Palacký University Olomouc
Faculty of Science
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# MASTER THESIS

Olomouc 2021 Tina Pourpakdelfekr

**Potential of Smart City through Modeling of Single Crossing (Case Study: Olomouc)**

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Olomouc, 2021

**Declaration**

The thesis entitled “Potential of smart city through modeling of single crossing (case study: Olomouc)” has been undertaken by me under the supervision of RNDr. Tomáš Fürst, Ph.D. at Palacký University Olomouc.

I declare that the information reported in this thesis is the result of my own study and it has not been previously submitted to any other institution. All the material obtained from the work of others is appropriately referenced and cited.

Pourpakdelfekr

Olomouc, 21 June 2021 Signature: ………………

**Acknowledgment**

I would like to thank my supervisor, RNDr. Tomáš Fürst, Ph.D., for helping me to gain deeper understanding of modeling and walking with me shoulder by shoulder through the way of writing my thesis.

I would also like to express my sincere gratitude to my family and friends for always supporting me and encouraging me to walk towards my dreams.

# UNIVERZITA PALACKÉHO V OLOMOUCI

Přírodovědecká fakulta

Akademický rok: 2019/2020

# ZADÁNÍ DIPLOMOVÉ PRÁCE

(projektu, uměleckého díla, uměleckého výkonu)

| | |
|---|---|
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| Studijní obor: | **Foresight for Environment and Development** |
| Téma práce: | **Potential of smart city through modeling of single crossing (case study: Olomouc)** |
| Zadávající katedra: | **Katedra rozvojových a environmentálních studií** |

## Zásady pro vypracování

Modern societies are struggling with traffic congestion, which negatively affects our standard of living. The monitoring and control of traffic congestion in cities is becoming a major complication in many countries. World economics need a fast and efficient transportation system. The main objective of this study is mitigating congestion by controlling traffic lights cycle structure and duration. Prioritizing intervention vehicles, improving public transportation, reducing air and sound pollution in urban areas are other outputs of this research.

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|---|---|
| Rozsah pracovní zprávy: | **20 – 25 tisíc slov** |
| Rozsah grafických prací: | **dle potřeby** |
| Forma zpracování diplomové práce: | **tištěná** |
| Jazyk zpracování: | **Angličtina** |

Seznam doporučené literatury:

1. Previous studies or related documentation including books, journal articles and theses
2. Data from government sources
3. Data inspection

Vedoucí diplomové práce: **RNDr. Tomáš Fürst, Ph.D.**
Katedra matematické analýzy a aplikací matematiky

Datum zadání diplomové práce: **14. května 2020**
Termín odevzdání diplomové práce: **25. dubna 2021**

L.S.

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V Olomouci dne 14. května 2020

**Abstract**

A smart sustainable city is a creative city that employs technology in order to enhance the quality of life and productivity of services while fulfilling different aspects of the lives of current and future citizens. Smart transportation is an essential part of a smart city and is a way of providing innovative services for various modes of transport and traffic management. It enhances security, boosts efficiency and contributes to a greener environment. Smart traffic management aimed to reduce traffic congestion, total waiting time, fuel consumption and air pollution. Controlling and improving traffic light parameters improves traffic volume, which affects crashes, loss of time and delays.

This thesis aimed to take a positive step for smart mobility in Olomouc based on the existing infrastructure. Fixed-time traffic lights are the most common type of traffic signals in Olomouc, which investigating the current system would be more economical. An optimization algorithm is coded in MATLAB in order to achieve the minimum total waiting time and optimum duration of states for a day.

The analysis of results suggests that time-of-day mode control is suitable by offering two scenarios for peak and non-peak periods. The total waiting time for both scenarios enhanced compared to the fixed-time scenario of 1 minute for each state. It was also investigated that by increasing the capacity of the intersection by managing the existing infrastructure, total waiting time per single vehicle would be improved as well. Decreasing the total waiting time makes the system more effective than it is today. In fact, by knowing the density of incoming cars in different directions, we can save a lot of time by programming the crossing. It is expected by decreasing the total waiting time and unnecessary stops at red lights, the air pollution would decrease as well in long term.

**Key words**: Smart mobility, fixed-time traffic control, waiting time, peak and non-peak periods, scenarios, optimization

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**Acronyms and abbreviations**

| | |
|---|---|
| AQI | Air Quality Index |
| AQMS | Air Quality Management System |
| GHG | Green House Gases |
| ICT | Information & Communications Technology |
| IoT | Internet of Things |
| TMS | Traffic Management System |
| TOD | Time of Day |

## CHAPTER 1 INTRODUCTION

### 1-1- Background

Rapid industrialization and urbanization lead to serious issues regarding traffic congestion (Ma et al., 2020). Congestions has been defined in a variety of ways by researchers. The most general definition is when the travel demand exceeds road capacity. As a result of traffic jams, communities have witnessed delays, inconveniences, severe air pollution and economic losses (Afrin & Yodo, 2020).

The cost of traffic congestion in Europe is projected to be 1 percent of GDP and equivalent of over EUR 100 billion, annually (Urban mobility, 2020). Based on the INRIX reports, the total number of hours lost in traffic a year during rush commute hours compared to free flow condition for Praha and Olomouc is 43 and 12 respectively (INRIX, 2020).

Recently, it has been clarified that traffic modeling and traffic signal control can enhance traffic operation at intersections. Optimizing traffic signal timings will help to improve the efficiency of the transportation system and reduce vehicles delay in urban territory (Ma et al., 2020). Traffic lights have played a vital role in urban traffic management and were first implemented in 1868 in London, since then they have significantly contributed to the mobility and safety of metropolitans (Jiao, 2016).

Modeling and simulation have become popular in traffic intersection studies. The moving objects can be simulated using mathematics models. By physically interfering with the current road structure, it is feasible to conduct tests and prevent errors before they are applied. In order to optimize the use of the available roads, traffic management is defined as a process of planning, performing, examining and controlling the flow of vehicles. On one hand, increasing traffic needs practical remedies, on the other hand, expanding and widening the existing communication network is not possible in all situations. Therefore, smart traffic management will be used to increase road capacity. Designers should take into account elements that can reduce amount of pollutants and thereby help to decrease the harmful effect of traffic on the urban environment (Małecki, 2016).

