctuations up to 19%
[9]	Minimizing total annual cost by optimally selecting various system components and renewable resources for a smartgrid.	Mixed Integer Linear Programming (MILP).
[10]	Solution of the problem of optimal generation distribution by dividing it into two phases, namely, the site planning model and the capacity planning model.	Mixed Integer Linear Programming (MILP). The authors argue that the model they proposed was computationally efficient with the best optimal solution, taking into account the current state of the system and the predictions for the future.

[11, 12]	The task includes the cost of exchanging energy with the main network, the cost of starting and shutting down, operating costs of distributed generators, payload on demand, penalty costs for forced reduction of load and leakage of renewable energy.	Mixed Integer Linear Programming (MILP). Provides an effective trade-off between low operating costs and good energy services for end users.
[13]	Optimal design and operation of an energy system consisting of heat and energy.	The proposed model was used to formulate a multipurpose function to minimize capital and operating costs along with CO_2 minimization.
[14, 15]	An economical smart microgrid network (CoSMoNet), which facilitates economic operations on the microgrid network.	A scheme based on integer linear programming (ILP) matches the excess energy in the storage elements of a microgrid network with the requirements of another microgrid network, the load of which cannot be compensated by their local power source.

Table 1.2: Critical analysis MG EMSs based on non-linear programming methods

Ref.	**Main stream**	**Innovation, features or approach**
[16]	System optimization with the objective function of maximizing income through the exchange of electricity between the microgrid and the main power grid	Non-linear function.
[17]	Performance evaluation of a hybrid renewable energy system.	Computing structure based on mixed integer non-linear programming.
[18]	The optimal controller for tracking the trajectory of non-linear systems. The presented scheme is used to ensure the efficient exchange of energy flows between various sources in the micronet using energy converters.	This task was formulated as a non-linear quadratic program that minimizes the quadratic cost function.

[19]	The task of planning operations for microgrids with renewable energy sources. This problem is associated with the allocation of the lowest cost per unit commitment (UC).	Integer non-linear programming. There are requirements for loads, the environment and system performance. A new concept of probability of self-sufficiency (PSS), which indicates the probability that the microgrid will satisfy local demand in a self-sufficient manner.
[20, 21]	The task of optimizing long-term planning with a net of renewable energy microgrid with a hybrid energy storage device in the form of a mixed quadratic program (MQP)	Take into account the lifetime, degradation, start-up / shutdown, operating costs of the hybrid system and energy storage system.

Table 1.3: Critical analysis MG EMSs based on stochastic control methods

Ref.	**Main stream**	**Innovation, features or approach**
[22]	The task of optimal modeling of reliability of microgrids and solving issues with battery scheduling.	Stochastic linear programming approach.
[23]	The task is to determine the performance of an autonomous microgrid that is capable to connect to other microgrids for adequate load maintenance.	A framework for Monte-Carlo sequential modeling has been developed.
[24]	Multipurpose optimization. The authors used three different types of algorithms at different stages, namely: a search algorithm with prohibitions, algorithms related to graph theory, and a probabilistic algorithm based on ”forward, backward, backward.”	The strategy of creating microgrids with optimized sufficient power. They claim that the proposed planning structure can help engineers and system planners to develop microgrids capable of working in island mode.
[25]	The task of planning microgrid reactive power. The authors used the multipurpose function to minimize losses and maximize the reactive power margin and voltage margin.	New stochastic programming algorithm. The authors claim that the algorithm for particle swarm optimization works better than the algorithm for stochastic programming.

Table 1.4: Critical analysis MG EMSs based on dynamic programming techniques

Ref.	**Main stream**	**Innovation, features or approach**
[26]	A dynamic model that requires consumers to submit energy demand graphs and actively monitor energy price signals is proposed. The microgrid is equipped with distributed generation, network connection, energy storage elements and various loads.	In this proposed scheme, a microgrid is required to transmit energy forecast information to the main grid. In addition, customers must engage in energy trading and respond to energy control signals in real time. Therefore, an intelligent system is presented that independently performs all these tasks without a request from the end users.
[27]	Creating a dynamic program that is used to minimize energy costs and increase battery life at the same time.	To do this, the authors suggested that the central controller of the microgrid should figure out the best scheme for charging and discharging the battery. This can be achieved by using electricity tariffs depending on the time-of-use (TOU). Household electricity consumption patterns are modeled with a mixture of Gaussian distributions.
[28]	The authors proposed a dynamic contract mechanism for regulating the energy purchase by microgrids over time.	The proposed contract establishes time-specific commitments for the purchase of microgrids to fulfill the demands of its load, while giving some flexibility to the microgrids in order to change future commitments. A stochastic dynamic program is used to update the commitments according to the current state of the storage and prediction of the future load.

[29]	An agent-based energy management system is introduced. It facilitates electricity trading between microgrids with demand response and distributed storage.	Dynamic programming is used to utilize diversity in end-user load consumption patterns and energy availability from distributed generation and storage. The proposed approach facilitates the response of demand in reducing peak demand and minimizing electricity cost.
[30]	The goal of the program is to minimize CO_2 equivalent emissions, fuel consumption, or a compromise between these two.	Presented a scheme of operational planning for the day ahead. The problem of adherence to units is solved by dynamic programming. To reduce uncertainty in the predicted values of solar energy or load, the smart energy manager recalculates the reference power values of the generators in 1 hour, if necessary.

Table 1.5: Critical analysis MG EMSs based on non-differential programming methods

Ref.	**Main stream**	**Innovation, features or approach**
[31]	The goal is to minimize the net cost of a microgrid, which includes distributed generation and storage costs, dispatch load utilities and transaction costs in the worst case due to the intermittent nature of renewable energy.	Formulated non-differential program.

1.7 Solution techniques of energy management problem

Different researchers used different solution techniques to solve the optimization framework that is concerned with energy management in microgrids. There are types of solution techniques, which are used to solve the energy management problem in

Figure 1.4. These solutions and the relevant works are discussed below. Here we briefly introduce main trends, approaches and features of different solutions. It can be noticed that it is possible to solve (or distinguish) a wide range of problems of energy management control, which are currently implemented, just using introduced approaches.

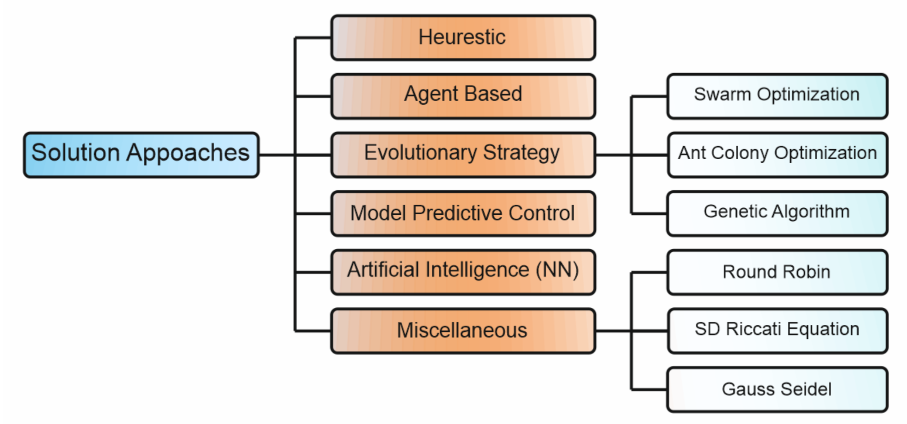

Figure 1.4: Solution types

Table 1.6: Critical analysis MG EMSs based on a heuristic approach

Ref.	**Results or suggestions**	**Methods or features**
[32]	This scheme facilitates the share of excess energy and local load on the grid. The authors argue that this approach reduces or prevents load shedding.	Control algorithms for managing distributed energy resources under various operating conditions in interconnected microgrids.
[33, 34]	Allow the energy storage device to control active power and minimize current harmonics, unbalance and reactive power introduced into the network due to disturbing loads.	An energy storage device is involved in energy management in accordance with a specific control strategy and additionally contributes to the improvement of power quality. For low voltage systems.
[35]	The procedure presented is a scenario-based search method that uses local automation and remote control strategies, taking into account the achievable benefits for each scenario.	The autonomous operation of the microgrid is based on energy storage devices that maintain a balance between generation and load.

[36]	Presents a decentralized approach to load management, which was implemented in the project Swiss2Grid.	Single households use a local algorithm based on local measurements of voltage and frequency, distributes the unloaded loads in time to minimize costs for the consumer and maximize network stability.
[11]	A multi-purpose approach involves an effective trade-off between low maintenance and good power consumption for end users.	The heuristic algorithm was used to solve the problem of the total cost of exchanging electricity with the main grid, the cost of starting and shutting down, operating costs of distributed generators, charges for the load in response to a request, penalties for forcing a reduction in load, and leakage of renewable energy.
[37, 38]	Solving the problem of planning distributed generators in different places.	The multipurpose function is normalized to form a minimized function of optimal costs when the production capacity and the number of distributed generators are known, as well as the need for various locations.
[39, 40]	The authors proposed a new active-power distribution algorithm capable of controlling the generation of microgrids in order to demand online in grid-binding mode. The algorithm also minimizes greenhouse gas emissions and optimizes the operating costs of distributed resources.	A heuristic approach based on the cost function of micro sources was tested to solve various problems of optimizing energy distribution. The authors argue that the scheme proposed by them surpasses other modern optimization methods in terms of global costs and emissions, system stability, and requirements for computing resources.

Table 1.7: Critical analysis MG EMSs based on agent based approaches

Ref.	Results or suggestions	Methods or features
[29, 41]	Creating an agent-based energy management system to facilitate electricity trading among microgrids with demand response and distributed storage. The proposed approach facilitates the demand response in reducing peak demand and minimizing the cost of electricity.	A way to use diversity in end-user consumption patterns and energy availability from distributed production and storage.
[42]	Authors propose a framework that supports the auction market in which energy sellers and buyers should practice trading.	This structure uses distributed energy storage as part of demand side management. This allows end users with low load priority to participate in demand response.
[43]	Authors proposed an agent-based intelligent power management system in order to simplify electricity trading between microgrids. It was found that demand response based on several agents successfully reduced the system peak in addition to customer benefit with a high priority index.	The system uses demand response, a variety of consumer energy consumption patterns and the availability of electricity from distributed generators as vital sources in the system's power management.

Table 1.8: Critical analysis MG EMSs based on an evolutionary approach

Ref.	Results or suggestions	Methods or features
[44]	Program that minimizes capital and annual operating costs for renewable energy, taking into account various system and unit limitations.	Optimal capacity planning using evolutionary strategy.
[45]	Daily operating costs and carbon emissions are minimized.	The authors focused on a mathematical model developed for optimal control of a smart polygeneration microgrid.

[46]	Multipurpose approach for formulating objective functions focusing on charge / discharge costs, losses and voltage profile.	The authors proposed an algorithm based on differential evolution for solving the problem. The Short Term Load Forecast (STLF) for microgrids has a very non-smooth and non-linear behavior of load time series. The characteristics of the time series of the load of traditional energy systems are described.
[47]	A new two-level prediction strategy is presented for STLF microgrids.	The proposed approach consists of a feature selection method and a prediction mechanism (including a neural network and an evolutionary algorithm) in the lower level as a forecaster. This approach is used as an advanced differential evolution algorithm in the upper level to optimize the predictor's performance. The proposed prediction strategy is estimated based on real data from a campus in Canada.

Table 1.9: Critical analysis MG EMSs based on the model-based prediction approach (MPC)

Ref.	Results or suggestions	Methods or features
[27, 48, 49, 50]	A multipurpose structure for modeling energy management in microgrids is considered. The proposed model believes that the microgrid consists of distributed generation, network connection, energy storage elements and various loads.	The Model Predictive Control (MPC) approach is used to minimize energy costs and increase battery life at the same time. For these purposes, the central controller of the microgrid must find the best charging and discharging circuit for the battery.
[20]	Energy management is solved by MPC, in order to maximize economic benefits microgrids while minimizing the use of each storage system costs.	The MPC approach is used to solve the optimization problem, which is to maximize the economic benefits and minimize the causes of degradation of each storage system.
[51, 52]	Provide continuous / discrete dynamics and switching between different operating conditions.	The installation is modeled using a mixed logical dynamics (MLD) structure.
[53]	At the operational management level, the authors focus on the concept of smart microgrids, which includes the interdependence between electrical, thermal and material flows. It is concluded that management strategies are necessary for the optimal operation of modern grid.	Optimal strategies for predictive management of multi-node microgrids that integrate heat pumps and co-generation plants.
[54]	Represent a predictive control method for a stochastic model for microgrid control.	The input data of the stochastic disturbance and the various restrictions imposed by the distribution lines and the battery level are taken into account.
[55]	They propose a predictive model management approach that gives better performance and overcomes the technical limitations associated with the rate of linear change.	Emphasis is placed on optimal control of dynamic dispatch and formulations of dynamic economic dispatch.

[56]	This article discusses the optimization of a microgrid operating in an environment that is similar to urban areas, combining both optimal planning of microgrid sources and demand response strategies implemented in district buildings. In particular, the entire system is optimized to create generation schedules, storage systems, electric vehicles, deferred and variable loads with minimal daily operating costs, as well as grid constraints. Binary and auxiliary variables were used to reduce the non-linearity of the model.	A method based on MPC is proposed to minimize the uncertainties associated with renewable resources and to reduce the complexity of the overall solution to the problem.

Table 1.10: Critical analysis MG EMSs based on neural network approach

Ref.	**Results or suggestions**	**Methods or features**
[57]	Approach of multi-level strategy Artificial Neural Networks (ANN) has been developed and trained using the Levenberg-Markurardt backpropagation algorithm.	The proposed idea can be used in real-time energy infrastructure in order to minimize the risks of a future energy crisis with increased reliability and unhindered interaction. Microgrids are deployed in different places.
[58]	Solutions to the complex problem of managing energy resources with a large number of resources, including electric cars connected to the electrical network.	Hybrid artificial intelligence technique, including methods of simulated annealing (SA) and ant colony optimization (ACO).
[59]	Determining the optimal amount of energy over a one-week period of time for hybrid renewable energy sources in order to minimize the power received from the power system and maximize the generation of electricity from renewable energy sources.	New recurrent neural network approach.

Table 1.11: Critical analysis MG EMSs based on the Round Robin approach

Ref.	Results or suggestions	Methods or features
[60]	Transactional and communication-based application energy consumption models are presented in a modified simple power consumption model (MSPC) server.	The Round Robin (RR) approach is used to select one of the servers for mixed production types, so that the total power consumption of the servers can be reduced.

Table 1.12: Critical analysis MG EMSs based on Gauss Seidel approach

Ref.	Results or suggestions	Methods or features
[16]	Maximizing balance / revenue through the exchange of electricity between the microgrid and the main power grid.	Fuzzy logic and Gauss Seidel (GS) is used. Five different scenarios are tested for local loading and microgrid assembly operations.

Table 1.13: Critical analysis MG EMSs based on SD Riccati control

Ref.	Results or suggestions	Methods or features
[18]	Minimizing the quadratic cost function.	The optimal controller for tracking the trajectory of non-linear systems. The developed optimal control law is the result of solving the Hamilton-Jacobi-Bellman (HJB) and S. D. Riccati equations. The HJB equation is used for non-linear systems with factorization depending on the state. The presented scheme is used to ensure the efficient exchange of energy flows between various sources in the microgrid using energy converters.

1.8 Summarizing information about microgrids

Thus, we have observed the reasons why one should change the energy generation from fossil fuel to energy generation from renewable sources. This is due to the world movement to renewable power sources, aspiration to restrain the rise of global warming temperature and reduce the emission of polluting substances into the environment.

Smart microgrid is a system that is placed on a certain object of energy generation and/or energy consumption. The system collects information about the object and gives instructions for correct usage of various system resources according to the objectives of microgrid.

As it was previously said, gradual replacement of energy generation methods by energy producers leads to the situation when energy will be produced uncontrollably. Therefore, the energy price at the different time instants will be changed. The price will also depend on demand, which should be offered to consumers at the exact moment. Because, it can happen that the generated energy at the exact moment of time will be lower than the consumer requires. In such case, it is necessary to utilize reserve power capabilities of energy producers to compensate the demand. And utilizing reserve power capabilities will increase the price of the energy.

In the modern realities, it is reasonable to use microgrids that will help to effectively solve all kind of problems.

Depending on the optimization goals, the microgrid concept can offer following set of solutions for distinct members of the market:

- Decrease of demand fluctuation
- Improvements of economical balance
- Minimization of overall (and individual) expenditure
- Solution for the problem of distributed generation
- Optimal equipment usage
- Prolonging the lifetime of battery
- Support of systems based on energy trade with other grids
- Optimal operational planning
- Planning of reactive power
- Minimization of harmful substances emission
- Improvements of quality of energy flow (frequency, voltage etc.)
- Using forecasting
- Implement more than one aforementioned solutions

1.9 Reasons for choosing Model Predictive Control

Thus, having introduced model and optimization aims, one can choose a method when the microgrid operates in the most efficient way.

However, from the wide range of optimization methods for microgrids, particular attention should be given to the method, which is based on Model Predictive Control (MPC).

Major functionality of MPC is based on the possibility to consider system limits and on the principle of re eding window. The control is based on minimization function, which takes the current system state and future system horizons. Therefore, the control of the object will depend not only on the current data, but the future possible system states (horizons) will be also considered; and symbioses between all possible signals to control the object will be searched taken into account preferences of the minimization function. Receding window allows each system step to update old system horizons and consider new prediction intervals.

For solving minimization function different variants of linear and non-linear programming can be chosen. It is worth noting simplicity of controller realization and sensible search of optimal control.

As it was demonstrated in the literature review section, MPC method perfectly copes with the following tasks:

- Operating with multi-purpose frameworks and distributed energy generation system
- Minimization of operational and energy prices
- Maximizing profit from the object
- Searching the optimal way of battery charging/discharging
- Prolonging life-time of the battery
- Managing several storage systems simultaneously (not only energy storages)
- Dynamic control and switching between operational conditions
- Tracking the behaviour the renewable energy sources.

One of the drawbacks of the method is that the system works poorly in such cases when input data (or system states) cannot be well-predicted. In other words, system states do not have the repeated period. However, if we consider the task that is connected with price profiles for electricity or profiles of power consumption by final buyer then it is highly possible that such profiles will depend on people's lifestyle, working time of enterprises, weather conditions and current season etc. Thus, the profiles have certain dependencies and, most important, they have periodicity. This helps us to organize horizons for such type of control and use the method for smart grid designing.

2 Simulation model of a benchmark microgrid

2.1 Short description of the model

In this part we will describe the choice of conception of the control object, its structure, key components and working profiles according to the geographical disposition of the system.

It was decided to take the microgrid from the work [61] as a basis.

The selected microgrid is a benchmark by CIGRE (Conseil International des Grands Réseaux Électriques i.e. International Council on Large Electric Systems). It is fairly representative and typical low voltage (LV) microgrid. We will consider only the part of the grid, which concerns only residential buildings. In this work the author suggested to improve the base system by adding energy generators (controllable and non-controllable) and energy storage. Thus, the system of districts consists of main electrical grid connection, step-down transformer, five final consumers, two blocks of solar panels, one wind turbine, one fuel cell and one energy storage, which is embodied in the form of batteries.

Figure 2.1 describes one linear electric power diagram of residential community. All main power parameters can be observed in scheme. Additional objects of electrical grid are highlighted with blue color. They play key role in smartgrid realization. Energy sources, which are typical for the current period for microgrid, are depicted in the scheme. Based on the synergy of this work of the block conception future energy supply optimization model will be realized.

Assume that the chosen residential area is situated in the northern region of Czech Republic. The electricity standard in the country forces us to use voltage of 230V and frequency of 50Hz.

The model does not consider power loses in wires. It is supposed that all objects in the system are close to each other. However, during the further development of the controller, the formula of overall power loses on energy distribution elements will be added. In other words the model will work correctly even if there is additional resistance on the energy delivery elements to the end consumers.

More detailed block parameters will be chosen during the scheme design. After developing optimization controller we will observe that some of the blocks does not work in a steady way or work incorrectly. By the reason, at this stage we will not be critical to the final parameters of separate system blocks that we choose. Only main operation principles will be described.

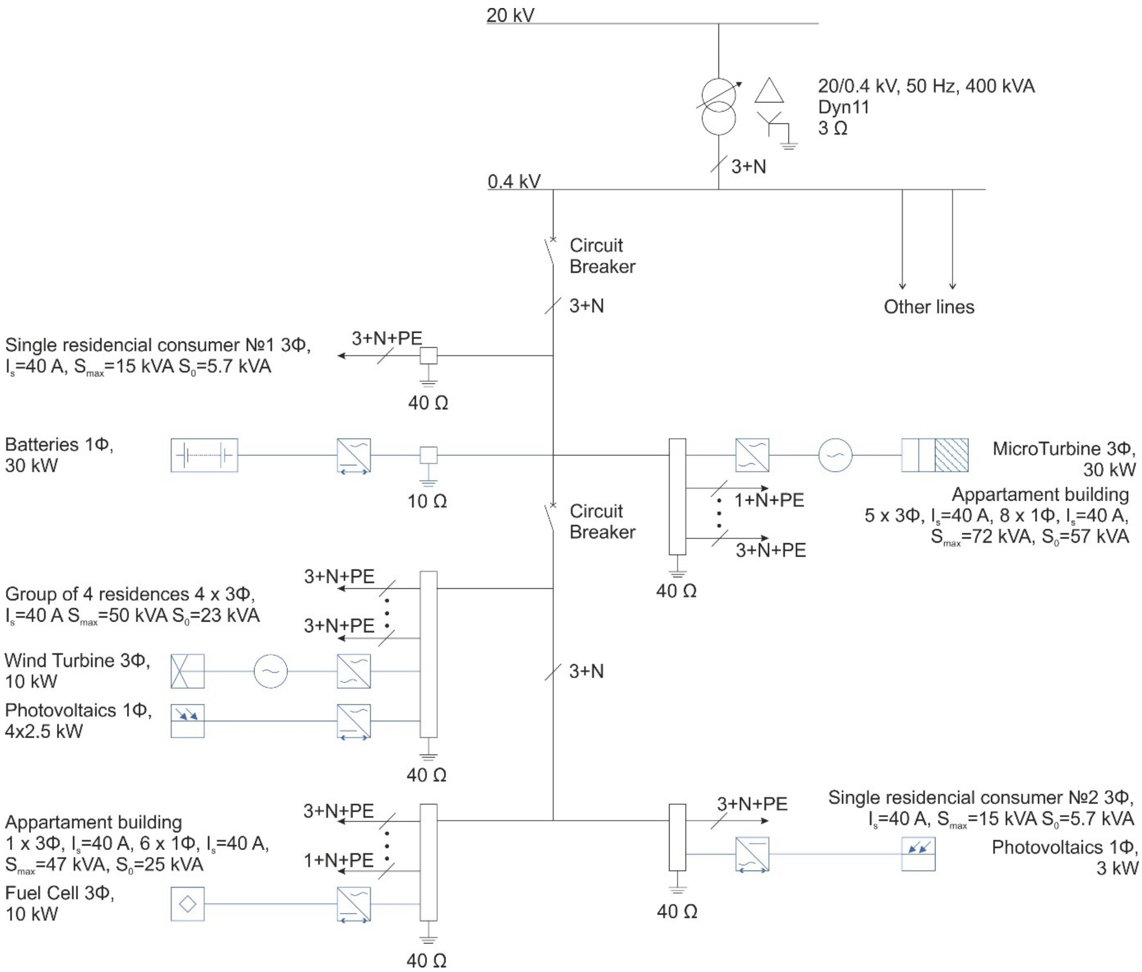

Figure 2.1: Benchmark LV microgrid network

2.2 Description of solving system method

The model design will be done in MatLab Simulink software. The software is multipurpose; it is possible to realize mathematical and physical models using blocks from different libraries. In our case we will use blocks from "SimScape / Electrical / Specialized Power System" library. With the help of the library it is possible to create electricity generators and electricity consumers.

The model design should be started with the choice of electrical circuit solving method. Within the framework of our task we will use modeling time intervals from several days to the whole year. It means that there is no need to calculate in detail the system state every split second.

«Powergui» block allows us to choose one out of three solving system approaches:

- Continuous, which uses uses a variable-step solver from Simulink
- Discretization of the electrical system for a solution at fixed time steps
- Phasor solution

Since all AC devices work on the frequency of 50 Hz and the speed of model simulation is essential for us then the solver which uses phasor is suitable for us.

The method uses Euler formula to represent harmonic signal as a complex function [62, 63]:

$$\mathrm{a}(t) = \mathrm{A} \cdot \cos(\omega t + \theta) = \mathrm{A}\frac{e^{i(\omega t+\theta)} + e^{-i(\omega t+\theta)}}{2} \tag{2.1}$$

Or in case of representation of real part only:

$$A \cdot \cos(\omega t + \theta) = \mathrm{Re}\left\{Ae^{i(\omega t+\theta)}\right\} = \mathrm{Re}\left\{Ae^{i\theta} \cdot e^{i\omega t}\right\} = A_i\angle\theta \tag{2.2}$$

where:
A – amplitude of harmonic signal;
ω – angular frequency of harmonic signal;
θ – phase of harmonic signal;
$Ae^{i\theta} = A_i$ – phasor;
$e^{i\omega t} = \angle\theta$ – vector of rotation angle.

Thus, using only formula 2.2, we can be independent from time t and manipulate only Phasor, provided that all harmonic signals have similar oscillation frequency. Such method greatly accelerates simulation in MatLab Simulink, but requires special description of signals.

In the further blocks description one should take into account that we neglect the dynamic work of device, expenditure for their activating and turning off (except energy storage).

2.3 Typical power generation and consumption models

There are two types of energy generators and one consumer model. We can generate electricity by the following methods:

1. With standard Three-Phase Source block
2. With specially created block that is controlled by power signal.

2.3.1 The part that describes external connection to the power grid

The first type of electrical signal generator is used to simulate microgrid connection to the main power grid. In this block we use Root-Mean-Squared voltage of 20 kV and signal frequency of 50 Hz. Depending on the necessary load the block always generates enough power at the current moment to meet the needs of final consumers. Principle of its work can be described with simplified formula of electrical power balance:

$$\overline{S}_{\text{maingrid}}(t) = \sum_{i=1}^{n} \overline{S}_{\text{consumer},i}(t) - \sum_{j=1}^{k} \overline{S}_{\text{generator},j}(t) \tag{2.3}$$

where:
$\overline{S}_{\text{maingrid}}(t)$ – apparent power coming from maingrid at the moment t
$\overline{S}_{\text{consumer},i}(t)$ – apparent power, which end consumer i requires at the moment t
$\overline{S}_{\text{generator},j}(t)$ – apparent power, which is generated by secondary source of electrical energy j at the moment t.

Step-down transformer 20/0.4 kV is set after the block. The scheme delta-wye transformation is used here.

2.3.2 The part that describes fixed electrical energy generation

The second electrical energy source gives fixed power at every point of time. Such sources are wind turbine, solar panels, microturbine, fuel cell and block of batteries, which function in discharge profile.

Let us consider the element of electrical energy generation using an example of subsystem that is implemented in microturbine.

Figure 2.2 consists of 2 voltmeters with line voltage (V_{ab}, V_{bc}) and 2 current sources with maximum oscillation amplitude I_a and I_b. Provided that the load is evenly distributed on three phases it is possible to present the power of source through the sum of powers on each phase. For this purpose we need to select one peak phase voltage from linear voltages:

$$\overline{V_{pA}} = \frac{1}{3}\left(\overline{V_{ab}} - \overline{V_{bc}} \cdot e^{-i120}\right) \tag{2.4}$$

where:

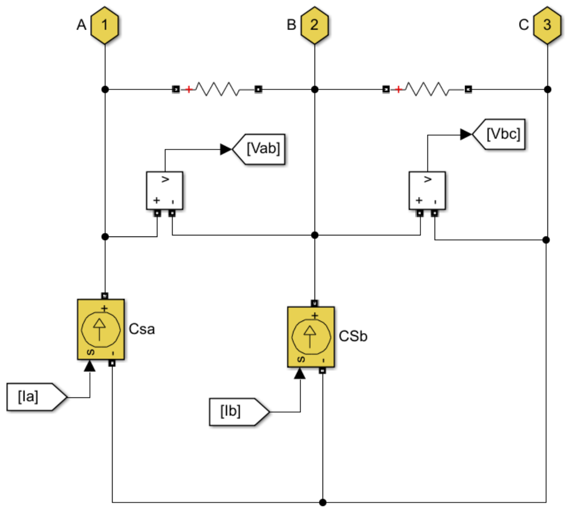

Figure 2.2: Controllable electrical energy generator (power part)

$\overline{V_{pA}}$ – Phasor of voltage of phase A [V].

Apparent power of three phase network in case of even load is following:

$$\overline{S} = \frac{3}{2} \cdot \left(\overline{V_{pA}} \cdot \overline{I^*_{pA}}\right) \tag{2.5}$$

where:

$\overline{I_{pA}}$ – phasor of current of phase A [A]

$\overline{I_{pA}}$ – conjugated phasor of current of phase A [A]

$\overline{S}$ – apparent power of electrical energy source [VA].

By combining formulas 2.4 and 2.5 one can obtain the value of current phasor, in accordance with linear voltage and necessary power:

$$\overline{I^*_{pA}} = \frac{2 \cdot \overline{S}}{\left(\overline{V_{ab}} - \overline{V_{bc}} \cdot e^{-i120}\right)} \tag{2.6}$$

Phasor for phase B is calculated by multiplying $\overline{I_{pA}}$ on rotary coefficient e^{-i120}.

Current on phase C will be equal to current which can be calculated with the help of Kirchhoff's first law [64].

Objects that use invertors or generators to convert electrical energy have angle φ between phase voltage and phase current. Consider power factor $\cos(\varphi) = 0.9$ for electrical energy generators and power factor $\cos(\varphi) = 0.95$ for invertors [65].

Power factor defines the ratio between active power to apparent power. In real engines power factor is changed according to the mode of operation. However, we will use fixed value of the coefficient for the model. In order to determine reactive power (Q) from active power (P) we can use coefficient of proportionality:

$$\begin{gathered} \tfrac{Q}{P} = \tan(\varphi) \\ \tfrac{Q}{P} = \tan(0.45) = 0.48 \end{gathered} \tag{2.7}$$

Figure 2.3 illustrates scheme for controlling power part of electrical energy generation using the example of microturbine.

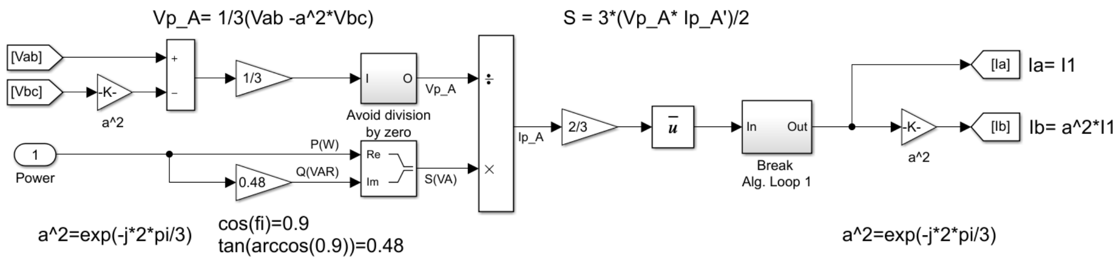

Figure 2.3: Controllable electrical energy generator (control part)

2.3.3 The part that describes end consumer

The area has 5 separated end consumers. In order not to complicate the model by separated calculation of power consumption on each dedicated supply lines, we combine powers from all parts of each end consumer into one final power value.

End consumer can be described in the same way as controllable generator with exception that end consumer will have negative power value on its input.

Generally, load in household network has value of $\cos(\varphi)$ close to one. We take $\cos(\varphi)$=0.98. Apparent power S comes to the input of energy consumption block. Coefficients for calculating active and reactive power are following:

$$\begin{aligned} \frac{P}{S} = \cos(\varphi), \frac{Q}{S} = \sin(\varphi) \\ \frac{P}{S} = 0.98, \frac{Q}{S} = 0.2 \end{aligned} \tag{2.8}$$

In Figure 2.4 one can observe the subsystem of electrical energy consumption for end user. Grounded neutral can be found here as well.

2.4 Control of energy consumption and generation blocks

In the work objects of controllable energy generation produce energy according to the amount of incoming primary energy. Primary energy for the renewable energy sources is speed of the wind and solar radiation. For turbine and fuel cell it is amount of energy that natural gas can emit per unit volume. The block of batteries is operated by signal from chosen controller, which is restricted with charge limit.

We describe dependencies that influence the power control signal below.

2.4.1 End consumer

Each end consumer has its own unique profile of electrical energy consumption. However, for our model averaged profiles of consumption were used. We took them from energy consumption statistic for north part of Czech Republic [66]. We chose 3 consumption profiles for our consumers. There are following:

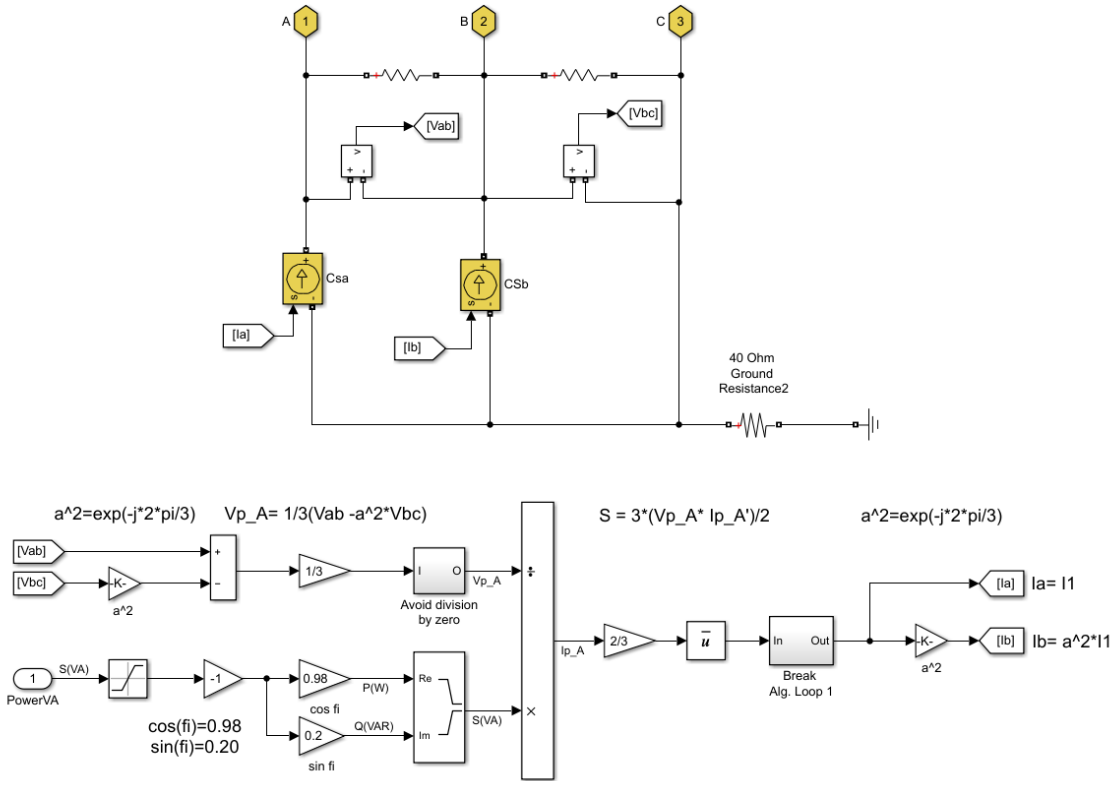

Figure 2.4: Controllable end energy consumer

- TDD5 – residential customer using electricity for heat storage heating
- TDD6 – residential customer using electricity for hybrid heating
- TDD7 – residential customer using electricity for direct heating or heat pump.

Typical energy consumption profiles for a week at different time moments are represented in Figure 2.5.

By multiplying power consumption coefficient of end user by maximal power, we can obtain typical profiles of real electricity consumption.

Typical example of controlling power consumption of the whole consumer is depicted in Figure 2.6.