### 1-2- Statement of the problem

Transportation is one of the main axes of smart cities. In order to move towards being a smart city, the implementation of smart traffic management is necessary.
In the majority of intersections, traffic is managed through the fixed signaling paradigm. Traditional traffic signals prevent cities from adjusting the signal length in response to increases in traffic flow, which could result in traffic jams. Since poor traffic signal is considered to be the cause of longer waiting time at intersections, a good traffic signal algorithm is important for decreasing $CO_2$ emissions. Calculating the total amount of accumulated delay time because of waiting for green signals for a whole year is huge. To enhance the efficiency of the transport system, the existing algorithms for signal timing optimization should be implemented. The

algorithm mentioned in our thesis will decrease the waiting time leading to fewer traffic jams in the city, reducing costs and pollutants produced by vehicles.

### 1-3- Objectives and Scope of the study

This study aims to examine the potential of the smart city through single crossing modeling. There are mainly three criteria for the optimization of traffic lights: capacity expansion, cycle length and delay reduction. In this study, almost all criteria are considered by designing an algorithm with the MATLAB programming language for a T-junction. The program intends to calculate the total waiting time of vehicles at signalized intersection and achieve the minimum waiting time for the optimum condition.

Study Scope: The proposed methodology use "pseudo" cycle lengths data to simulate a traffic model for an intersection in Olomouc.

### 1-4- Research questions

**General question**

Does the mentioned algorithm have the potential to reduce vehicles' total waiting time?

**Sub-question**

i. Does the implementation of the mentioned algorithm have the potential to reduce total waiting time during peak/non-peak hours?
ii. Does the implementation of the mentioned algorithm have the potential to reduce air pollutants?
iii. Does the mentioned algorithm have the potential to be used in practice as a step towards smart mobility?

### 1-5- Organization of the study

The thesis is formed in five chapters. Chapter 1 discusses the necessity of smart mobility in urban areas and a description of the objectives and the scope of the study. Chapter 2 describes the state of the art, where the foresight techniques with the emphasis on modeling are briefly discussed. Then, an overview of smart cities and the importance of smart mobility as one of the main pillars of smart cities is provided, followed by examples of Prague as a smart city in the Czech Republic. Chapter 3 starts with a brief introduction of different traffic congestions and traffic lights and an algorithm for the optimization of T-junction in Olomouc is proposed. Chapter 4 documents the results in form of three scenarios, two of them were used for the peak and non-peak periods and one was used for the case of increasing the capacity of an intersection. Finally, the last chapter presents the conclusions and recommendations that were achieved during this study.

## CHAPTER 2 STATE OF THE ART

### 2- Introduction to foresight and future thinking

The initial use of foresight was considered as a policy tool to overcome obstacles in the way of technology and innovation systems. As the success of foresight projects was proven, it became more accepted to describe future activities (Miles, 2010). Many scholars believed foresight can be used as a future-oriented tool, it does not mean that foresight can foresee a predetermined future, but a chance to create and shape a favorable future (Maia, 2013).

Foresight as an effective tool can be used to predict the future of smart cities. In the recent era, smart cities are struggling with climate change, environmental pollution and population growth, which can significantly affect economic development. Urban decision-makers can use foresight outputs as a set of data to prepare and create long-term strategies for the evolution of smart nations. In order to improve the quality of life, health and economic activities in smart cities, decision-makers need to manage upcoming challenges. Foresight as a flexible and transparent approach can smooth the sustainability and development path of smart cities. By considering all aspects (social, economic, environmental, etc.) of current actions and discovering hidden obstacles, foresight helps to prevent their occurrence. The main idea behind foresight is social engagement. A broad range of participants from various spheres: scientists, non-governmental organizations, city development expertise, entrepreneurs that take part in the foresight process helps to construct a more realistic vision of the development of future cities and provide multidimensional aspects of the problem (Szpilko, 2020).

### 2-1- Foresight tools and techniques

Future thinking techniques and methods are wide and due to their complexity, are not obviously defined. Adopting suitable foresight techniques can play an important role in the success of projects; selected approaches should go hand in hand in various steps of foresight. Magruk (2015) pointed out that choosing foresight activities only from a single category could impoverish the output as they have been fed from the same resource; therefore, the most preferred model is a selection of methods in each stage from different classes with balanced references without limiting the flexibility of foresight (Magruk, 2015).

Based on the nature of foresight activities, methods can be characterized as follow (Turturean, 2011):

- Qualitative (methods providing definitions to events and perceptions based on subjectivity or creativity; scenario writing, interviews, brainstorming, etc.),
- Quantitative (methods measuring variables, applying statistical analysis and using or generating valid and reliable data (for instance socio-economic indicators); trend extrapolation, modeling, patent analysis[1], etc.),

[1] Patent analysis is an important method for determining and analyzing market trends. It allows visualizing technological trajectories and monitoring ongoing organizational developments (Rodriguez et al., 2014).

- Semi-quantitative (methods implementing mathematical approaches to quantify subjectivity, rational judgments of experts; cross-impact analysis, roadmapping, Delphi).

Popper (2008) summarized the frequency of used methods into three categories as following:

1- Most frequently used techniques are qualitative ones like literature review, expert panels and scenarios. 2- Commonly used techniques including surveys, interviews, Delphi, scanning, SWOT analysis, extrapolation and brainstorming and 3- less frequently techniques are roadmapping, simulation and modeling, backcasting, gaming, etc (Popper, 2008).