2.4.2 Solar panel

Solar panels convert sunlight into direct current due to the property of semi conductive materials that demonstrate photoelectric effect. It is necessary to connect voltage invertor to the solar panel in our grid. It will convert direct current to alternating three phase current [67]

In selecting solar panel in catalogue one can find following performance characteristics that were obtained with Standard Test Conditions (STC) (Solar radiation – $1000\frac{W}{m^2}$, air mass (AM) – 1.5, cell temperature – 25°C)

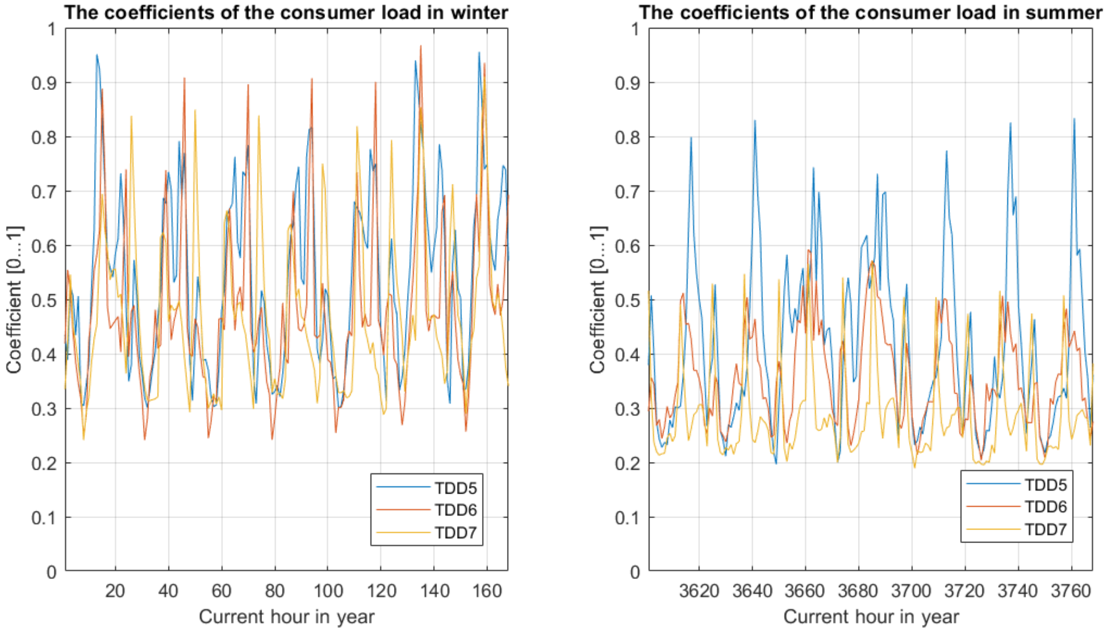

Figure 2.5: Coefficients of electricity consumption for various end consumers in different time intervals

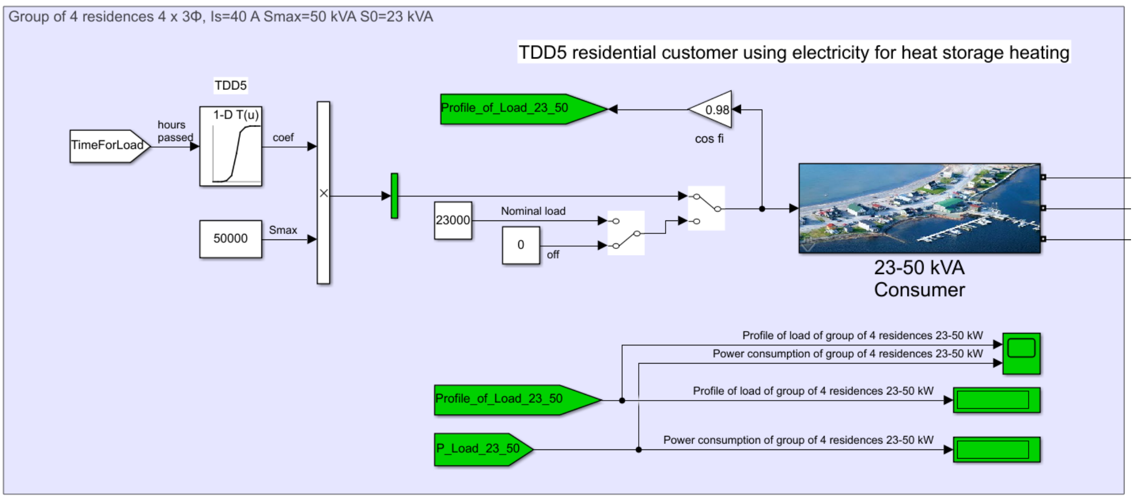

Figure 2.6: Typical example of controlling the group of 4 residencies that use TDD5 profile

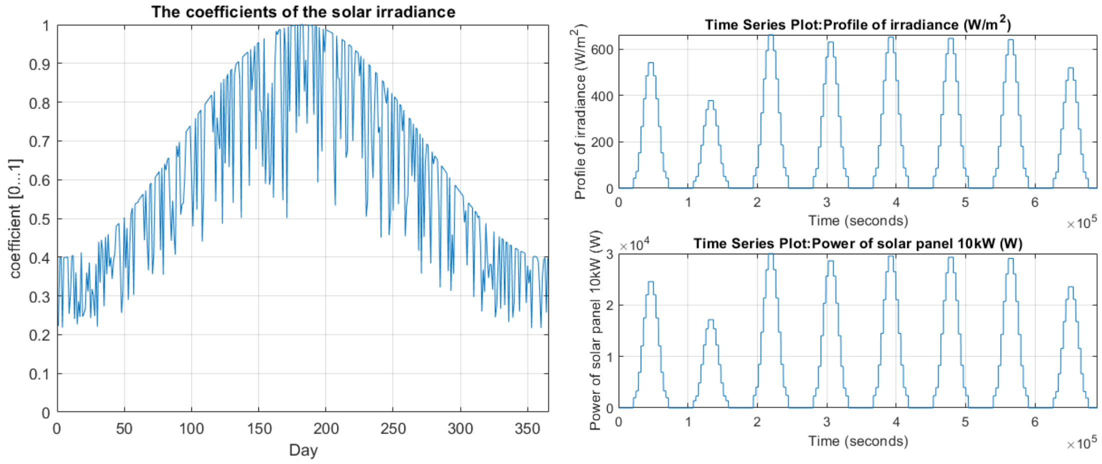

Figure 2.7: The graph of day coefficients during the year (left); solar radiation started from day 276 (upper right); power that is generated by solar panel 10kW (right down)

$P_{\text{solarstcmax}}$ – emitted power with solar radiation of 1000 W/m^2 [W]
A_{sp} – effective area of solar panel [m^2]
η_{Sp} – efficiency of solar panel (0.21).
We will also need efficiency of voltage invertor:
η_{inv} – efficiency of voltage invertor (0.95).

Thus, power P_{solarsys} that is come to the three phase grid from solar panel depending on present solar radiation W_{ir}(t)

$$P_{solarSys} = A_{sp} \cdot \eta_{sp} \cdot \eta_{\text{inv}} \cdot W_{\text{ir}}(t) \tag{2.9}$$

In this diploma thesis profiles of solar radiation are generated manually as a multiplication of two profiles:

- typical profile of solar radiation (0...1000 W/m^2) based on the length of night period during a year
- maximal power coefficient of solar radiation during a year (0...1).

These profiles were generated based on the solar radiation profile of city Basel [68].

2.4.3 Wind turbine

Wind turbine is a device that transforms kinetic energy of the wind into electricity. Wind turbine consists of rotor with blades, gearbox, generator, break system, control block and corps [69].

Such model has speed limit of the rotor (maximal and minimal rotational velocity). Kinetic energy of wind with mass m, moving with speed u to the direction of thickness x:

$$U_{\text{wind}} = \frac{1}{2} \cdot m \cdot u(t)^2 = \frac{1}{2}(\rho \cdot A \cdot x)u(t)^2 \tag{2.10}$$

where:
A – cross-section area of wind flow $[m^2]$
ρ – air density $[kg/m^3]$
x – the thickness of the parcel[m]
u(t) – velocity of wind flow $\left[\frac{m}{s}\right]$.
Wind power P_{wind}, in turn, is a time derivative of kinetic energy:

$$P_{\text{ wind }} = \frac{dU_{\text{ wind}}}{dt} = \frac{1}{2} \cdot \rho \cdot A \cdot u(t)^2 \cdot \frac{dx}{dt} = \frac{1}{2} \cdot \rho \cdot A \cdot u(t)^3 \tag{2.11}$$

The power, which wind turbine can receive from the wind and inject the transformed stream of electricity into the grid, depends on pair of efficiency ratio:

η_{wind} – efficiency of wind energy transformation into electrical energy. The ration cannot be more than 59.3% (determined by Betz's law)

η_{wtGen} – efficiency of generator and gearbox.

Now, we have formula of wind turbine power depending on the speed of the wind:

$$P_{WT} = \frac{1}{2} \cdot \eta_{\text{ wind }} \cdot \eta_{\text{wtGen}} \cdot \rho \cdot A \cdot u(t)^3 = K_{\text{ wind }} \cdot u(t)^3 \tag{2.12}$$

Efficiency values, wind flow area and wind density belong to the construction parameters. If we know rated power of wind turbine and rated wind velocity we can calculate coefficient K_{wind}.

Wind velocity profile at a high of 10 m from the ground can be found in meteorological diaries [70]. Wind velocity profile and corresponding wind turbine power are illustrated in Figure 2.8. The turbine starts to generate electricity when speed velocity is higher or equal to 2 m/s, maximal wind velocity is 12 m/s and nominal speed of 10 m/s.

2.4.4 Microturbine

Microturbine is a modular system for creating thermal energy and electrical energy. Microturbines need minimal maintenance; have a long lifetime. Modern microturbines are easily embedded into electrical grid for parallel usage [71, 72]

Efficiency of turbines much depends on ambient temperature. However, in order to simplify simulation and for the future configuration of controller, we will use permanent constant value of microturbine block efficiency in this work.

Simulated microturbine works on natural gas. In our work we consider only energy generation and neglect thermal power.

Injected natural gas has the higher heating value: $W_{\text{HHV}} = 40\,[MJ/m^3]$

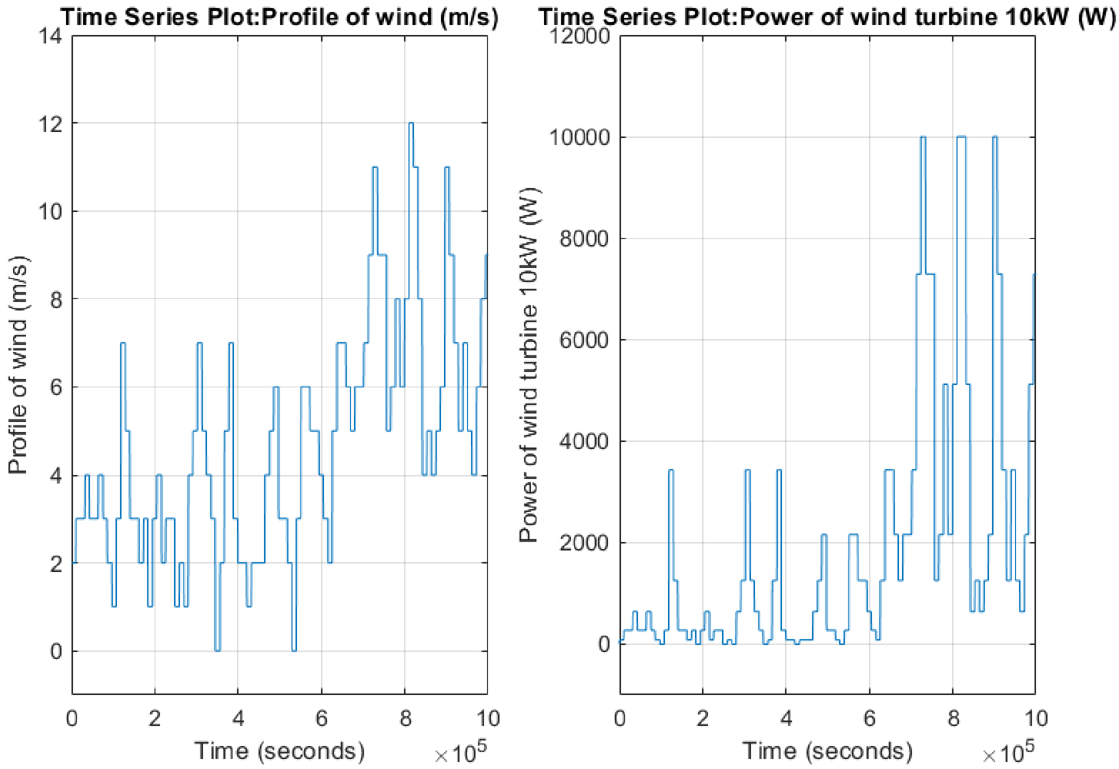

Figure 2.8: Wind velocity profile that starts from 240$^{\text{th}}$ day (left); power that generated by wind turbine (right)

Volume of natural gas that is injected into microturbine during the time interval for generating nominal power can be calculated as follow:

$$Q_{MTnom} = \frac{Q_{MTHHV}}{W_{\text{HHV}}} \tag{2.13}$$

where:

Q_{MTnom} – Volume of natural gas that is injected into microturbine during the time interval for generating nominal power $[m^3/hr]$

Q_{MTHHV} – nominal energy flow that is injected into micriturbine with natural gas during the time for nominal power generation [MJ/hr].

Thus, efficiency of microturbine under the standard operating conditions is following:

$$\eta_{MT} = \frac{P_{MTnom}}{Q_{MTHHV}} \cdot \frac{3600}{10^6} \tag{2.14}$$

where:

η_{MT} – electrical efficiency of microturbine under the standard operating conditions

P_{MTnom} – nominal power of microturbine under the standard operating conditions [W].

Thus, microturbine power at the current moment can be presented as a formula:

$$P_{MT} = \eta_{MT} \cdot \frac{1}{3600 \cdot 10^6} \cdot Q_{MTHHV}(t) \tag{2.15}$$

where:

P_{MT} – electrical power that is generated by microturbine at the current point of time [W].

2.4.5 Fuel cell

In this work we will use Solid-oxide fuel cells (SOFC).

Solid-oxide fuel cells are a new and upcoming technology that are gaining attention from many researchers. Fuel cells rely on chemical conversion of energy and do not require the use of a steam power turbine. These cells are much more efficient than the current methods of energy production. This new technology uses natural gas in a chemical reduction and oxidation (redox) reactions instead of burning fossil fuels – the main cause of air pollution. Solid oxide fuel cells are proving to be important to solve the energy problem in the future [73].

Today SOFC is characterized by high working temperature of 800-1000 °C and high common efficiency up to 90%. Electrical efficiency reaches the value of 50%. Moreover, SOFC does not require around-the-clock service and can operate autonomously up to 4 years. The main problem that prevents SOFC to be popular is high price of fuel cells [74].

In the contexts of this work we ignore the description of starting and stopping fuel cell. It is done due to the reason that we will use higher sampling time of the system than the intervals of starting and stopping the fuel cell.

The volume of gas that is injected into SOFC for rated power generation is calculated as follow:

$$Q_{F\text{Cnom}} = \frac{P_{F\text{Cnom}}}{W_{\text{HHV}} \cdot 10^6 \cdot \eta_{FC}} \tag{2.16}$$

where:
Q_{FCnom} – volume of natural gas that is injected into SOFC during the time for rated power generation $[m^3/s]$
η_{FC} – electrical efficiency of SOFC under the standard operating conditions (0.4)
$P_{F\text{Cnom}}$ – rated power of SOFC under the standard operating conditions [W].
Power of SOFC at the current point of time is calculated as follow:

$$P_{FC} = 10^6 \cdot \eta_{FC} \cdot W_{\text{HHV}} \cdot Q_{FC}(t) \tag{2.17}$$

where:
P_{FC} – electric power that is generated by SOFC at the current point of time depending on delivered volume of natural gas [W]
$Q_{FC}(t)$ – volume of natural gas that is injected into SOFC during the time $[m^3/s]$

2.4.6 Energy storage

Energy storage is indispensable part of any smart microgrid. There is a number of typical solutions for electrical energy storage such as batteries, supercapacitors or flywheel energy storage. Batteries as energy storage are well-suited in case when we need to minimize self-discharging of the storage, obtain highly efficient charge and discharge as well as enough cycles of recharging and discharging, avoid conversion of active power into reactive.

It is worth to highlight Lithium-iron-phosphate (LiFePO4 or LFP) batteries. They are distinguished by:

- High current of charging and discharging
- Value of voltage and current during the process of charging/discharging (almost the same in the process of battery's capacitance change in the range 20-90%)
- Large number of recharge cycles
- Low self-discharge value (lower than lead-acid batteries)
- Efficiency around 92% (96% for discharging and recharging)

One should keep in mind that such type of batteries is not recommended to use at the temperature higher than 30°C discharge lower than 20% and charge more than 90%. Going beyond the limits is sharply reflected in lifetime of the batteries.

Thus, a reference signal of power will control the block of batteries. The output is power that is injected to the grid. State of charge (SOC) will limit the input value. The value of battery state at the next period of time can be described with the following formula:

$$Soc_{k+1} = Soc_k + \left(P_{char} \cdot \eta_{char} - \frac{P_{dis}}{\eta_{dis}} \right) \cdot \frac{\Delta T}{Cap} \cdot 100, \tag{2.18}$$

With condition that:

$$Soc_{min} \leq Soc_{k+1} \leq Soc_{max} \tag{2.19}$$

where:

Soc_{k+1}, Soc_k – state of battery charge at the moments k+1 and k [%]

Soc_{min}, Soc_{max} – minimal and maximal state of battery charge (0 % and 100% respectively). For controller description we will use safe limits of charging/discharging during operational time [%];

$P_{\text{char}}, P_{\text{dis}}$ – power that is come from and to the grid during the process of battery charging and discharging respectively [W]

$\eta_{\text{char}}, \eta_{\text{dis}}$ – charging and discharging efficiency of battery block respectively

ΔT – sampling time [s]

Cap $= P_{dis}/I_{rms} \cdot AH$ – capacity of the battery [Wh]

AH – capacity of the battery [A $\cdot$ hr]

I_{rms} – discharging/charging current of the battery [A]

The charging/discharging current I_{rms} is proportional to controlling power:

$$I_{rms}(t) = \begin{cases} -\eta_{\text{char}} \cdot \frac{I_{\text{char}}}{P_{\text{char}}} \cdot P_{\text{batt}}(t), & P_{\text{batt}}(t) < 0 \\ \frac{1}{\eta_{\text{dis}}} \cdot \frac{I_{\text{dis}}}{P_{\text{dis}}} \cdot P_{\text{batt}}(t), & P_{\text{batt}}(t) \geq 0 \end{cases} \tag{2.20}$$

It should be taken into account that it is not possible to charge and discharge the battery at the same time. Such restriction is used further for controller description [75].

Inner structure of batteries block is described in Figure 2.9. The block controls the proper battery charging, energy storage and allows switching off the battery with signal "State". The controlling signal "Power" comes directly from the controller.

2.5 Cost calculation of microgrid

To feed simulated microgrid two purchased sources are used: electrical energy and natural gas. The total electricity cost is combined both from electric energy cost and distribution cost. Electricity costs can be positive and negative depending on whether we buy the electricity from the grid or sell it. Costs profiles can be obtained from Day-Ahead Market [76]. Let us indicate the electricity cost at the current period of time as $cost^{el}(t)$.

Distribution costs rely heavily on tariffs that are provided by electric energy distributor. Unlike electric energy costs end users pay for energy distribution in both cases whether they buy or sell electricity. Moreover, when end energy consumer pays for distribution, distributor of electric energy provides consumers with

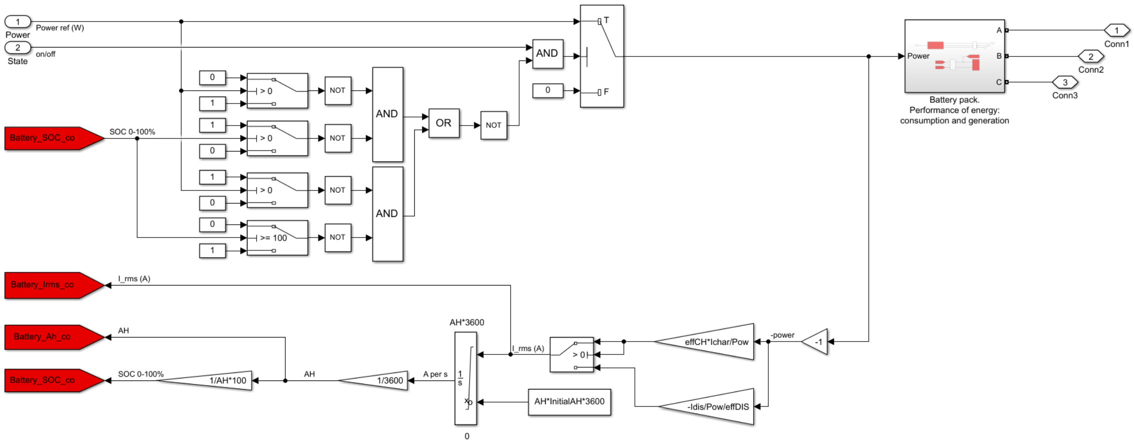

Figure 2.9: Inner structure of battery block

certain amount of reactive power depending on active power. In our case we do not utilize reactive power in an explicit form as we do not have specific reactive power consumers (power factor of consumers is 0.98). Let us take the average distribution cost as $cost_{dist}^{el} = 1000K\check{c}/MWh$.

The cost of utilizing natural gas is received from calculating total amount of energy that is supplied with gas and from gas distribution price. Various type of natural gas has various valueW_{HHV}. By the reason the calculation of gas price is performed in MWh. Price correlation of natural gas during the year is insignificant. Let us take the total cost of gas and gas distribution as $\mathrm{cost}^{gas} = 800K\check{c}/MWh$.

$$\mathrm{cost_{mg}(t)} = \mathrm{cost^{el}(t)} \cdot \mathrm{P^{el}_{MG}(t)} + \left|\mathrm{cost^{el}_{dist}} \cdot P_{\mathrm{MG}}\mathrm{(t)}\right| + \mathrm{P^{gas}_{MG}(t)} \cdot \mathrm{cost^{gas}} \tag{2.21}$$

where:

$\mathrm{cost_{mg}(t)}$ – distribution cost for microgrid in the time moment t $[K\check{c}]$

$\mathrm{P^{el}_{MG}(t)}$ – power from the main electricity grid that is utilized by microgrid [W]

$\mathrm{P^{gas}_{MG}(t)}$ – power from gas pipeline that is utilized by microgrid [W].

Figures 2.10 and 2.11 show realization of cost estimation to supply microgrid with energy from main electrical grid and natural gas pipeline.

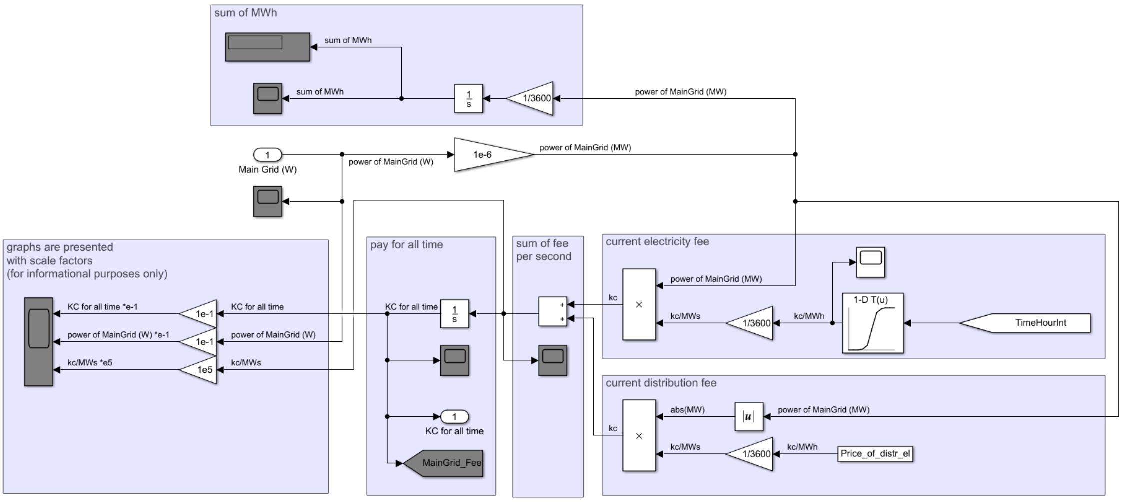

Figure 2.10: Subsystem of calculating costs of electricity usage

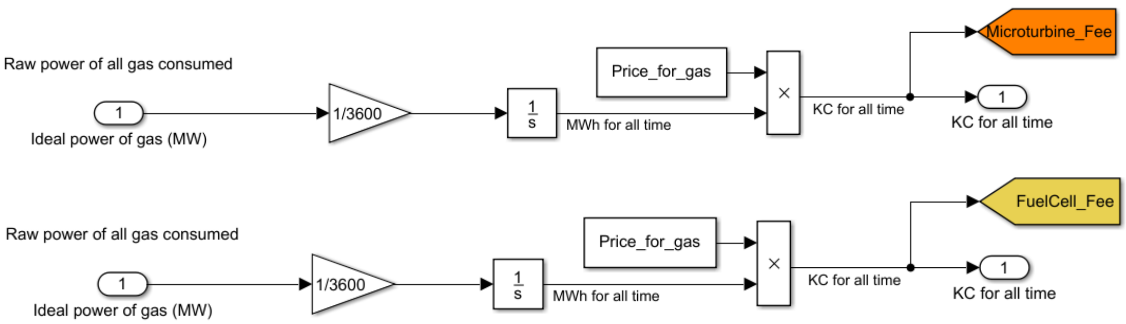

Figure 2.11: Subsystem of calculating costs of natural gas usage: cost of microturbine (upper part); costs of fuel cell (bottom part)

3 Design of economic model predictive controller

3.1 Controller structure

The aim of this work is economical optimization of microgrid in the environment where energy price and power consumption correlate in time. In order to obtain it we need to complicate our microgrid with energy controller by creating smartgrid. In section 1.9 the choice of Model Predictive Control was collaborated. Such controller guarantees the best results of energy optimization taking into account future situations provided that forecasts were done sufficiently accurate.

Thus, MPC structure can be represented by two components:

- Part of generation future event horizons based on forecasting
- Part of cost minimization based on constrain matrix and obtained horizons.

Design of each part will be considered below.

3.1.1 Part of generation future event horizons

In order to obtain the best prediction it is necessary to learn profiles based on which the energy cost is formed. These profiles are cost profile and load profile. Cost for natural gas and electricity distribution were taken as constants, thus, in our case, we will consider only profile of energy cost correlation and profile of total end users' consumption. Figure 3.1 describes load and cost electrical energy annual profiles. On these graphs one can see that the time series are not stationary (they have drift).

However, if to have a look to these profiles on a short period of time (Figure 3.2), then it is possible to notice that they have repeating structure (seasons). It is due to the people' rhythm of live and supply/demand of generation company. Profiles of the current week have similar structure as profiles of the previous week. It is possible to say the same for the nearest days.

Based on profiles learning it is possible to realize forecasting using $ARIMA(p,d,q)$ (AutoRegressive Integrated Moving Average) model. Such prediction model can work with non-stationary series by transforming series into stationary series. It is done by subtracting of some order (usually first or second is enough) from original time series ("ARIMA Models and the Box–Jenkins Methodology" in [77]).

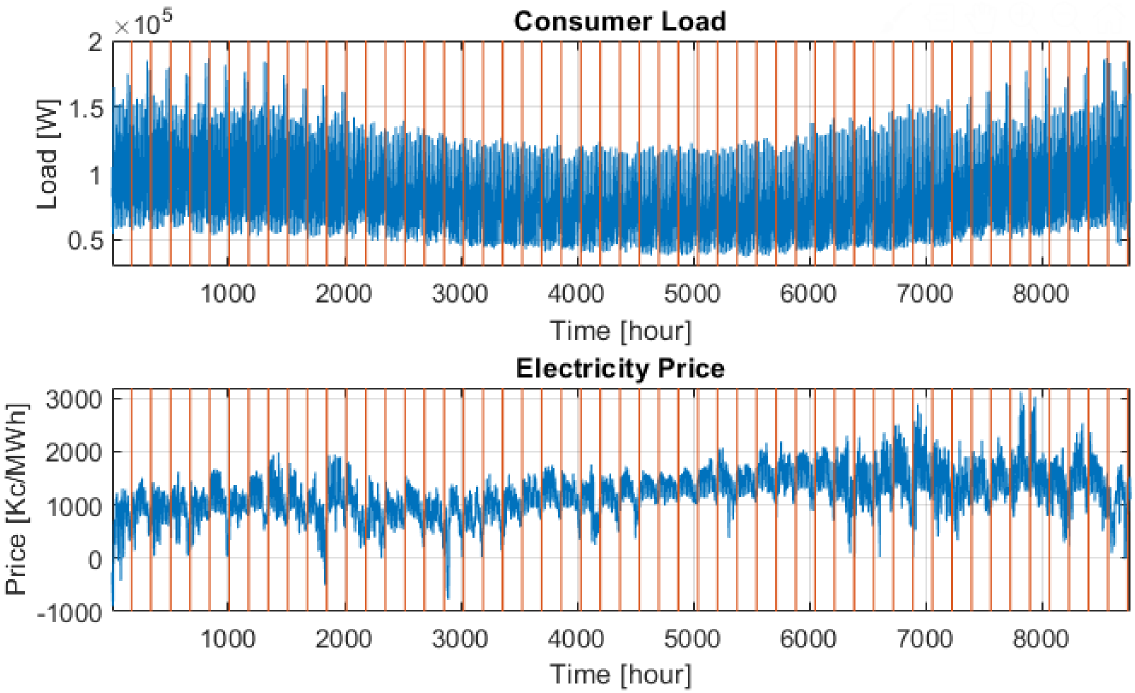

Figure 3.1: Annual profiles of load and electricity cost. Orange lines indicate weeks

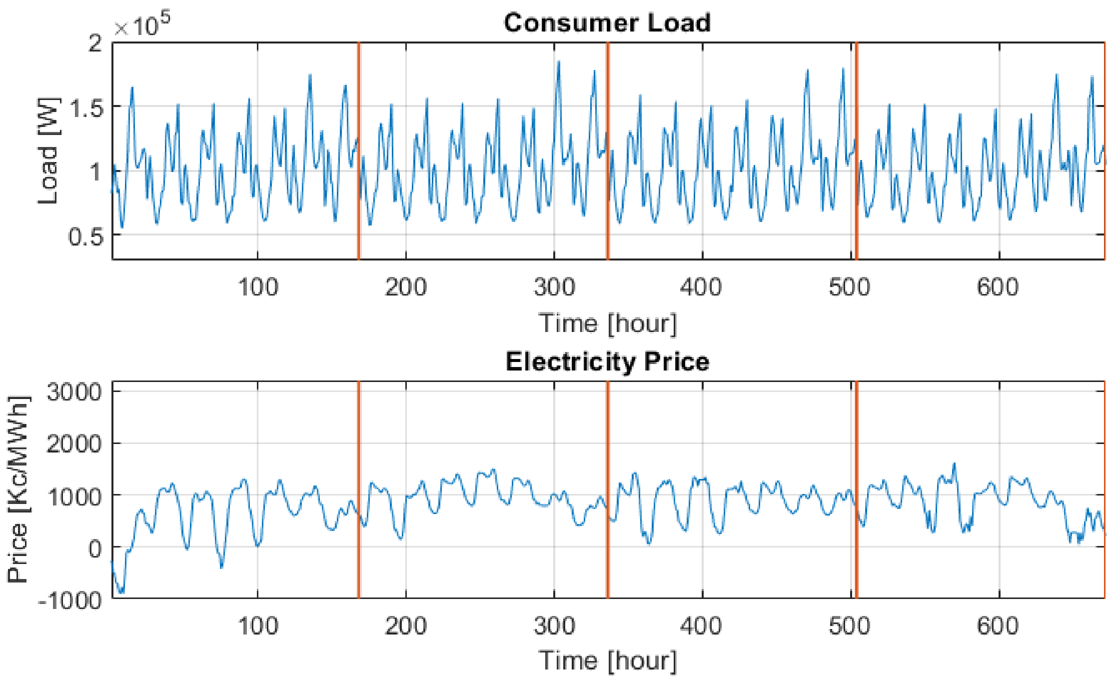

Figure 3.2: Profiles of load and electricity cost for a month. Orange lines indicate weeks

Thus, structure of model prediction *ARIMA*([1,24,168],1,[1,24,168]) will be written in the following form:

$$\begin{aligned}\left(1-\varphi_1\mathrm{L}-\varphi_{24}\mathrm{L}^{24}-\varphi_{168}\mathrm{L}^{168}\right)&(1-\mathrm{L})^1\mathrm{y_t}=\\&=\mathrm{c}+\left(1+\theta_1\mathrm{L}+\theta_{24}\mathrm{L}^{24}+\theta_{168}\mathrm{L}^{168}\right)\varepsilon_\mathrm{t}\end{aligned}\tag{3.1}$$

where:

L – lag operator, sampling by hours ($L\cdot x_t=x_{t-1}$)

φ_i – autoregressive (AR) part parameters (AR) for lag i

$\mathrm{y_t}$ – value of object at the time moment t

c – model constant

θ_i – parameter of moving average (MA) part for lag i

ε_t – prediction error that is presented as white noise (normal distribution with zero average).

Let us express predicted value from formula 3.1

$$\mathrm{y_{t+1}}=\mathrm{y_t}+\Delta\mathrm{y_t}\tag{3.2}$$

$$\begin{aligned}\mathrm{y_{t+1}}=&\mathrm{y_t}+\mathrm{c}+(\varepsilon_\mathrm{t}+\theta_1\varepsilon_\mathrm{t-1}+\theta_{24}\varepsilon_\mathrm{t-24}+\theta_{168}\varepsilon_\mathrm{t-168})+\\&+(\varphi_1\Delta\mathrm{y_{t-1}}+\varphi_{24}\Delta\mathrm{y_{t-24}}+\varphi_{168}\Delta\mathrm{y_{t-168}})\end{aligned}\tag{3.3}$$

where:

$\Delta\mathrm{y_t}=(1-\mathrm{L})^1\mathrm{y_t}$ – difference of the first order between neighboring samples of the system

$\mathrm{y_{t+1}}$ – predicted value of the time moment t+1, with using ARIMA model

In this work, parameters of the ARIMA model are selected with Econometrics Toolbox™ based on the data from profile of electricity price correlation during 2018 and profile of total model load at the same period of time. Total load for choosing ARIMA coefficients is calculated as a power of all end consumers during the time, excluding distribution loses and power that is emitted from renewable energy sources. It is also worth to mention that for the correct prediction performance in practice, either ARIMA coefficients should be regularly recalculated or neural models should be used.

In this optimizer model the coefficients for ARIMA models are calculated only once. There are several reasons. It is possible to calculate coefficients of the model in "MATLAB Function" from Simulink environment, but it is not possible to export them from "mxArray" structure. This is due to the inability of code generation of the method in Simulink and problems with preinitialization of data. In turn, the component of model "I" and degenerate seasonality provide correctness of predictions with the presence of data drift and allow to operate even at long intervals of time without coefficients retraining. It was proven on the one-year interval during the prediction block design. It is also worth noting that for the correct predictions performance in practice, either ARIMA coefficients should be systematically recalculated, or neuronal models should be used.

Let us consider the algorithm of ARIMA(p,d,q) model building without using applications. For the first time, systematic approach of model building was explained by Box and Jenkins in 1976. The study of time series included the following steps:

- evaluation model parameters and diagnostic verification of model adequacy
- using model for prediction.

Thus, it is necessary to obtain stationary series. For programmatic evaluation of time series stationarity, statistical tests of presence of single root (for example, ADF-test) are conducted [78]. If the series is non-stationary, sequential difference operator is taken and value d (difference order) is obtained. Differencing is repeated till the moment when series becomes stationary. In practice, the value of d is not usually higher than 2.

Next, exterior view of the model and hypothesis about value p (autoregressive order) and q (moving average order) are formed. In our case, p and q are lag vectors, which describe the contribution of seasons (for example, day ago, week ago and so on).

The next stage is model identification and parameters estimation (constants and coefficients of lag operators). Maximum likelihood method (MLM) is used for this purpose. To identify parameters, usually non-linear programming solver is used.

Once the identification process is finished, it is necessary to check the model for adequacy. It is done with the help of residue study. The residue should be similar to white noise. For this reason Q-statistic of Ljung–Box (Ljung–Box test) that is applicable to the residue is used:

$$Q^{*} = n(n+2)\sum_{k=1}^{m}\frac{r_k^2}{n-k} \leq \chi^2_{1-\alpha,h} \tag{3.4}$$

where:
n – sample size
m – maximum lag number
r_k – coefficient of autocorrelation function
$\chi^2_{1-\alpha,h}$ – is the $1-\alpha$ -quantile of the chi-squared distribution with h degrees of freedom.

From several possible types of models the models with higher precision and the models with fewest parameters should be selected. Theses conditions can be described with information criteria of Schwarz and Akaike. For the final selection both conditions should be specified. Below is one of the examples of Schwarz criterion that combines both selection conditions:

$$SBIC = \ ln\left(\frac{\sum_{t=1}^{n}\varepsilon_t^2}{n}\right) + \frac{(p+q)\ ln(n)}{n} \tag{3.5}$$

To estimate the accuracy of the prediction mean absolute percentage error is used:

$$MAPE = \frac{100\%}{H}\sum_{t=1}^{H}\left|\frac{X_t - \widehat{X_t}}{X_t}\right| \tag{3.6}$$

where:
X_t – real value
$\widehat{X_t}$ – predicted value
H – prediction interval.

If $MAPE$<10%, then prediction was done with high accuracy; 10%<MAPE<20% – prediction is good; 20%<MAPE<50% – prediction is satisfied; MAPE >50% – poor prediction [79].

In the implementation of the algorithm in Simulink a problem arises. The problem is connected with code generation of non-linear programming (fmincon). Possible solutions of the problem are described in the following section 3.1.2.