### 2-1-1- Simulation and modelling in foresight studies

Modeling, simulation and gaming are techniques that assist individuals to figure out their decision impacts before taking action. These techniques are flourishing as their computerization of structure and rules allow sophisticated systems to deal with many variables to be displayed graphically and dynamically. Modeling and simulations not only are used in foresight and planning but they are used among the wide domain of activities including entertainment, designing, education and research. Understanding the rules and limits of modeling play an important role in demonstrating the real world. Considering sophisticated models, they can be time-consuming and expensive (Jackson, 2013). Simulation gaming as a form of role-playing is one of the oldest foresight techniques. The most popular simulation is war gaming which has been used by military strategists. Modeling refers to the use of computer-based models, based on statistical relations from two or three variables in a simple model to hundreds or more variables in more complex models (Popper et al., 2008).

One way of identifying threats and deal with plausible problems in a more interactive way is using Combine Simulation Approach (CSA). Scenario analysis and discrete-event computer simulation have been combined in this method. Scenarios will assist policy makers, planners and stakeholders in gaining a better understanding of the future consequences of specific decisions. Numerical simulation needs a simulation tool (simulation language) and the modeler, who employs the simulation tool to construct and analyze a model. Narrative simulation is appropriate to investigate contradictions through alternative future scenarios. Numerical modeling via sensitivity analysis can assist the narrative simulation to explore the response of the certain output variables to a certain change of input values. Narrative simulation aids in the study of potential functional linkages, while numerical simulation adds to the understanding of the extent to which these interactions affect one another.

CSA is useful to increase the awareness about possible challenges in the future, capacity building of collaboration between different actors and policy building. The interesting fact is that CSA does not focus on all aspects of the reality but instead on specific aspects of a system and prepares scenarios based on that issue. Those aspects that cannot be numerically simulated will be described by narrative simulation and later the sophistication and contradictions inherent in the narrative simulation will be explained by numerical modeling. Typically, the procedure begins with a scenario (based on the area of concern), and then translated into input and output variables that can be used in a simulation model. The combination of the two methods can illustrate both narratives and numerical models in a clear way. Participatory biases, reproduction, number fascination, hyperopia creation, losing the connection between the narrative and numerical approach are some drawbacks of using this technique (Hansen et al., 2016)

## 2-2- Smart cities

Cities play an important role in human life and economic activity. They have the potential to provide development opportunities to their inhabitants; however, many problems occur as they grow in size and complexity. Cities must balance their development, maintaining economic stability, while improving social adherence, environmental efficiency and enhancing the standard of living for their inhabitants. The idea of smart cities as the result of new technological innovations develops as a way to accomplish more efficient and sustainable cities (Monzon, 2015).

The Institute for Management Development in partnership with Singapore University for Technology and Design (SUTD) published the 2020 Smart City Index. A total of 109 cities were surveyed and ranked based on economic, technological data and the perception of residents about the smartness of their cities. This report determines the important role of technology in the COVID-19 pandemic and suggested that cities that have been able to integrate technology, leadership and powerful culture of "living and acting together" should be able to better endure the most disruptive consequences of this pandemic. Smart cities at the top of the list seem to cope better with the unforeseen threats of the pandemic. The top 10 smart cities are mentioned in the table 2.1 (IMD, 2020).

Table 2.1. Top 10 smart cities, 2020 (IMD, 2020)

| Rank | City |
|---|---|
| **1** | Singapore |
| **2** | Helsinki |
| **3** | Zurich |
| **4** | Auckland |
| **5** | Oslo |
| **6** | Copenhagen |
| **7** | Geneva |
| **8** | Taipei City |
| **9** | Amsterdam |
| **10** | New York |

Different faces of smart city including intelligent city, virtual city, digital city, information city are all perception that ICT is essential to future operation of the city (Batty et al., 2012). Table 2.2 presents part of terms and concepts used by different sectors involved in areas related to future cities.

Table 2.2. Terminology of smart cities (Eremia et al., 2017)

| Domain | Social | Economic | Governing |
|---|---|---|---|
| Garden cities | Participative cities | Entrepreneurial cities | Managed cities |
| Sustainable cities | Walkable cities | Competitive cities | Intelligent cities |
| Eco- cities | Integrated cities | Productive cities | Productive cities |
| Green cities | Inclusive cities | Innovative cities | Efficient cities |
| Compact cities | Just cities | Business-friendly cities | Well-run, well-led cities |
| Smart cities | Open cities | Global cities | Smart cities |
| Resilient cities | Livable cities | Resilient cities | Future cities |

Two main terms about cities are used among researchers, practitioners and decision-makers, that is "future cities" and "future of cities" (Eremia et al., 2017):

- Future of cities: term adopted to describe a way for maintaining the needs of communities in the future, taking into account their position in the future, as well as the challenges and risks they will encounter, in order to assist residents to properly react to any situation. Future of cities is related to traditional thinking, strategy and policy.
- Future cities: reflects the public's perception of the attributes of the cities (how they will operate, what structures they will rely on, how they will communicate with people, the authorities, the investors and the world in which they will reside). This term is connected to the trend of separating urban spheres into new fields, such as architecture, civil construction, energy, information technology and ecology.

There is a wide variety of definitions for smart cities while innovation in city administration, its facilities and infrastructures is a common definition of this term. When defining the smart city, it is important to consider all urban aspects, because the main objective of the smart city is to provide a modern solution in which all facets of the city are considered interconnected in the reality. Focusing only on one aspect (technological, ecological) does not mean that the whole ecosystem's challenges have been resolved. According to the definitions, infrastructures are a core part of the smart city, and technology as a facilitator makes it possible, yet the combination, interaction and convergence of all systems becomes fundamental for a city to be genuinely smart. Smart cities as a holistic management approach reflect a balance of the technological, economic and social factors involved in an urban area (Monzon, 2015).

It is still believed that smart city is a fuzzy concept. Based on a study by the Center of Regional Science at the Vienna University of Technology, a ranking of 70 European middle size cities can be made along six main dimensions. Smart economy, smart mobility, smart environment, smart people, smart living and smart governance are these dimensions. Features and factors of smart city is demonstrated in the table 2.3. Regarding these six axes, a definition by Caraglie et al (2011) was created:

"*We believe a city to be smart when investments in human and social capital and traditional (transport) and modern (ICT) communication infrastructure fuel sustainable economic growth and* *a high quality of life, with a wise management of natural resources, through participatory governance* (Caragliu et al., 2011)."

Table 2.3. Features and factors of smart city (Naydenov, 2018)

| Smart Economy (Competitiveness) | Smart People (Social & Human capital) | Smart Governance (Participation) | Smart Mobility (Transport and ICT) | Smart Environment (Natural resources) | Smart Living (Quality of life) |
|---|---|---|---|---|---|
| Creative spirit<br>Entrepreneurship<br>Economic visions & trademarks<br>Productivity<br>Flexibility of labor market<br>International embeddedness<br>Ability to transform | Level of qualification<br>Tendency to lifelong learning<br>Social and ethnic plurality<br>Flexibility<br>Innovation<br>Cosmopolitanism/ open mindness<br>Participation in public life | Participation in decision-making<br>Public & social programs<br>Transparent governance<br>Political strategies & perspectives | Regional reachability<br>(Inter)national accessibility<br>Accessibility of ICT - infrastructure<br>Sustainable, innovative & secure transport networks | Attractivity of natural conditions<br>Pollution<br>Environmental conservation<br>Sustainable resource management | Cultural programs<br>Health conditions<br>Individual safety<br>Accommodation quality<br>Education services<br>Touristic attractivity<br>Solidarity |

The main feature among these components is that they are linked and can create data, which can be used for the appropriate use of resources and enhancing the function. The smart city is a system of interconnected structures. The interaction of such a large number of systems necessitates transparency and standardization, which are the cornerstones of smart city development. Different cities have different goals and tasks, but all smart cities share three main characteristics. The first is the availability of information and communication technology systems. ICT infrastructure is critical for the efficient implementation of new services as well as assuring the potential to provide new services in the future. The second criterion is the presence of a well-designed and integrated administrative structure in the city. Different systems of the intelligent city will perform in the presence of uniform standards. Smart citizens are the third aspect of a smart city. Technology us worthless without experienced consumers who can communicate with smart services (Naydenov, 2018).

Smart city rankings are a tool that helps the cities to recognize their assets and opportunities for positioning and to maintain and expand competitive advantages in specific resources compared to other cities of similar size. Based on a project by TUWIEN team, a new city sample was chosen for the ranking. A feasible sample was specified based on two factors: cities should be of medium-sized and they should be covered by available and related datasets, of which 77 cities were selected. 74 indicators that characterize the factors of a smart city were chosen from publicly accessible data. In order to compare the various indicators and obtain results for each city, it is important to standardize the values and aggregate the values on the indicator level. The final smart city ranking is shown in the table below (smart-cities.eu, 2014):

Table 2.4. Ranking of European medium-sized smart cities (smart-cities.eu, 2014)

| | City | Smart Economy | Smart People | Smart Governance | Smart Mobility | Smart Environment | Smart Living | Total |
|---|---|---|---|---|---|---|---|---|
| **LU** | LUXEMBOURG | 1 | 18 | 56 | 4 | 16 | 4 | 1 |
| **DK** | AARHUS | 2 | 3 | 6 | 3 | 19 | 27 | 2 |
| **SE** | UMEAA | 24 | 5 | 2 | 34 | 1 | 13 | 3 |
| **SK** | ESKILSTUNA | 21 | 1 | 7 | 24 | 3 | 41 | 4 |
| **DK** | AALBORG | 10 | 11 | 5 | 14 | 14 | 10 | 5 |
| **SE** | JOENKOEPING | 32 | 13 | 3 | 11 | 2 | 26 | 6 |
| **DK** | ODENSE | 13 | 9 | 4 | 20 | 9 | 40 | 7 |
| **FI** | JYVASKYLA | 23 | 8 | 1 | 47 | 5 | 25 | 8 |
| **FI** | TAMPERE | 16 | 2 | 15 | 31 | 12 | 14 | 9 |
| **AT** | SALZBURG | 27 | 24 | 29 | 2 | 27 | 1 | 10 |

### 2-2-1- Smart cities challenges

It is important that the flourishing of the cities keep pace with the population growth, economic development and social progress. In order to achieve a sustainable model of urban development, the smart city model can be used for better city administration and planning. Demographic changes, financial crisis and other challenges are current obstacles that need to be solved, albeit future problems of urban areas must be considered in an integrated way, each step in city administration has a long-term effect, as is suggested in the document of the European Commission "Cities of Tomorrow". Challenges in European cities regarding of the smart governance models, they must be more agile to be able to combine top-down policies with bottom-up programs and informality. Smart economy models are related to the productive framework of the city, implementing a multimodal public transportation infrastructure, promoting alternatives to vehicle-based mobility, and making public transportation accessible and affordable to all inhabitants are three main keys of smart mobility that would enable cities to reduce traffic jams and emissions while enhancing accessibility. The main goals of smart environment models are reducing land use in order to expand our cities, reduction of energy consumption and emission of pollutants. Smart people action field is about decreasing the unemployment rate and enhancing solidarity and improving the standards of living. Finally, the main concerns in smart living are providing affordable housing, improving medical situations and decreasing the criminal rate (Monzon, 2015). All the challenges of a smart city in European cities are stated in the table below:

Table 2.5. Challenges of European cities (Monzon, 2015)

| Governance | Economy | Mobility | Environment | People | Living |
|---|---|---|---|---|---|
| Flexible governance | Unemployment | Sustainable mobility | Energy saving | Unemployment | Affordable housing |
| Shrinking cities | Shrinking cities | Inclusive mobility | Shrinking cities | Social cohesion | Social cohesion |
| Territorial cohesion | Economic decline | Multimodal transport system | Holistic approach to environmental and energy issues | poverty | Health problems |
| Combination of formal and informal government | Territorial cohesion | Urban ecosystems under pressure | Urban ecosystems under pressure | Ageing population | Emergency management |
| | Mono-sectoral economy | Traffic congestion | Climate change effects | Social diversity as source of infrastructure | Urban sprawl |
| | Sustainable local economies | Non-car mobility | Urban sprawl | Cyber security | Safety and security |
| | Social diversity as source of innovation | ICT infrastructure deficit | | | Cyber security |
| | ICT infrastructure deficit | | | | |