Let us demonstrate *Econometrics Toolbox*^{TM} performance. The application is called with "econometricModeler" command. The researched profile is imported with "Import" button. In this example we will show the performance with electricity costs. For load profile actions will be the same. We can make tests with time series, for example, we can check its stationarity and choose necessary conditions (differential order, seasons, number of lag operators) for it. On the "Models" tab, choose "ARIMA" type of the model and specify lag vectors as it is shown in Figure 3.4. After pressing "Estimate" button we obtain Figure 3.3. On the right side of this Figure best parameters for coefficients of chosen ARIMA model are selected. Quality of prediction can be evaluated with variance of error and parameters in "Goodness of Fit" window. It is possible to obtain best result with implementation of this approach by changing structure of ARIMA model and using patterns of time series.

In Figure 3.2 one can clearly see that profiles have similar structure from week to week. However, there is a variable ε_{t}, whose value in the future event horizon is unknown and we take it as zero. For correct MPC operating properly predicted horizons of variables are necessary. It should be taken into account that it is mandatory to predict not only the next value y_{t+1}, but the whole series of numbers $\{\mathrm{y_{t+1}, y_{t+2}, \ldots, y_{t+N}}\}$. Prediction models deal well with value selection on a short front time interval (N). Future behavior of horizons is not precise; however it is possible to trace clear base structure of future profiles. By the reason it is worth to limit the maximal length of horizon by 7 days in order to the last rely on the real error feedback with coefficient of 168 (where 168 is 7 days multiplied by 24 hours).

We will consider the performance of ARIMA prediction model on exact profiles of the model:

In Figure 3.5 one can see that the prediction of load is performed with sufficient precision even without error ε_{t}. Electricity cost correlates with more uncertainties, but in that case we use Day-Ahead Market. It means that we know the exact electricity prices for the whole next day. That fact minimizes the error of prediction due to the fact that we construct our prediction for the interval of 2-7 days, instead

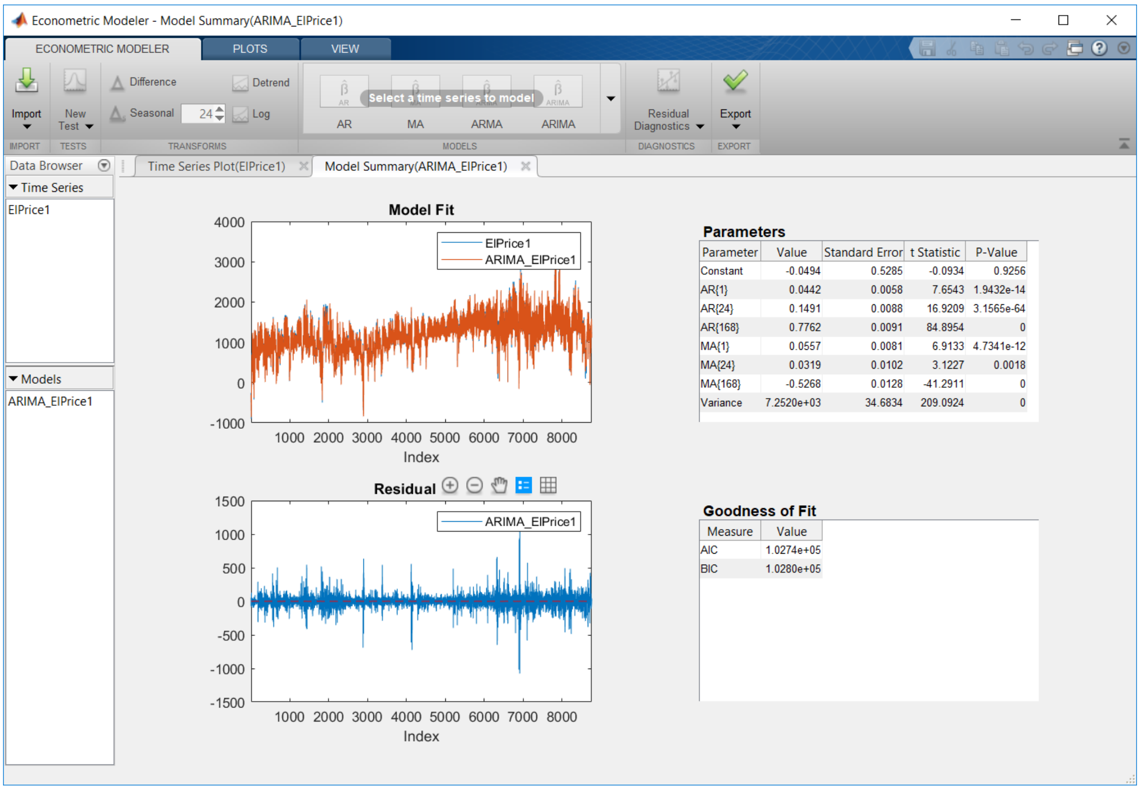

Figure 3.3: $EconometricsToolbox^{TM}$ and ARIMA model parameters for electricity costs profiles

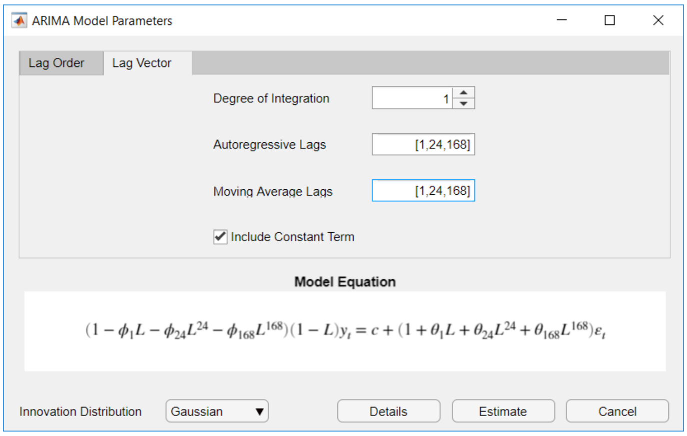

Figure 3.4: Setting of ARIMA model: degree of integration, lags vectors, presence of constant and distribution type

of the whole week.

Such predictions are conducted in the block of "MATLAB Function" in real time with discretization of 3600 seconds. Inputs of the block are the value of system time in hours, required length of final horizons in days, approximate load profile for the quickest ARIMA stabilization (calculated with excluding distribution loses and energy that was generated with renewable energy sources) and current total load of

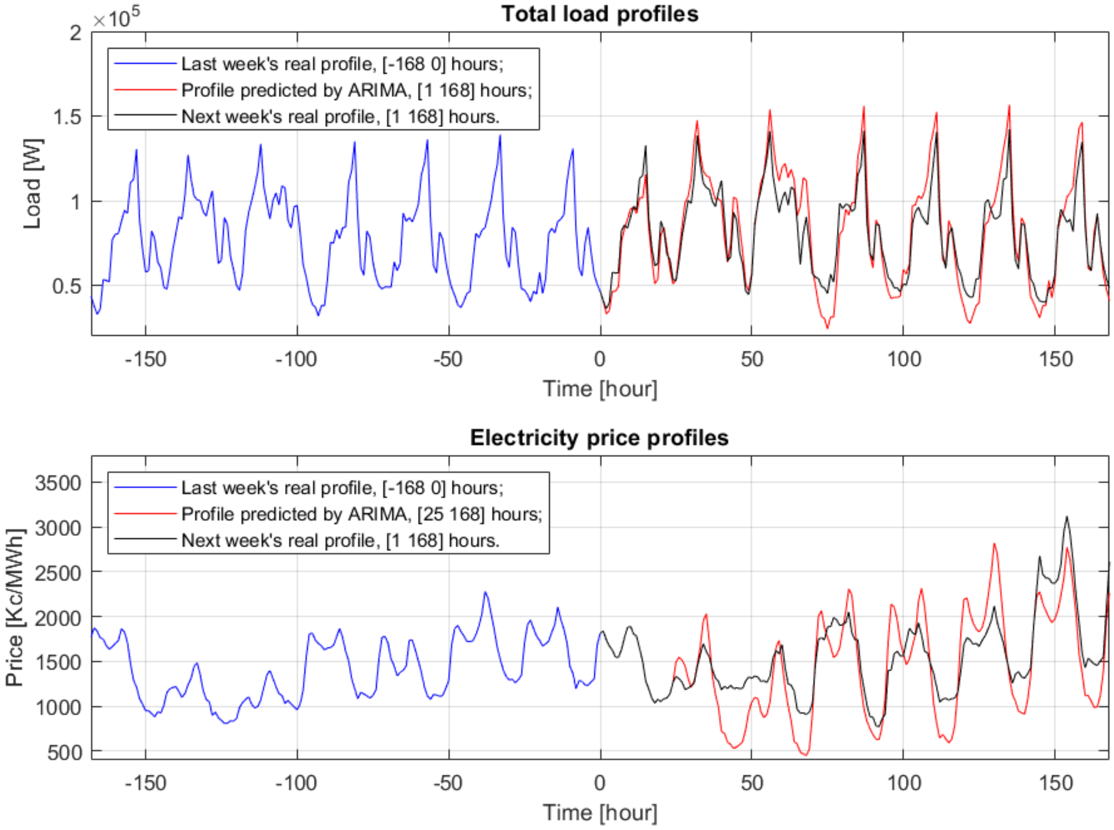

Figure 3.5: Profiles of load and electricity price for the last and for future week. Prediction that was done with ARIMA model is highlighted by red color

the system.

Exterior view of the ”MATLAB Function” block for prediction variables is depicted in Figure 3.6. All input and output flows are signed together with their dimensions. By utilizing information about previous profiles and current value, the block generates prediction horizons (re eding window) for 168 hours ahead for each parameter.

Output flows put in rectangles are valuable for us, because they are actually the input for the block of cost minimization. All other outputs are used only for collecting information about predictions. The listing of the function can be found in appendix A.

3.1.2 The part of cost minimization

The main aim of our work is cost minimization of microgrid. Only when we use MPC we achieve cost minimization not only for the current moment of time, but for the whole assumed final event horizon taking into account dynamic of the system. At its core is iterative optimization model that tries to minimize cost function J every time moment [3].

Let us define the type of MPC, which we will use in that work:

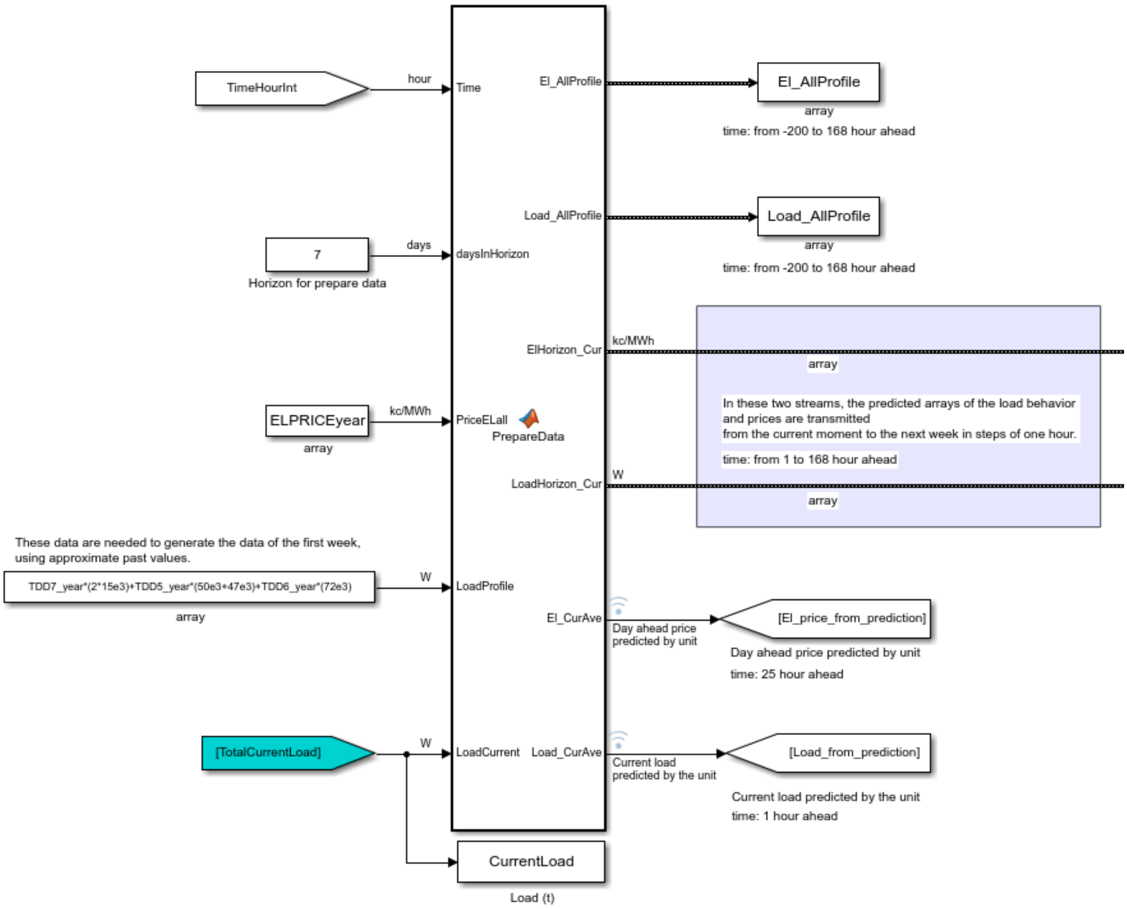

Figure 3.6: Exterior view of "MATLAB Function" block for prediction variables with all input and output flows

- Sampling time of the controller and horizons is 3600 second (1 hour)
- Control horizon equal to the length of input horizons.
- Controller will use linear programming. All functions, which are connected with energy generation/consumption in microgrid, are described with linear control law (2.5, 2.9, 2.12, 2.15, 2.17, 2.20); otherwise they will be transformed into linear (2.18) with the help of integer variables
- Linear minimization function. Controller must minimize (2.21) on the interval $[t; t + T_{hor}]$. Such function is not linear, but further it can be transformed into linear

Let us define the form of minimization function. Function 2.21 has module in its structure. However, if to divide the electricity power from microgrid into positive (obtained from main grid) and negative (injected from smartgrid) then the function on the whole event horizon will have the following form:

$$\begin{gathered} J\left(t, T_{hor}\right) = \sum_{h=t}^{t+T_{hor}} \left(Cost^{el}(h) + Cost^{el}_{dist}\right) \cdot P^{el,pos}_{MG}(h) + \\ + \left(Cost^{el}(h) - Cost^{el}_{dist}\right) \cdot P^{el,neg}_{MG}(h) + Cost^{gas} \cdot \left(P^{MT}_{MG}(h) + P^{FC}_{MG}(h)\right) \end{gathered} \tag{3.7}$$

where:
T_{hor} – time of used horizon [hour]
$\mathrm{P}^{\mathrm{el},pos}_{\mathrm{MG}}(\mathrm{h}) \geq 0$ – positive power from main grid at the moment of time h [W]
$\mathrm{P}^{\mathrm{el},neg}_{\mathrm{MG}}(\mathrm{h}) \leq 0$ – negative power from main grid at the moment of time h [W]
$\mathrm{P}^{\mathrm{MT}}_{\mathrm{MG}}(\mathrm{h})$ – full power of natural gas energy that supplies microgrid at the moment of time h [W]
$P^{\mathrm{FC}}_{\mathrm{MG}}(\mathrm{h})$ – full power of natural gas energy that supplies fuel cell at the moment of time h [W].

If the minimum of function 3.7 is found correctly, it is no longer possible that variables $P^{el,pos}_{MG}(h)$ and $\mathrm{P}^{\mathrm{el},neg}_{\mathrm{MG}}(h)$ will be concurrently equal to zero.

If we want that function 3.7 works correctly under the system conditions, we need to impose functional limits. Limits can be:

- Strict-value equality ($A_{eq} \cdot x = B_{eq}$)
- Non-equality constraints of possible values ($A \cdot x \leq B$ and $lb \leq x \leq ub$).

X is a vector of $[N_{gen} \cdot T_{hor}]$ element dimension. Vector x is a minimization decision in the form of supplied power for each system element, battery state and supplementary variable for each hour of event horizon. For correct understanding of things that will be described further it is worth to pay particular attention to the order of variables, which are defined in this vector. Vector x can be schematically presented in the following form:

$$
\begin{gathered}
x = \\
[[P_{MG}^{el,pos}(1),\quad P_{MG}^{el,neg}(1),\quad P_{MG}^{MT}(1),\quad P_{MG}^{FC}(1),\quad P_{char}(1),\quad P_{dis}(1),\quad Soc(1),\quad b_k(1)], \\
[P_{MG}^{el,pos}(2),\quad P_{MG}^{el,neg}(2),\quad P_{MG}^{MT}(2),\quad P_{MG}^{FC}(2),\quad P_{char}(2),\quad P_{dis}(2),\quad Soc(2),\quad b_k(2)], \\
\vdots \\
[P_{MG}^{el,pos}(T_{hor}), P_{MG}^{el,neg}(T_{hor}), P_{MG}^{MT}(T_{hor}), P_{MG}^{FC}(T_{hor}), P_{char}(T_{hor}), P_{dis}(T_{hor}), Soc(T_{hor}), b_k(T_{hor})]]
\end{gathered}
\tag{3.8}
$$

N_{gen} – number of minimized system parameters for each hour. Equals 8 for this system

A_{eq}, B_{eq} – matrices of strict size limitation $[T_{hor}+1; N_{gen} \cdot T_{hor}]$ and $[N_{gen} \cdot T_{hor}; 1]$ respectively

A,B – matrices of conditional size limitation $[4 \cdot T_{hor}; N_{gen} \cdot T_{hor}]$ and $[4 \cdot T_{hor}; 1]$ respectively

lb, ub – vectors of lower and upper limit of output variable x. Each is of size $[N_{gen} \cdot T_{hor}]$

With strict limitation we describe the required amount of power that should be provided to the smart microgrid at the time moment h to cover customer needs. The amount of energy, which was injected into grid at the time moment h, can be described through components of vector x with following expression:

$$
\mathrm{T}L(\mathrm{h}) = \mathrm{P}_{\mathrm{MG}}^{\text{el, pos}}(h) + \mathrm{P}_{\mathrm{MG}}^{\text{el,neg}}(h) + \eta_{MT} \cdot P_{\mathrm{MG}}^{\mathrm{MT}}(h) + \eta_{FC} \cdot P_{\mathrm{MG}}^{\mathrm{FC}}(\mathrm{h}) + \eta_{\text{char}} \cdot \mathrm{P}_{\text{char}}(h) - \eta_{\text{dis}} \cdot \mathrm{P}_{\text{dis}}(h)
\tag{3.9}
$$

where:

$\mathrm{T}L(h)$ – total power that should be provided to the microgrid; taken from event horizon

Thus, the first part of matrix A_{eq} is a null matrix, where on the main diagonal there are efficiency vectors of all system elements in the following order T_{hor} times:

$$
\begin{bmatrix} 1, & 1, & \eta_{MT}, & \eta_{FC}, & \eta_{char}, & -\eta_{dis}, & 0, & 0 \end{bmatrix}
\tag{3.10}
$$

And the first part of matrix B_{eq} is horizon of total power at each time moment.