Based on the report of "The state of African cities 2014" (UE, 2014) in the majority of southern Mediterranean cities, demographic pressures, accelerated urbanization and environmental challenges are generating more disadvantages than advantages. While the populations of these regions are exponentially increasing, their development paradigm is far from a sustainable model. The less-developed situation leads the issues to be oriented towards accomplishing the basic services to their citizens. Development models in these cities must be updated based on the condition of the areas. The main issues in this part of the world are the scarcity of resources, poor transportation and infrastructure conditions, poverty and insecurity, government instability and lack of smartphones or ICT technology. Therefore, making the required technologies accessible and promoting literacy services to increase the awareness of the society to the necessary ICT will be another obstacle for the implementation of smart city projects. If current challenges are not tackled, the concerns that European cities are facing today can become future issues in the south. Smart city models must solve the present issues while forecasting the potential issues cities will face in the future (Monzon, 2015). Challenges of Mediterranean cities are mentioned in the table 2.6:

Table 2.6. Challenges of South and East Mediterranean cities (Monzon, 2015).

| Governance | Economy | Mobility | Environment | People | Living |
|---|---|---|---|---|---|
| Low urban institutional capacities | High infrastructures deficit | Lack of public transport | Scarcity of resources | Urban poverty and inequality | Slum proliferation |
| Instability in governance | Shortage in access to technology | High infrastructure deficit | Water scarcity | Shortage in access to technology | Urban violence and insecurity |
| Gap between government and governed | Economy weaknesses and lack of competitiveness | pollution | Climate change effects | Specific problems of urban youth | Rapid growth and urban sprawl |
| Unbalanced geographical development | Specific problems of urban youth | Rapid growth | Pollution | Threats to cultural identity | Deficit of social services |
| Deficit of social services | Limited urban based industries | | Rapid growth and urban sprawl | Low educational level | Threats to cultural identity |
| | Unbalanced geographical development | | | | Urban poverty and inequality |

### 2-2-2- Example of Smart cities in the world

1. Singapore

Singapore is often named among the smartest cities. The smart Nation project, which was launched in 2014, focuses on Singapore's smart city growth. The government aimed to create a technical infrastructure for the world's first smart city. Singapore's Infocomm Media Development Authority was created to monitor the development of both hard and soft technology. This included the standardization of the use of IoT and the development of smart city platforms. The smart nation platform was designed to be a modern communication network that offers heterogeneous networks, ubiquitous connectivity and national IoT sensor and data analytics ability. With regard to this platform, companies and the government would be able to provide smarter services for the residents.

Singapore's strategic goal is to make more use of its limited space by using more effective, reliable and safer vehicles, as well as improved transportation methods and systems. In these programs, autonomous vehicles seem to play a significant part: three trials of self-driving sedans are ongoing or have been completed, as are four trials of autonomous shuttle buses of different sixes, including automated on-demand shuttles, driverless electric minibus service for tourists, self-driving shuttle buses on the university campus and a bigger 40-seater electric bus (Shamsuzzoha et al., 2021).

2. Helsinki

Helsinki is regarded as one of Europe's top six smart nation projects. It has been named as the European capital of smart tourism in 2019, as well as owning the best digital twin in the Kalastama district, the most creative and the best medium-sized state for foreign investments in Europe, and the third-best nation for start-up companies in the world. There are many projects in Forum Virium Helsinki with the goal of making the city the world's most functional smart city. They can be listed into four major headlines: IoT, Smart City, Smart Mobility and Forum Virium, which includes two projects focusing on the implementation of a European AI ecosystem and the collaboration of the smart city development of Finland's six largest cities.

The IoT project covers initiatives that range from developing innovative ICT technology for the city infrastructure to modeling digital applications to encourage visitors to the city. When looking more closely at Smart Mobility initiatives, four major research trends emerge: utilization of low carbon energy, production of advanced cars, smart mobility services and transportation systems. The five smart mobility solutions piloted in the ports along the Helsinki-Tallinn ferry route share similar trends. To alleviate pollution, the first prototype tests a line management system that controls vehicle movements at downtown passenger terminals. The next project investigates how transport service packages manage passenger flow. These packages could provide services such as free drinks as part of the ticket price. The third initiative focuses on the use of intelligent containers as short-term storage for travelers' purchases. Citizens' shared economy concepts may also make use of the same containers. Fourth, a hands-free tram ticketing system is being tested to investigate how the traveler's movements could be optimized. The last project examines the travel patterns of ferry passengers in the city using anonymized telephone subscriber location data (Shamsuzzoha et al., 2021).

3. Comparing among two smart cities

Singapore has a unique advantage over Helsinki. Being a small island city state, any smart city project will inevitably have a national and government dimension as well. As a result, Singapore has rapidly developed into Singapore's Smart Nation. Scaling the smart city operations in Helsinki to the national level will be even more complicated since Finland's cities and rural districts lack the same level of connectivity and infrastructure efficiency as Singapore. Singapore's multi-ethnic national heritage gives the advantage to accommodate migrants and ethnic distinctions that can arise during urban expansion. Similarities and differences of the first and second smartest city in the world have been illustrated below:

Table 2.7. Comparison of Helsinki and Singapore (Shamsuzzoha et al., 2021).

| Indicators | Helsinki | Singapore |
|---|---|---|
| City size | Small | Medium |
| City age | Medium | Young |
| Available resources | Small | Large |
| Smart city initiative | Forum Virium | Smart Nation |
| Strategy development direction | Bottom-up | Top-down |
| Domestic cooperation | Active<br>Inner-city | Active<br>National coordination |
| International cooperation | Active<br>Bidirectional | Active<br>Unidirectional |
| National reach | None | Active |
| Smart data technique | City<br>Residents | Government<br>Residents |

| | | |
|---|---|---|
| Smart traffic method | Public transport<br>Martitime transport<br>Autonomous buses | Public transport<br>Autonomous vehicles<br>Autonomous freight |

In a conventional top-down direction, Singapore's smart city vision comes straight from the prime minister's office while Helsinki seems to be more inclusive and supporting bottom-up participation from the residents. Helsinki still seems to be the most interconnected with foreign collaboration, half due to its limited resources and a half due to the readily available EU collaboration. Singapore is eager to collaborate with and learn from foreign professionals.