Another function of strict limit is setting initial conditions. In the operation of our controller the dynamic of battery charging should be considered. Initial condition of battery charge is indicated as follow:

$$
A_{eq}(T_{hor}+1; 7) = 1; B_{eq}(T_{hor}+1) = Soc(0)
\tag{3.11}
$$

Thus, the final form of strict limit matrices are described below:

$$
\mathrm{A}_{eq} = \begin{bmatrix}
1, & 1, & \eta_{MT}, & \eta_{FC}, & \eta_{char}, & -\eta_{dis}, & 0, & 0, & \cdots & 0, & 0, & 0, & 0, & 0, & 0, & 0, & 0 \\
0, & 0, & 0, & 0, & 0, & 0, & 0, & 0, & \cdots & 0, & 0, & 0, & 0, & 0, & 0, & 0, & 0 \\
 & & & \vdots & & & & & \ddots & & & & \vdots & & & & \\
0, & 0, & 0, & 0, & 0, & 0, & 0, & 0, & \cdots & 1, & 1, & \eta_{MT}, & \eta_{FC}, & \eta_{char}, & -\eta_{dis}, & 0, & 0 \\
0, & 0, & 0, & 0, & 0, & 0, & 1, & 0, & \cdots & 0, & 0, & 0, & 0, & 0, & 0, & 0, & 0
\end{bmatrix},
\tag{3.12}
$$

$$B_{eq} = \begin{bmatrix} TL\,(1) \\ TL\,(2) \\ \vdots \\ TL\,(T_{hor}) \\ Soc(0) \end{bmatrix}. \tag{3.13}$$

Before further describe the limits we need to understand physical limits of battery – it cannot charge and discharge at the same moment of time. By the reason integer variable $b_k(h) \in [0; 1]$ is introduced. This variable restricts simultaneous charging and discharging. In order to describe integer variable it is necessary to complicate optimization type with mixed-integer linear programming, Considering the variable, power of charging/discharging of battery at the time moment h can be described with following intervals [75]:

$$0 \leq \mathrm{P_{dis}}(h) \leq \mathrm{P}_{\mathrm{dis}}^{max} \cdot (1 - b_k(h)) \tag{3.14}$$

$$0 \leq \mathrm{P}_{char}(h) \leq \mathrm{P}_{char}^{max} \cdot (b_k(h)) \tag{3.15}$$

Two-sided inequalities 3.14 and 3.15 can be transformed into one-sided inequality of the form:

$$\frac{\mathrm{P}_{char}(h)}{\mathrm{P}_{char}^{max}} - b_k(h) \leq 0 \tag{3.16}$$

$$\mathrm{P_{dis}}(h) + \mathrm{P}_{\mathrm{dis}}^{max} \cdot b_k(h) \leq \mathrm{P}_{\mathrm{dis}}^{max} \tag{3.17}$$

Low limits 3.14 and 3.15 are described further with vectors lb and ub. Such approach avoids adding extra variables into matrices of limitation and, thus, increases the speed of performing optimization.

The main advantage of MPC controller is planning optimal control of battery charging/discharging at every step. The controller finds an optimal plan of action on the whole expected event horizon considering limits and all intermediate states of the system.

Due to the operational constraints that were described in section 2.4.6 we introduce limits on possible states of battery charge at each time moment:

$$20\% \leq Soc(h) \leq 90\%. \tag{3.18}$$

Let us specify the state of battery charge with the formula that arises from 2.18 at the time moment T_{hor}:

$$Soc(0) + \sum_{i=1}^{T_{hor}} P_{char}(i) \cdot \eta_{char} \cdot k - P_{dis}(i) \cdot \frac{k}{\eta_{dis}} \leq Soc_{\max}^{90} \tag{3.19}$$

Let us combine formulas 3.18 and 3.19 and bring the inequality to the form of non-equality constraint; we will get the following expressions that define the degree of freedom of battery charge on the whole event horizon:

$$Soc(0) + \sum_{i=1}^{T_{hor}} P_{char}\left(i\right) \cdot \eta_{char} \cdot k - P_{dis}\left(i\right) \cdot \frac{k}{\eta_{dis}} \leq Soc_{max}^{90} \tag{3.20}$$

$$-Soc(0) - \sum_{i=1}^{T_{hor}} P_{char}(i) \cdot \eta_{char} \cdot k - P_{dis}(i) \cdot \frac{k}{\eta_{dis}} \leq -Soc_{min}^{20} \tag{3.21}$$

where:
$k = \frac{\Delta T}{\text{cap}} \cdot 100$ – constant
Soc_{max}^{90} – maximal safe operational status of battery charge that equals to 90%
Soc_{min}^{20} – minimal safe operational status of battery charge that equals to 20%.

Thus, matrices of non-equality constraint are matrices 3.22 and 3.23. Each of the matrix is conditionally divided into 3 parts:

1. The part, which is described with formula 3.20, that controls the upper limit of battery charge state at each prediction step considering previous values. This part in matrix A has form of lower triangular matrix.

2. The part, which is described with formula 3.21, that controls the lower limit of battery charge state at each prediction step considering previous values. This part in matrix A has form of lower triangular matrix.

3. The part, which is described with formulas 3.16 and 3.17, which controls the limit of concurrent battery charge and discharge at each prediction step. This part in matrix A consists of blocks that describe aforementioned condition by the size of [2;8] elements. The elements is located on the main diagonal.

$$
A=\begin{bmatrix}
0,0,0,0,\eta_{char}k,-k/\eta_{dis},1,0, & \cdots & 0,0,0,0, & 0, & 0, & 0,0\\
0,0,0,0,\eta_{char}k,-k/\eta_{dis},1,0, & \cdots & 0,0,0,0, & 0, & 0, & 0,0\\
\vdots & \ddots & & \vdots & & \\
0,0,0,0,\eta_{char}k,-k/\eta_{dis},1,0, & \cdots & \multicolumn{4}{c}{0,0,0,0,\eta_{char}k,-k/\eta_{dis},0,0}\\
\\
0,0,0,0,-\eta_{char}k,k/\eta_{dis},-1,0, & \cdots & 0,0,0,0, & 0, & 0, & 0,0\\
0,0,0,0,-\eta_{char}k,k/\eta_{dis},-1,0, & \cdots & 0,0,0,0, & 0, & 0, & 0,0\\
\vdots & \ddots & & \vdots & & \\
0,0,0,0,-\eta_{char}k,k/\eta_{dis},-1,0, & \cdots & \multicolumn{4}{c}{0,0,0,0,-\eta_{char}k,k/\eta_{dis},0,0}\\
\\
0,0,0,0,\quad 1/P_{char}^{max},\quad 0,\quad 0,-1, & \cdots & 0,0,0,0, & 0, & 0, & 0,0\\
0,0,0,0,\quad 0,\quad 1,\ 0,P_{dis}^{max}, & \cdots & 0,0,0,0, & 0, & 0, & 0,0\\
\vdots & \ddots & & \vdots & & \\
0,0,0,0,\quad 0,\quad 0,\quad 0,0, & \cdots & 0,0,0,0, & 1/P_{char}^{max}, & 0, & 0,-1\\
0,0,0,0,\quad 0,\quad 0,\quad 0,0, & \cdots & 0,0,0,0, & 0, & 1, & 0,P_{dis}^{max}
\end{bmatrix}, \tag{3.22}
$$

$$
B=\begin{bmatrix}
Soc_{max}^{90}\\
Soc_{max}^{90}\\
\vdots\\
Soc_{max}^{90}\\
\\
-Soc_{min}^{20}\\
-Soc_{min}^{20}\\
\vdots\\
-Soc_{min}^{20}\\
\\
0\\
P_{dis}^{max}\\
\vdots\\
0\\
P_{dis}^{max}
\end{bmatrix}. \tag{3.23}
$$

The last restriction is lower and upper limits of all variables of vector x. Vectors lb and ub have repetitive structure for every hour of horizon:

$$lb = \begin{bmatrix} 0 \\ P^{el,\ neg}_{MG,\ min} \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ \vdots \\ 0 \\ P^{el,\ neg}_{MG,\ min} \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \quad ub = \begin{bmatrix} P^{el,\ pos}_{MG,\ max} \\ 0 \\ P_{MTnom}\eta_{MT} \\ P_{FCnom}\eta_{FC} \\ P^{max}_{char} \\ P^{max}_{dis} \\ 100\% \\ 1 \\ \vdots \\ P^{el,\ pos}_{MG,\ max} \\ 0 \\ P_{MTnom}\eta_{MT} \\ P_{FCnom}\eta_{FC} \\ P^{max}_{char} \\ P^{max}_{dis} \\ 100\% \\ 1 \end{bmatrix}, \tag{3.24}$$

where:

$P^{el,\ pos}_{MG,\mathrm{max}}$, $P^{el,\ neg}_{MG,\mathrm{min}}$ – maximal and minimal power that can be exchanged with main grid of energy supply [W].

To find minimum of weight function 3.7 under condition of all limits we will use *intlinprog* function. The function finds minimum of weight function by using mixed-integer linear programming solver. Its conditions are defined below:

$$\min_x J^T x \ subject\ to \begin{cases} x(intcon)\ are\ integers \\ A \cdot x \leq B \\ A_{eq} \cdot x = B_{eq} \\ lb \leq x \leq ub \end{cases} \tag{3.25}$$

In MATLAB this function has the following form:

$$x = intlinprog(J,intcon,A,b,Aeq,beq,lb,ub) \tag{3.26}$$

In 3.26 function J is written as a vector with linear coefficients. Vector *intcon* contains indexes to output integer coefficients of vector x. Under the conditions of our work its content will be roughly as follow: $[8, 16, \ldots, 8 \cdot T_{hor}]$. With this vector we restrict the range of possible values for variable $b_k(h)$ [80].

It is worth considering that it is not possible to generate code for MATLAB solver MILP for costs minimization and for MATLAB solver NLP for searching ARIMA model parameters. In order to overcome these issues it is possible to implement block with subprogram of C++ into the model. Regarding MILP programming [81] it is possible to work with open source C++ libraries, for example, CBC (Coin-or Branch and Cut) [82]. Problem description of MILP for CBC is the same as it is for *intlinprog*. Only realization methods are vary. For the future implementation of the optimizer into industrial environments it is necessary to descried the MILP (and NLP) solvers through embedded blocks, which support code generation in C language. In our work MILP solver is realized with the help of *intlinprog*.

The exterior view of ”MATLAB Function” block for cost minimization is depicted in Figure 3.7. Input of the block:

- The length of using horizons (in days). Pay attention that in the block of future horizons generation we developed horizons of seven-day length. However, the block of cost minimization can use the part of predicted horizon, for example, the first part of the horizon. For instance, in Figure 3.7 it equals to 3. It was done in such way in order to control the contribution of prediction error. The further studying of the horizon length can be found in the following chapter 4.

- Three cost horizons of the seven-day length (electricity, electricity distribution, total costs for gas)

- Load horizon of the seven-day length

- Technical characteristics of battery; highlighted with red color (nominal power, nominal capacity, initial state of charge, charge efficiency, discharge efficiency)

- Technical characteristics of microturbine; highlighted with orange color (nominal power and efficiency)

- Technical characteristics of fuel cell; highlighted with yellow color (nominal power and efficiency)

Changing parameters of generating block model directly influences MPC behavior. More detailed description of these parameters will be shown in the next chapter 4.

Functional outputs are outputs of nominal power of microturbine, fuel cell and battery. All other outputs are given for informative purposes.

Listing of function of the block can be found in appendix B.

Thus, we have weight function of MPC controller 3.7 that defines approximate costs on the whole horizon. To find optimal behavior, we search the minimum of the function under the strict and non-equality conditions, which are described with matrices 3.12, 3.13, 3.22, 3.23, 3.24. These limits set necessary plan of energy generation; give a certain margin of battery charge state variable; restrict operational indicators of real system objects. Horizon of controller manipulating is equal 1, and that means that from the all predicted values of the whole horizon we output only first six ($x[1{:}6]$), which are responsible for system behavior in the next hour. In an hour all calculations are repeated again.

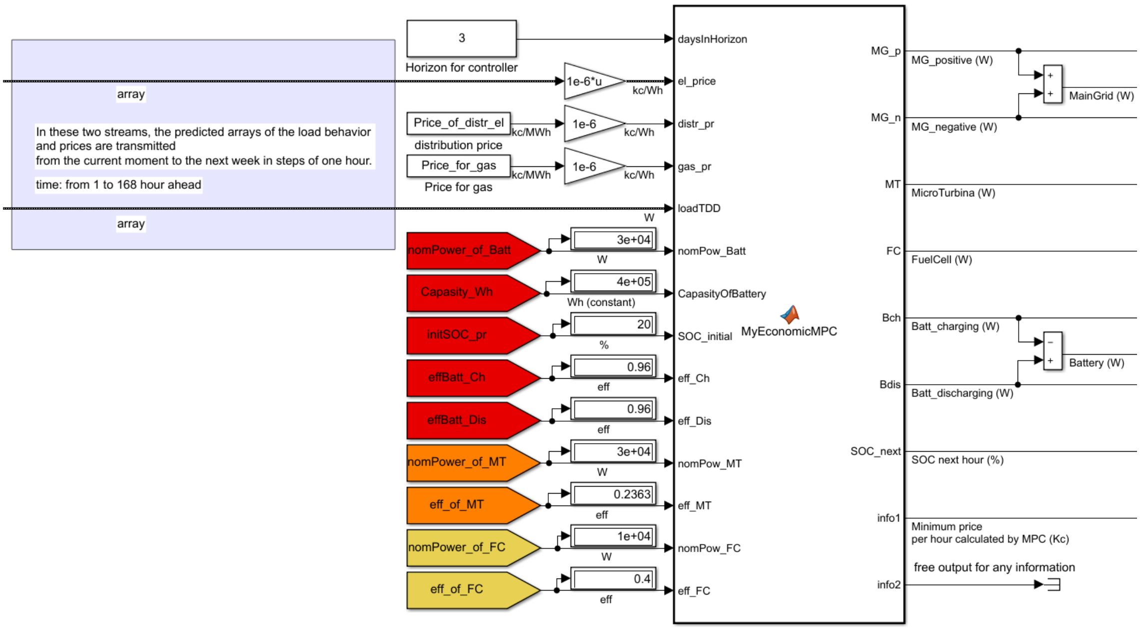

Figure 3.7: External view of "MATLAB Function" block for cost minimization with all input and output flows

4 Analysis of the results

4.1 Check of smart microgrid model efficiency

In chapter 2 we designed electrical grid model of micro-district with different sources of distributing energy generation. In chapter 3 we synthesized horizons prediction block and MPC controller. Let us now demonstrate that our system and controller perform correctly.

Main model parameters with MPC controller during 3 days with one-day horizon are depicted in Figure 4.1. One step in histogram equals to one hour. Correct functionality can be checked with a glance to the outer value of graphics of current electricity load and current electricity cost. If to take the total power of all electrical sources at current hour then we should have the total power load at the same hour.

Charging and discharging mode are directly proportional to the electricity cost. Start and end of battery charging/discharging are calculated based on prediction in a way to choose optimal time of necessary actions, which will influence future system states. For example, controller calculates the moment of start of the battery charge in order to charge the battery till required level on time. It is done to cover future predicted load peak according to future costs as effectively as possible. The same principle acts reversely for discharging.

It is possible to observe that fuel cell operates most of the time due to its high efficiency (it was checked with one-year modulation). On the other hand, there is a microturbine whose efficiency is almost half of the fuel cell efficiency. Thus, it operates only in the case when electricity cost and required power reach certain thresholds. It is worth to say that under current conditions microturbine operates less than 10 hours during a year. It means that microturbine implementation in the configuration of smart microgrid is hugely inefficient.

Also it should be noted that under these conditions smart microgrid never feeds electrical energy back into the main grid. It happens due to the following reasons:

- High load of end users
- Low total electricity generation by distribution energy sources
- High cost threshold, which is related to electricity distribution costs, that we pay in any cases (whether we buy or sell).

Special attention should be given to the length of horizons. With reducing horizons length prediction accuracy increases and, thus, correctness of controller operation increases as well, but its reaction rate for inert system devices, such as battery,

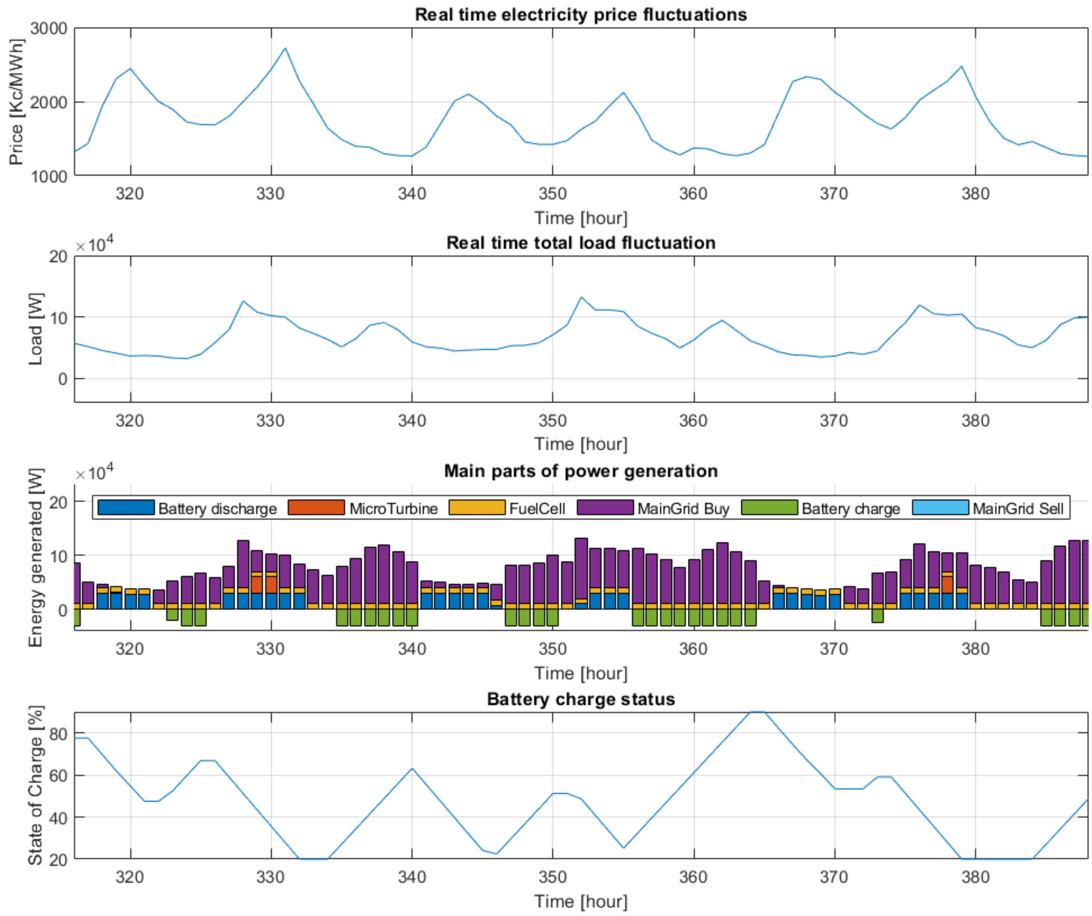

Figure 4.1: Graphics that represent behavior of the model with MPC with one-day horizons

decreases. On the other hand, with increasing horizons length we increase prediction error, but provide enough margin time for inert system devices. That is why it is necessary to choose optimal horizons length for each smart microgrid depending on inert system part and horizons behavior (oscillation frequency and amplitude). Figures 4.2 and 4.3 show how horizons length affects controller behavior (with lengths of 3 hours and 7 days). For illustrative purposes the same modeling interval with similar horizons as depicted in Figure 4.1 was taken.

4.2 Impact of system parameters on optimization quality

The same controller for different systems can show different saving costs. In this section we will describe how much parameters modification of smart microgrid objects influences economic benefit. We will not consider the task of purchase amortization of one or another electricity generator. But we will examine how various parameters affect the behavior.

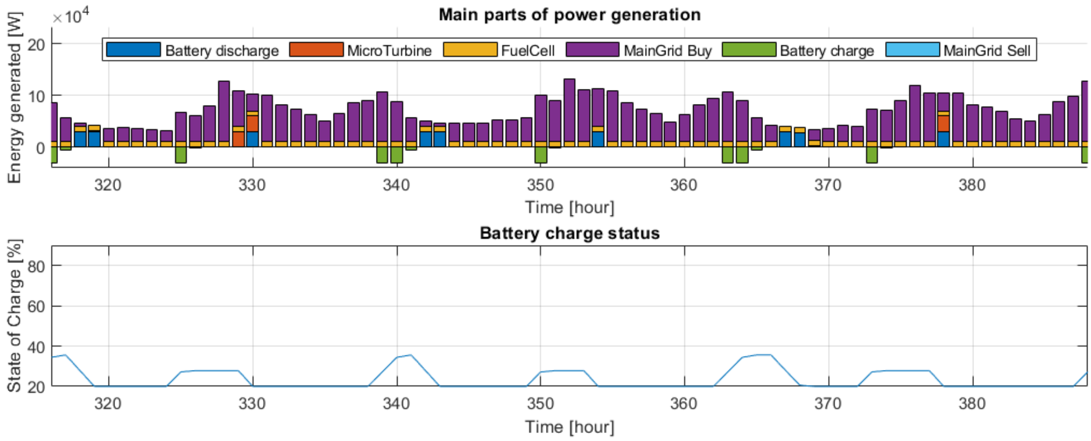

Figure 4.2: Graphics that represent behavior of the model with MPC with three-hour horizons

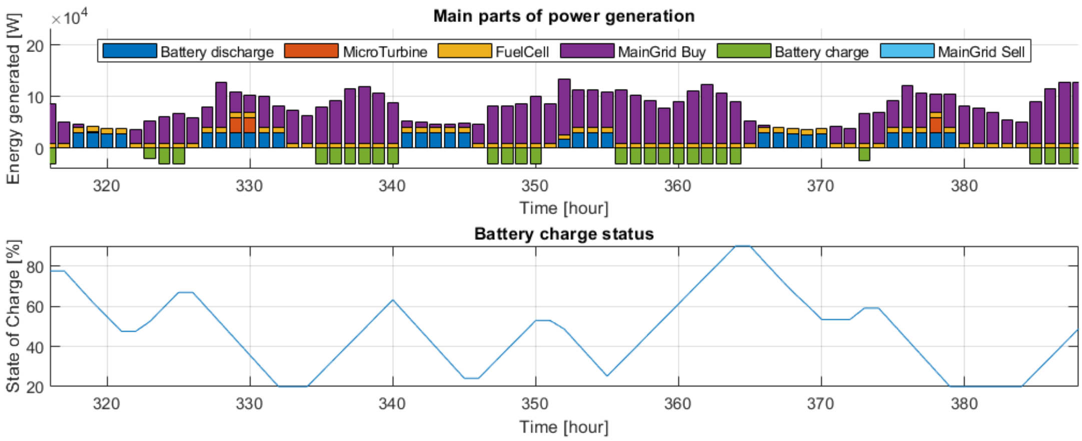

Figure 4.3: Graphics that represent model behavior with MPC and with seven-day horizons

To evaluate the smart microgrid saving costs we need to define initial cost value. This initial cost value will be the value of electricity costs of microgrid, which is supplied only from main grid, over the same period of time without controlled energy sources (batteries, microturbines, fuel cells). By comparing this value with value of costs when we use MPC, we can obtain saving costs of controller performance as well as the saving costs of the whole system.

Optimal horizons length is 3 days. It is exactly the length when we can consider the change of real system profiles in advance (preparation to weekends, when profiles view differs markedly from weekdays profiles view). We can also consider prediction error.

Tables below present the information about saving costs of system modeling with MPC controller depending on parameters change from original parameters (OP) of the system in the modeling range of 70 days. Efficiency of the model with MPC is taken at the moment of full discharge.

Table 4.1: Saving costs of MPC with different parameters of smart microgrid (part 1)

Parameter	***0.1·OP***	***0.5·OP***	***OP***	***1.5·OP***	***2·OP***
Length of horizons (OP = *3 days*)	4.3662	5.1737	5.1696	5.1697	5.1708
Total power rating of solar panels (OP = *13 kW*)	4.6112	4.8661	5.1696	5.4814	5.7869
Rated power of wind turbine (OP = *10 kW*)	5.1256	5.1459	5.1696	5.1943	5.2249
Rated power of microturbine (OP = *30 kW*)	5.1247	5.1469	5.1696	5.1917	5.1941
Rated power of fuel cell (OP = *10 kW*)	2.9180	3.9232	5.1696	6.3937	7.6260
Rated power of battery (OP = *30 kW*)	2.9094	4.0938	5.1696	5.8144	6.0780
Nominal capacitance of the battery (OP = *2000 Ah*)	3.0328	4.4742	5.1696	5.4053	5.4891

Table 4.2: Saving costs of MPC with different parameters of smart microgrid (part 2)

Parameter	***OP-0.06***	***OP-0.03***	***OP***	***OP+0.03***	***OP+0.06***
Efficiency of microturbine (OP = *0.2363*)	5.1224	5.1174	5.1696	5.3753	5.9526
Efficiency of fuel cell (OP = *0.4*)	3.7629	4.4622	5.1696	5.8365	6.4354
Total efficiency of the battery (OP = *0.92*)	4.3412	4.7537	5.1696	5.5982	6.0624

Approximated curves based on the data from tables 4.1 and 4.2 are shown in Figure 4.4. The graph provides us with some certain conclusions for each parameter:

- Length of the horizons stops affecting smart microgrid saving costs after the value of 1.5 days. However, horizons length should be increased with increasing inertness of the system. For instance, when we increase capacity of the batteries or decrease their speed of charging/discharging. Prediction error does not play a major role with increasing horizons length.

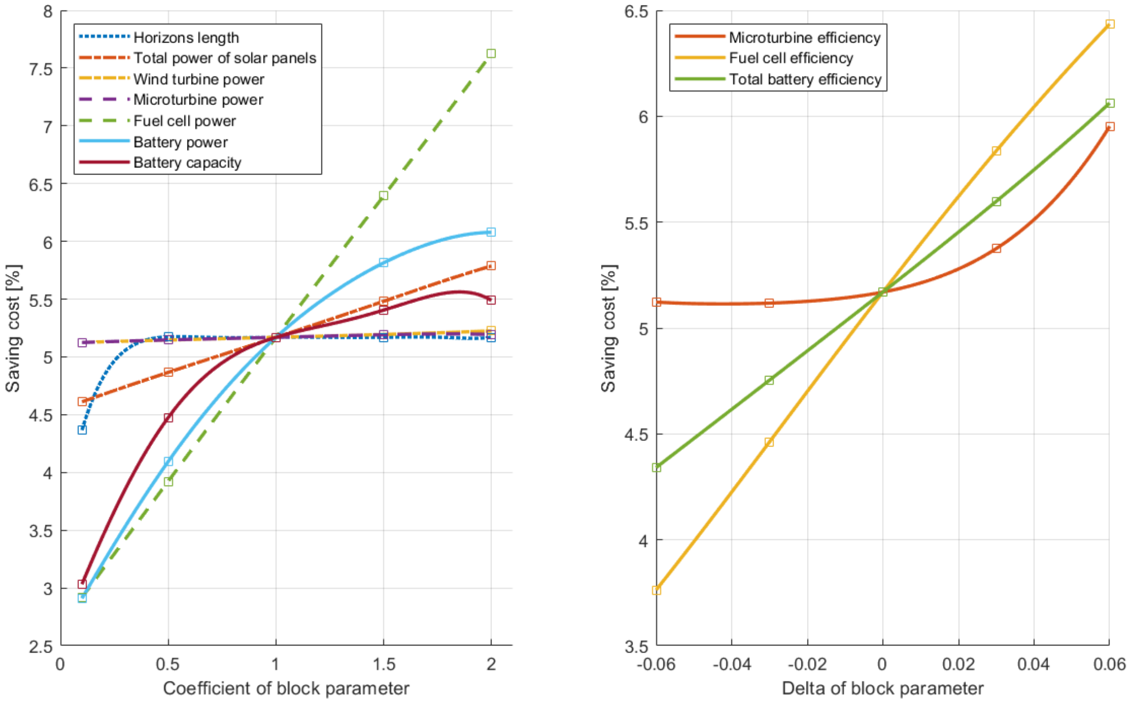

Figure 4.4: Graphics of behavior of the model with MPC with changed original parameters of smart microgrid

- For given weather profiles one can notice that increase of solar panels power contributes significantly to the saving costs of smart microgrid in comparison with wind turbine. It is connected with profiles shape, which controls solar panels and wind turbine. Depending on the geographical location of the smart grid, contribution of renewable energy sources to cost saving can vary.

- Original parameters of microturbine are set in a way that it is not used most of the time. However, if to increase efficiency of microturbine, saving costs of smart microgrid increases exponentially. It is also connected with high power rating of microturbine, which is not utilized in comparison with fuel cell that has lower power, but high efficiency. In practice, microturbine efficiency depends on environmental temperature, but this distribution is not realized in the model.

- Fuel cell makes significant contribution to the saving costs of smart microgrid. It can potentially raise greatly the overall saving costs, but we do not consider big value of cost in $K\check{c}/W$ for its installation and possible operating costs. If to compare fuel cell with microturbine, the operating costs and costs for installation of the latter one in several times lower.

- Power and battery capacitance contribution exponentially decays as these parameters are increased separately. However, if to vary these parameters simultaneously then we can contribute well to the total saving costs. Furthermore, the efficiency of charging/discharging has a profound impact on smart microgrid saving costs. This value has physical limit and for given battery types does not exceed 0.96 at the current moment.

On the basis of the conclusions, which were made based on Figures 4.4, it is possible to construct a number of structure concepts of smart microgrid. There is a variant to balance power of all controlled distributed generators or invest in key of them by bringing their performance characteristics to perfection. For example, let us demonstrate some variants of smart microgrid settings.

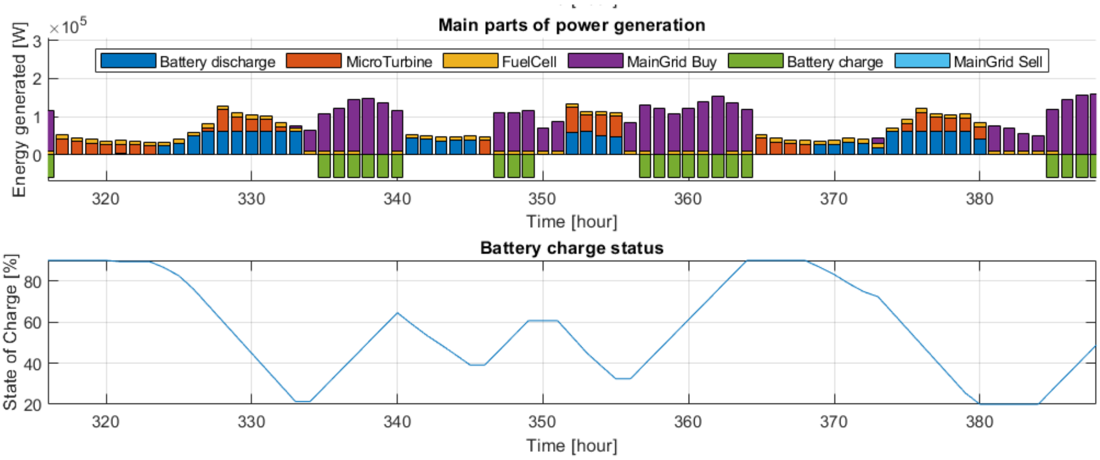

Figure 4.5: Graphics of behavior of the model with MPC with three-day horizons and chosen system parameters for even power generation

To balance contribution of each energy sources microturbine power can be increased to 65 kW, its electrical efficiency can be raised to 0.3 (to its possible operating limit) and efficiency of fuel cell can be decreased to 0.35. Battery power and capacitance can be increased twice the original parameters. Thus, it is possible to receive the saving costs of 6.9% of smart microgrid on the time interval of 70 days. Figure 4.5 illustrates that all electrical energy generators operate evenly, but the total saving costs left much to be desired.

Let us consider the second setting variant. We will select the maximal saving costs, which are obtained with MPC controller, without alternative non-renewable power sources (without microturbine and fuel cell). Bring the battery parameters to ideal: total efficiency – 0.94, power is increased by 20 times, capacitance is increased by 10 times. With this setting, discharge battery power can cover total maximal load of the microgrid. Sometimes there are moments of selling energy into the main electricity grid. Saving costs in some cases can reach the value of 15% with the length of three-day horizons. However, such enormous increase of battery power has limit of contribution to saving costs. Much higher saving costs can be received if to improve all other sources of electricity generation.

Let us consider the third variant of the setting. Return all system parameters back to their original ones. If we increase power and capacitance of the battery five times, total efficiency to 0.94 and switch off all gas energy generators then the saving costs of smart microgrid, which we obtain, will be 11.6%. At the same time electricity will not be sold to the main grid, because the controller supposes that it is not efficient.

To further improve saving costs it is necessary, either to increase power of renewable energy sources, or add alternative energy sources that will be sometimes better when electricity prices are high.

By increasing rated power of solar panels in three times, the saving costs rises to 12.7%. There are moments when energy is excess and it is sold to the main grid. Costs for electricity fall significantly in general, since renewable energy affects directly the total power of smart microgrid. After adding high-performance fuel cell with power of 15 kW and efficiency of 0.45, total saving costs of smart microgrid grows for 70 days to 17.1%. In some cases, saving costs of such system reaches the value of 21%. Hence, adding microturbine, even with increased efficiency to 0.3, does not lead to the considerable saving costs in general, it was decided to reject its usage in this example. The best saving costs were obtained with three-day horizon length. Thus, Figure 4.6 depicts profiles of system behavior with modified parameters.

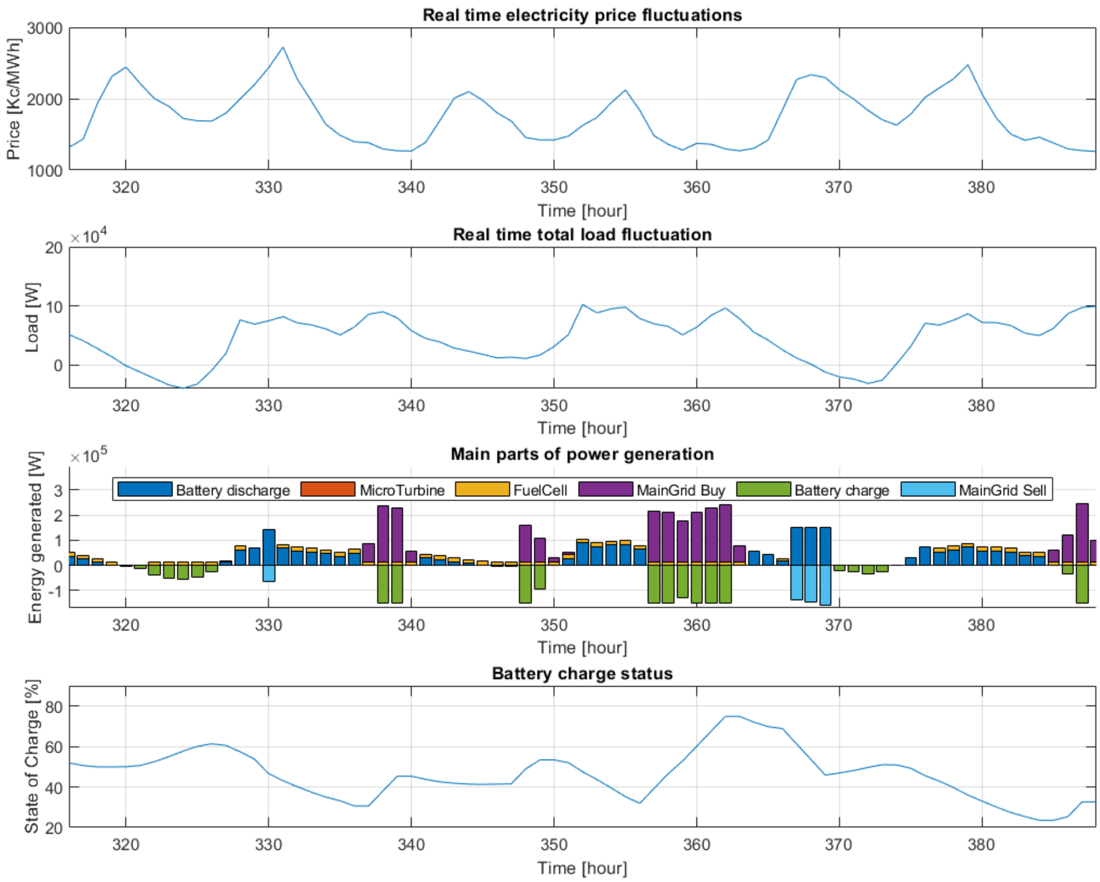

Figure 4.6: Graphics of behavior of the model with MPC with three-day horizons and chosen system parameters for maximal system saving costs

When one choose parameters of generators she or he should consider average amount of power that is necessary to generate and number of energy sources, on which the average amount of power will be divided. Frequently, one should refuse implementing wide range of electricity generators and use only key and effective energy sources, because the last bring more benefits than inefficient energy sources.