### 2-3- Smart transportation

Mobility is an important component of nowadays rapidly growing cities. The movement of people and goods inside the city is critical for the growth of the economy and daily life. The European Commission's Green Paper (2007) established a sketch towards a new culture for urban mobility; (1) Proposing alternatives to private automobiles including walking, cycling, public transport or motorcycles. (2) Increasing the efficiency of travel by connecting the various modes of transportation. After implementing congestion-reduction policies, authorities should foster co-modality and allocate more capacity to it. (3) Introducing smart control systems administration as an efficient tool for reducing traffic congestion. These three options were reported in this paper (Arce-Ruiz et al., 2016).

There are four axes of smart city based on the European Initiative on smart cities (2010) including buildings, heating and cooling systems, electricity and transport. The objectives of smart transportation are (Djahel et al., 2015):

- Sustainable form of transportation
- Smart public transportation networks based on real-time data
- Traffic Management Systems (TMS) to avoid traffic jams
- Safety and green applications like decreasing fuel consumption, pollutant emissions or energy consumption

Smart traffic management systems are the key aspect of smart cities and are used to manage traffic volume as well as minimizing traffic jams. Citizens must get where they need to go on time and rescue teams must arrive at their destination as quickly as possible. Traditional traffic signals are inflexible and do not respond to shifting traffic conditions. Cars waiting in ques for traffic lighting turning to green consume gas and pollute the environment. During rush hour, cars and pedestrians will require equal opportunities to cross the intersections, while at night; there would be no need to pause at a pre-fixed traffic signal. Traffic signals at every particular intersection will be linked to any other traffic signals in the region, ensuring that traffic flows smoothly in the area (Sandhu et al., 2015). By implementing wireless sensing equipment and communication technologies, along with simulation and modeling tools, researchers are trying to make the traffic management systems more effective in the present and future. The interruption of emergency services, such as police, fire and rescue operations, ambulance services, etc., is one of the most serious consequences of traffic congestions. In the event of accidents, thefts, or criminal threats, individual human lives, general population wellbeing and financial conditions depend on the effectiveness and promptness of emergency vehicle services. Another critical issue is the increasing number of car accidents. These accidents are most frequent near congested highways when drivers prefer to drive faster, before or after facing traffic jams to compensate for the time wasted. These crashes have many negative effects on an individual, group and public levels, which may be compounded if emergency vehicles are involved in an accident.

A traditional traffic management system is made up of many complementary stages. The first stage is Data Sensing and Gathering (DSG) where a heterogeneous road monitoring tool analyzes traffic variables (traffic volumes, speed, road segment occupancy) and transfers this information to a central agency on a regular basis. Second, data will be fused during the Data Fusion, Processing and Aggregation (DFPA) to export valuable information. During Data Exploitation (DE) phase, processed data will be used to assess ideal paths for vehicles, short-term traffic predictions and other statistical knowledge. Final data will be reported to the end consumer, which can be drivers, authorities, private businesses, using smart devices. Existing traffic management systems do not show adequate and reliable road traffic data to allow granular and timely network monitoring and management. The process of increasing the quality by updating and maintenance such equipment is not cost-effective. Smart traffic management systems must overcome these limitations. An ideal traffic management system for smart cities should accomplish the following criteria (Djahel et al., 2015):

- Ensure higher precision in predicting traffic situations and greater reliability in coping with emergency conditions on the road.
- The ability to effectively control traffic across various sizes and characteristics of road networks.
- In order to help policymakers to maintain road networks and optimizing route constructing, provide real-time traffic modeling and mapping
- Ensure that current processes and emerging technology are integrated and that the evolution of these systems is managed.

In order to improve the quality of the smart traffic system, different scholars recommend different ways. For instance, by installing low-cost vehicle detection sensors every 500 meters in the middle of the road, public traffic data will be collected by the Internet of Things (IoT) and will be transferred for data processing. The real-time streaming data then is reported for Big Data analytics. There are many computational manuscripts that can be used to calculate traffic density and propose recommendations using predictive analytics. This method will be cost-effective and delivers better services by simultaneously deploying traffic reports (Sharif et al., 2018). The IoT and wide accessibility of Cloud resources are assisting us in developing mechanisms to simplify transportation networks and optimizing the use of current infrastructures (Khanna et al., 2019). Another example of IoT based traffic management is where the traffic flow can be dynamically managed by onsite traffic officers using a digital system like their smartphones or can be tracked and managed via the Internet. In Makkah in Saudi Arabia, traffic pattern changes dynamically because of constant religious journeys during the year, therefore there is a need for additional traffic control algorithms. The officer will access to embedded pc through his/her smartphone and type the IP address of the Raspberry Pi (RPi) in the web browser on the smartphone. All the RPi's are interconnected through the Internet cloud, which helps to prevent traffic delays and rapidly addressing any potential traffic issues (Misbahuddin et al., 2015). IoT can also be used as a hybrid method (combination of centralized and decentralized) to utilize traffic density on highways. For this purpose, an algorithm is developed to effectively control different traffic conditions. Traffic density as input is collected from cameras, sensors on roadsides and then controls traffic signals. Another Artificial Intelligence-based algorithm is used to forecast potential traffic volume in order to reduce traffic jams. In addition, during a congested, RFIDs are used to prioritize the emergency vehicles. Smoke alarms are also part of the system in case of fire on the roads to identify the situation. The decentralized method optimizes and improves effectiveness as the system continues to run even if a regional or centralized server failed. The centralized server links nearby rescue departments in emergency situations. Furthermore, a user can check about potential traffic levels on certain routes, to save time spent stuck in traffic. It also collects valuable data in graphical formats that can asset policymakers in future road mapping (Javaid et al., 2018).