It is also important to keep balance for types of energy generation devices in the microgrid. When electricity is expensive smart microgrid can always use gas energy sources or cover the load with renewable energy sources. Improvement of one electricity generation type till perfection has always economical and rational limit.

Alternative variant of costs optimization is minimization of power load by increasing power of renewable energy sources. The choice of system parameter for real smart microgrid is done according to main optimization aim and set of economic condition. It is essential to consider fluctuation of energy costs profiles, fluctuation of load profiles, profiles of weather for given territory, lifetime of energy generators, generators efficiency and rate deprecation. To verify visually the correct choice of parameters the model of this diploma thesis can be used.

5 Conclusions

In this diploma thesis we consider introduction to the smart microgrid conception: their purpose, structure and possible variants of mathematical realization, which are presented in the work as literature review. Conclusion of obvious advantage of the method based on MPC is made, with condition that system profiles (load, cost, weather) of the method have predictable behavior.

We choose an abstract object of residential community of northern part of Czech Republic, which is connected to the main electricity grid and has a number of distributed controlled (microturbine, fuel cell, battery) and uncontrolled (solar power and wind turbine) electricity sources. Each element of the object is described in MATLAB Simulink and controlled with profiles of real historical data for 2018.

Two main changing system profiles – profiles of total power and electricity costs – are explored. ARIMA models for generating future objects horizons of the seven-day length are selected. The method of selecting prediction model parameters is described. The next step is to choose the method of solving optimization task of MPC controller: mixed-integer linear programming (MILP). Weight function and restriction matrices are created based on the method. Weight function describes possible minimum cost for object electrification during the whole horizon. Restriction matrices are used to describe power requirements and functional limits of objects.

Afterwards we verify adequacy of smart microgrid performance for chosen object and made conclusion about controller solutions at certain time moments. Then we evaluate potential abilities and main parameters contribution of each element to the total saving costs of smart microgrid. Finally, we offer some recommendations about selecting elements for smart microgrid.

We described problematic points that are connected with code generation, limits and approaches of MATLAB for implementation of developed optimizer into industrial platforms. The possibility of transferring the controller into LabView was not considered, as there is no necessity, since MATLAB currently supports code generation for many various platforms.

Based on the synthesized system it is possible to choose components for smart microgrid considering all range of requirements and limits; check efficiency of the components and their behavior in real profiles of costs, load and weather.

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A Part of horizons synthesis

```
function [ El_AllProfile, Load_AllProfile, ElHorizon_Cur,
    LoadHorizon_Cur, El_CurAve, Load_CurAve] = PrepareData(
    Time, daysInHorizon, PriceELall, LoadProfile,
    LoadCurrent)
% Number hours in day:
Nhour=24;
% Array Parameters for Prediction:
% Number of items back;
NumPreviousVal=200;
% Index showing the current state of the system;
CurInx=NumPreviousVal+1;
% An index showing the current state of the system
% every other day to predict electricity.
DayAheadInx=CurInx+Nhour-1;

%% PROFILE OF ELECTRICITY COST

% AllProfE - an array for prediction with past values of
    the system
% and future [-NumPreviousVal:daysInHorizon*Nhour].
% IntProfE - an array of first-order differences of the
    same length.
% ErrProfE - an array of errors of same length.
% PrevCost - previous cost.
persistent AllProfE IntProfE ErrProfE PrevCost;

% We get the cost for the day ahead.
ElCurrentDayAhead=PriceELall(Time+Nhour-1);

% ARIMA Parameters:
% regresive part;
AR1_E=0.0442;
AR24_E=0.1491;
AR168_E=0.7762;
% average part.
```

```
C_E=-0.0494;
MA1_E=0.0557;
MA24_E=0.0319;
MA168_E=-0.5268;

% If arrays are not created, then we form them:
if isempty(AllProfE)

    % Main Profile.
    AllProfE=PriceELall(Time-NumPreviousVal:Time+
        daysInHorizon*Nhour);
    AllProfE(DayAheadInx)=ElCurrentDayAhead;

    % Previous Cost.
    PrevCost=PriceELall(Time+Nhour-2);

    % Integral Profile.
    IntProfE=zeros(1,length(AllProfE));
    IntProfE(1)=AllProfE(1);
    for h=2:length(AllProfE)
        IntProfE(h)=AllProfE(h)-AllProfE(h-1);
    end

    % Error Profile.
    ErrProfE=zeros(1,length(AllProfE));

    % Past predicted value a day ahead.
    El_CurAve=AllProfE(DayAheadInx);

else
    % Otherwise, convert the arrays for the new prediction.
    % We shift the arrays of the current value and error
    % by one value to the left. On the right are zeros.
    for h=1:length(AllProfE)-1
        AllProfE(h)=AllProfE(h+1);
        ErrProfE(h)=ErrProfE(h+1);
    end
    AllProfE(length(AllProfE))=0;
    ErrProfE(length(AllProfE))=0;
    % We consider the error of the previous prediction.
    ErrProfE(DayAheadInx)=PrevCost-AllProfE(DayAheadInx);
    % We derive the previous prediction.
    El_CurAve=AllProfE(DayAheadInx);
    % Update current cost.
    AllProfE(DayAheadInx)=ElCurrentDayAhead;
```

```
    % Remember the previous cost.
    PrevCost=ElCurrentDayAhead;

    % We form a new array of 1 order differences.
    IntProfE(1)=AllProfE(1);
    for h=2:length(AllProfE)
        IntProfE(h)=AllProfE(h)-AllProfE(h-1);
    end
end

% From the next hour of the next day to the end of the horizon:
for h=DayAheadInx+1:(CurInx+daysInHorizon*(Nhour)-1)+1
    % We consider the current difference;
    IntProfE(h-1)=C_E+ErrProfE(h)+MA1_E*ErrProfE(h-1)+MA24_E*ErrProfE(h-24)+MA168_E*ErrProfE(h-168)+AR1_E*IntProfE(h-1)+AR24_E*IntProfE(h-24)+AR168_E*IntProfE(h-168);
    % We consider the prediction.
    AllProfE(h)=AllProfE(h-1)+IntProfE(h-1);
end

% We display the entire predicted horizon from the current hour.
ElHorizon_Cur=AllProfE(CurInx:length(AllProfE)-1);

% We display the entire working profile.
El_AllProfile=AllProfE;
%% PROFILE OF LOAD

% AllProfL - an array for prediction with past values of the system
% and future [-NumPreviousVal:daysInHorizon*Nhour].
% IntProfL - an array of first-order differences of the same length.
% ErrProfL - an array of errors of same length.
% PrevLoad - previous load.
persistent AllProfL IntProfL ErrProfL PrevLoad;

% ARIMA Parameters:
% regresive part;
AR1_L=0.0349;
AR24_L=0.0766;
AR168_L=0.8596;
% average part.
```

```
C_L=-4.3071;
MA1_L=-0.2026;
MA24_L=0.2809;
MA168_L=-0.3288;

% If arrays are not created, then we form them:
if isempty(AllProfL)

    % Main Profile.
    AllProfL=LoadProfile(Time-NumPreviousVal:Time+
        daysInHorizon*Nhour);
    AllProfL(CurInx)=LoadCurrent;

    % Previous Load.
    PrevLoad=LoadProfile(Time-1);

    % Integral Profile.
    IntProfL=zeros(1,length(AllProfL));
    IntProfL(1)=AllProfL(1);
    for h=2:length(AllProfL)
        IntProfL(h)=AllProfL(h)-AllProfL(h-1);
    end

    % Error profile.
    ErrProfL=zeros(1,length(AllProfL));

    % Past predicted value a hour ahead.
    Load_CurAve=AllProfL(CurInx);

else
    % Otherwise, convert the arrays for the new prediction.
    % We shift the arrays of the current value and error
    % by one value to the left. On the right are zeros.
    for h=1:length(AllProfL)-1
        AllProfL(h)=AllProfL(h+1);
        ErrProfL(h)=ErrProfL(h+1);
    end
    AllProfL(length(AllProfL))=0;
    ErrProfL(length(AllProfL))=0;
    % We consider the error of the previous prediction.
    ErrProfL(CurInx)=PrevLoad-AllProfL(CurInx); %-1
    % We derive the previous prediction.
    Load_CurAve=AllProfL(CurInx);
    % Update current load.
    AllProfL(CurInx)=LoadCurrent;
```

```
    % Remember the previous load.
    PrevLoad=LoadCurrent;

    % We form a new array of 1 order differences.
    IntProfL(1)=AllProfL(1);
    for h=2:length(AllProfL)
        IntProfL(h)=AllProfL(h)-AllProfL(h-1);
    end
end

% From the next hour to the end of the horizon:
for h=CurInx+1:(CurInx+daysInHorizon*Nhour-1)+1
    % We consider the current difference;
    IntProfL(h-1)=C_L+ErrProfL(h)+MA1_L*ErrProfL(h-1)+MA24_L*ErrProfL(h-24)+MA168_L*ErrProfL(h-168)+AR1_L*IntProfL(h-1)+AR24_L*IntProfL(h-24)+AR168_L*IntProfL(h-168);
    % We consider the prediction.
    AllProfL(h)=AllProfL(h-1)+IntProfL(h-1);
end
% We display the entire predicted horizon from the current hour.
LoadHorizon_Cur=AllProfL(CurInx:(CurInx+daysInHorizon*Nhour-1));

% We display the entire working profile.
Load_AllProfile=AllProfL;
end
```

B Part of cost minimization

```
function [MG_p, MG_n, MT, FC, Bch, Bdis, SOC_next, info1,
    info2] = MyEconomicMPC(daysInHorizon, el_price, distr_pr
    , gas_pr, loadTDD, nomPow_Batt, CapasityOfBattery,
    SOC_initial, eff_Ch, eff_Dis, nomPow_MT, eff_MT,
    nomPow_FC, eff_FC)
% Specify functions that will not be generated in the code.
coder.extrinsic('intlinprog','optimoptions');
% CurrentCharge - current SOC.
% Aeq - strictly constrained matrix, which is defined once.
% A, B - matrices are not strictly constraints that are
    defined once.
% LB, UB - lower and upper bound of vector x.
persistent CurrentCharge Aeq A B LB UB;
% Since this function receives a backing window,
% the current time is always 1, in terms of the input data.
time=1;
% The number of variables for one hour of predictions.
Ngen=8;
% The number of hours in the horizon.
HorHour=24*daysInHorizon;

%% BATTERY SETTINGS
% Initialize the initial charge of the battery once.
if isempty(CurrentCharge)
    CurrentCharge=SOC_initial;
end
% Determine the rated power of charging and discharging the
    battery.
Pch_max=nomPow_Batt; Pdis_max=nomPow_Batt;
% We determine the constant Kbatt for the battery.
delT=1; Cap_Batt=CapasityOfBattery;
Kbatt=delT/Cap_Batt*100;
% Determine the maximum and minimum battery charge limit.
SOCmax=90; SOCmin=20;

```

```
%% READ THE HORIZONS
% We read horizons with the condition of the specified length in hours.
% Horizons cost:
pr_el=el_price(time:time+HorHour-1);
pr_distr=ones(1,HorHour)*distr_pr;
pr_gas=ones(1,HorHour)*gas_pr;
% Load Horizon:
pr_load=loadTDD(time:time+HorHour-1);
%% DETERMINATION OF EFFICIENCY
effMG_p=1; effMG_n=1; effMT=eff_MT; effFC=eff_FC; effCHAR=eff_Ch; effDIS=eff_Dis;

%% DESCRIPTION OF STRICT LIMITATIONS
if isempty(Aeq)
    Aeq=zeros(HorHour+1,HorHour*Ngen);
    k=1;
    for i=1:Ngen:HorHour*Ngen
        % Description of elements to cover the specified load:
        Aeq(k,i)=effMG_p;
        Aeq(k,i+1)=effMG_n;
        Aeq(k,i+2)=effMT;
        Aeq(k,i+3)=effFC;

        Aeq(k,i+4)=-effCHAR;
        Aeq(k,i+5)=effDIS;

        k=k+1;
    end

    % Record the initial value of the battery charge:
    Aeq(HorHour+1,7)=1;
end

% Load Horizon Record.
Beq=zeros(HorHour+1,1);
Beq(1:HorHour,1)=pr_load';
% Record the initial value of the battery charge:
Beq(HorHour+1,1)=CurrentCharge+1;

%% DESCRIPTION OF NO STRICT LIMITATIONS
% Defined once.
if isempty(A)
    A=zeros(2*HorHour+2*HorHour,HorHour*Ngen);
```

```
    B=zeros(2*HorHour+2*HorHour,1);
    % Description of the first part of the matrix A.
    % Restrictions on the upper limit of charging.
    for i=1:Ngen:HorHour*Ngen
        for k=1:HorHour
            if (i/Ngen-k)<=0
                A(k,i+4)=effCHAR*Kbatt;
                A(k,i+5)=-Kbatt/effDIS;
            end
        end
    end
    A(1:HorHour,7)=ones(HorHour,1);
    % Description of the second part of the matrix A.
    % Restrictions on the lower limit of charging.
    A(HorHour+1:2*HorHour,:)=-A(1:HorHour,:);

    % Description of the third part of the matrix A.
    % Restriction on the simultaneous
    % charging and discharging of the battery.
    k=2*HorHour+1;
    for i=1:Ngen:HorHour*Ngen
        A(k,i+4)=1/Pch_max;  A(k,i+7)=-1;
        A(k+1,i+5)=1;         A(k+1,i+7)=Pdis_max;

        k=k+2;
    end

    % Description of the first part of the matrix B
    B(1:HorHour,1)=SOCmax+1;
    % Description of the second part of the matrix B
    B(HorHour+1:2*HorHour,1)=-SOCmin-1;
    % Description of the third part of the matrix B
    for i=(2*HorHour+1+1):2:2*HorHour+2*HorHour
        B(i,1)=Pdis_max;
    end
end

%% DESCRIPTION OF THE LIMITS OF THE VECTOR X
% Defined once.
if isempty(LB)
    LB=zeros(1,HorHour*Ngen);
    UB=zeros(1,HorHour*Ngen);
    % The limits of the positive power of the MAINGRID (
        MG_p).
    for i=1:Ngen:HorHour*Ngen
```

```
            LB(i)=0; UB(i)=2e6;
        end
        % The limits of the negative power of the MAINGRID (MG_n).
        for i=2:Ngen:HorHour*Ngen
            LB(i)=-2e6; UB(i)=0;
        end
        % The power limits of the gas entering the microturbine (MT).
        for i=3:Ngen:HorHour*Ngen
            LB(i)=0; UB(i)=nomPow_MT/effMT;
        end
        % The power limits of the gas entering the fuel cell (FC).
        for i=4:Ngen:HorHour*Ngen
            LB(i)=0; UB(i)=nomPow_FC/effFC;
        end
        % Limits of negative battery power (charge).
        for i=5:Ngen:HorHour*Ngen
            LB(i)=0; UB(i)=Pch_max;
        end
        % Limits of positive battery power (discharge).
        for i=6:Ngen:HorHour*Ngen
            LB(i)=0; UB(i)=Pdis_max;
        end
        % The physical limits of the state of charge of the battery (SOC).
        for i=7:Ngen:HorHour*Ngen
            LB(i)=0; UB(i)=100;
        end
        % Limits of auxiliary integer variable (b_k).
        for i=8:Ngen:HorHour*Ngen
            LB(i)=0; UB(i)=1;
        end
    end
%% LINEAR WEIGHT FUNCTION OF COST AT ALL HORIZON
CostHor=zeros(1,HorHour*Ngen);
% The coefficients for the purchase of electricity.
CostHor(1,1:Ngen:HorHour*Ngen)=pr_el;
CostHor(1,1:Ngen:HorHour*Ngen)=CostHor(1,1:Ngen:HorHour*Ngen)+pr_distr;
% The coefficients for the sale of electricity.
CostHor(1,2:Ngen:HorHour*Ngen)=pr_el;
CostHor(1,2:Ngen:HorHour*Ngen)=CostHor(1,2:Ngen:HorHour*Ngen)-pr_distr;
```

```
% Cost of gas for microturbines.
CostHor(1,3:Ngen:HorHour*Ngen)=pr_gas;
% Cost of gas for fuel cell.
CostHor(1,4:Ngen:HorHour*Ngen)=pr_gas;

%% DEFINITION OF A INTEGER VARIABLES (intcon)
% The vector of indices of integer variables of the vector x.
% Indicates the indexes on the variable b_k:
intcon=8:Ngen:HorHour*Ngen;
%% CREATE OPTIMIZATION PARAMETERS
opt=optimoptions('intlinprog','Heuristics','basic');
%% MINIMUM POSITION (linprog)
% We find a minimum in the condition of these restrictions.
[x, fval, exitflag]=intlinprog(CostHor,intcon,A,B,Aeq,Beq,LB,UB,[],opt);
% Redefine output dimensions.
X = coder.nullcopy(zeros(size(CostHor')));
X=x;
%% FORMING OUTPUT FUNCTION
% Multiply the total power at the current time
% by the corresponding element efficiency.
MG_p=X(1)*effMG_p; MG_n=X(2)*effMG_n; MT=X(3)*effMT; FC=X(4)*effFC;
% Display battery power directly.
Bch=X(5); Bdis=X(6);
% Determine the state of charge of the battery by the end of the next hour.
CurrentCharge=CurrentCharge+(effCHAR*X(5)-X(6)/effDIS)*Kbatt;
% Display this value.
SOC_next=CurrentCharge;
%% FORMING ADDITIONAL INFORMATION OUTPUTS
% Calculated price by the controller for the next hour.
info1=(X(1)+X(2))*pr_el(1)+abs((X(1)+X(2))*distr_pr)+(X(3)+X(4))*gas_pr;
% Additional free output.
info2=0;
end
```

C Enclosed files

Tables:

- TDD_year.mat – annual load profiles
- ELPRICEyear.mat – annual electricity cost
- initial_data.mat – supported data of the model and profile of solar radiation based on the length of the night
- K_irridiance_year.mat – annual indexes of solar radiation
- SpeedOfWind.mat – annual wind speed

Models:

- SmartMicroGrid.slx – model of residential district with real time optimization

External views:

- SmartMicroGrid.pdf – external view of main model with controller

Support scripts:

- calcult_eff_end.m – draws approximation lines of efficiency based on change of system parameters
- myMPC.m – listing of cost minimization function from the model (MILP)
- Pred.m – displays graphics with predicted profiles from given time interval
- ProfileOfIrridiance.m – forms the profile of solar radiation based on the length of the night
- Prediction.m – listing of horizon prediction function (ARIMA)
- Results.m – displays profiles, power histogram and charge state
- SolPan.m – displays graphics of solar radiation
- StationarSequence.m – displays load graphics in the specified interval