We can conclude that many new problems and challenges for societies are raised by smart cities and smart transportation infrastructure. Initially, a well-designed governance framework and suitable organizations and agencies are needed for smart cities and smart transportation networks with the aim of serving the residents. Next, there are concerns about fairness and equality. The development of modern internet-connected devices, the mass processing of personal data and the emerging application of big data have all increased concerns about privacy and individual liberty. Smart transportation must not become a big brother network that monitors and controls consumers' decisions. The progress of high-tech systems should also be inclusive, with fewer technologically inclined demographic classes benefiting from the opportunities and growth. Finally, creating a smart city with smart transportation is expensive and time consuming. This evolution could mean that the private sector becomes more involved on a broader scale, leaving more space for government action. This may also imply a reinterpretation of public-private partnerships for the construction, management, operation and ownership of critical infrastructure (transport sector). Smart cities, smart transport and smart transportation infrastructure all contribute to a transformation of the city's design (Carnis, 2018).

### 2-4- Effects of smart transportation on air quality in smart cities

Air pollution is a serious environmental problem in urban areas and metropolitan cities. In the EU, air pollution is one of the critical causes of preventable illnesses and premature death. The most serious pollutants in Europe in terms of being toxic to humans are particulate matter (PM), $NO_2$ and ground-level ozone ($O_3$). Based on the EEA report (2020), air pollutants can be classified into primary and secondary groups. Primary pollutants are directly released into the environment, while secondary pollutants are produced in the atmosphere by chemical reactions and microphysical processes from precursor pollutants. The main sources of air pollutants in the EU are (1) Transportation divided into road and non-road including air, rail, sea and inland water transport; (2) residential, industrial and institutional; (3) energy supply including fuel production, distribution and energy production; (4) engineering and extractive manufacturing; (5) agriculture; and (6) waste including waste water management (EEA, 2020). Key pollutants are shown in the table below:

Table 2.8. Key primary and secondary pollutants (EEA, 2020)

| **Key Primary Pollutants** | **Key Secondary Pollutants** |
|---|---|
| Particulate matter (PM) | PM |
| Black carbon (BC) | Ozone ($O_3$) |
| Sulphur oxides ($SO_x$) | $NO_2$ |
| Nitrogen oxides ($NO_x$) | Oxidized volatile organic compounds (VOCs) |
| Ammonia ($NH_3$) | |
| Carbon monoxide (CO) | |
| Methane ($CH_4$) | |
| Non-methane volatile organic compounds (NMVOCs) | |
| Polycyclic aromatic hydrocarbons (PAHs) | |

Controlling and monitoring air pollution is important for implementing mitigation policies and raising environmental awareness among the public. Data on air pollution can be monitored using a variety of techniques and technology. Traditional environmental monitoring techniques, for instance, air quality monitoring stations are accurate but costly and inconvenient. To comply with environmental regulations and guidelines, these expensive and precise air quality monitoring stations are used based on chemical analyzers. In general, they are less widely used in cities and provide sensing information with poor spatial resolution. Therefore, air quality monitoring services based on low-cost and sensitive sensors that are embedded in wireless sensor networks deployed at high spatial resolution in smart cities can be an efficient method for monitoring, decision support and public awareness. These low-cost electrochemical sensors can be used to monitor several air pollutants such as CO, $NO_2$, $SO_2$ and $PM_{10}$ (Penza et al., 2014).

When facing traffic-related air pollution, it is critical to understand the volume and structure of traffic as well as the openness of the space next to the road. The topography of space near the crossroad is important and it must take into consideration. It is suggested that sampling must be taken from different measuring sites to monitor air pollution including (Banja, 2009):

1. Background sites are areas where pollution levels are measured far away from sources. Concentrations in the urban backgrounds are typically much more consistent and slightly smaller than near the roads.
2. Street canyon is formed when high buildings on both sides enclose the area near the roads. They are the most visited parts of the cities. While traffic in these canyons may not be intense, the average speed of cars is low because of the small widths of the roads. Concentrations in canyons rise due to lower windiness and a smaller volume of pollutants available for dispersion.
3. Open sites have lower concentrations as the emissions have more space for diffusion and dispersion. Thus, in these sites concentration are a function of traffic density and wind conditions.

4. Neighboring sites are located more than 200 meters from the street and are not affected directly by the traffic.
5. School sites are located inside the school or in their garden. Since some schools are close to the streets, they are likely to be influenced by traffic in their surroundings.

Despite the rise in road traffic, air quality in metropolitan areas in the EU is expected to improve for traffic-related pollutants. The key drivers of this trend are technological advancements in vehicle engines and fuels in reaction to the EU standards. In most European cities, however, road traffic is the most significant cause of nitrogen oxides, carbon monoxide and benzene. PAH rates in cities are also influenced by traffic. Furthermore, reports show that primary traffic emissions account for between one-fourth and a half of the fine PM mass in urban regions. Levels of traffic-related pollutants are considerably higher in urban areas with heavy traffic, in contrast; ozone levels are lower in congested crossroads and in urban regions (Schwarze et al., 2005).

In order to enhance our understanding of the processes that contribute to air pollution impacts from transportation emissions, more research is needed. There are still some uncertainties about the presence and dynamics of cause and effects for urban pollutants from road traffic, especially for $NO_2$ and particles, which seem to be two major concerning air pollutants (Costabile & Allegrini, 2008). Several researchers discovered positive correlations between traffic density and nitrogen oxides like NO, $NO_x$ and $NO_2$. However, the findings on the relationship between vehicle density and particulate matter were unclear; some noted that rising $PM_{10}$ levels in urban regions may be attributed to increased traffic, while others pointed to very weak or null correlations. Overall, the relationship between air quality and traffic remains unclear due to the many factors that must be considered. First, multiple resources, including car circulation, residential and industrial sectors, contribute to the recorded concentrations of pollutants in urban areas, which are not easy to record. As a result, determining the impact of traffic on pollutant levels is difficult due to the uncertainty of the data. Second, the distance between air quality control stations and roadways has a direct impact on the relation between measured pollutant concentrations and congestion, resulting in site-specific findings and assumptions. Meteorological variables namely precipitation, wind speed and direction, temperature, relative humidity, thermal inversions, all have an important impact on emitting and transport of pollution especially in the case of $PM_{10}$. Finally, because of slow and/or lagged photochemical reaction processes, delays between emitting sources and recording stations can happen. One consequence of investigating all these effects is the appearance of a causal correlation between decreased traffic volumes and increased air quality, which cannot be reliably measured (Rossi et al., 2020).

According to the figure 2.1, Emissions of main pollutants such ax $NO_x$ have decreased substantially in the road transport sector. At the EU level, policy measures have been taken to mitigate air pollution caused by transportation while allowing for sectoral development. Regulating emissions by implementing more strict emission levels or imposing fuel quality standards are examples of such measurements (EEA, 2020).

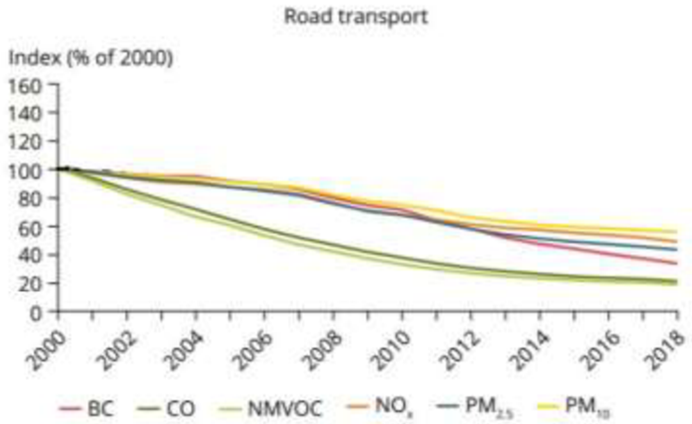



Figure 2.1. Development in the EU emissions between 2000 and 2018 (EEA, 2020)

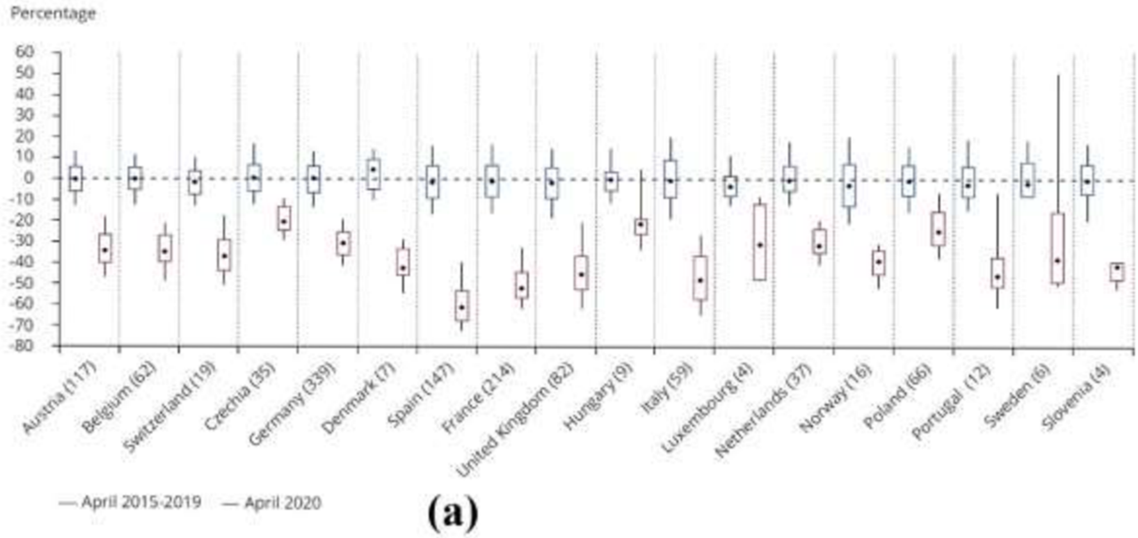
The global Transforming our world: the 2030 Agenda for Sustainable Development strategy and the Paris Agreement set specific goals in the mobility sector in order to solve the problems of sustainable urban development and climate change. The European Union's current long-term vision for climate-neutral cities is focused on smart mobility strategies for a prosperous future. Many studies about the effects of intelligent mobility on the environment have been conducted. Mobile control systems, traffic performance actions, bicycle-sharing systems, public transportation enhancement, shared mobility, smart car routing devices have yielded positive outcomes for air pollution mitigation.

Cities are now implementing a variety of smart mobility technologies, which may help to shift the citizens' behavior and habits. Vehicle navigation technologies, e-parking, e-ticketing, e-pass, info-mobility signage, self-driving cars, walking bus, bike or vehicle, demand-responsive transportation, vehicle sharing are examples of these implementations (Cepeliauskaite et al., 2021). Canales et al. (2017) has shown that in London, Mexico City and San Francisco, dynamic planning and ticketing applications could minimize greenhouse gases by 500000 tons annually while increasing public transportation use. Using on-demand electric minibuses instead of fixed-route diesel buses could help mitigation of GHG and $PM_{10}$ by more than 80% and $NO_x$ emissions by up to 95% per bus route in these cities. Ride-sharing services for first and last-mile trips to and from public transport stations could reduce GHGs and regional air pollution per-trip by 55-80%. According to the scientific research, intelligent mobility can help to reduce air pollution. (Canales et al., 2017). Depending on local requirements, European cities are now incorporating smart city planning objectives and actions into their urban planning documents.

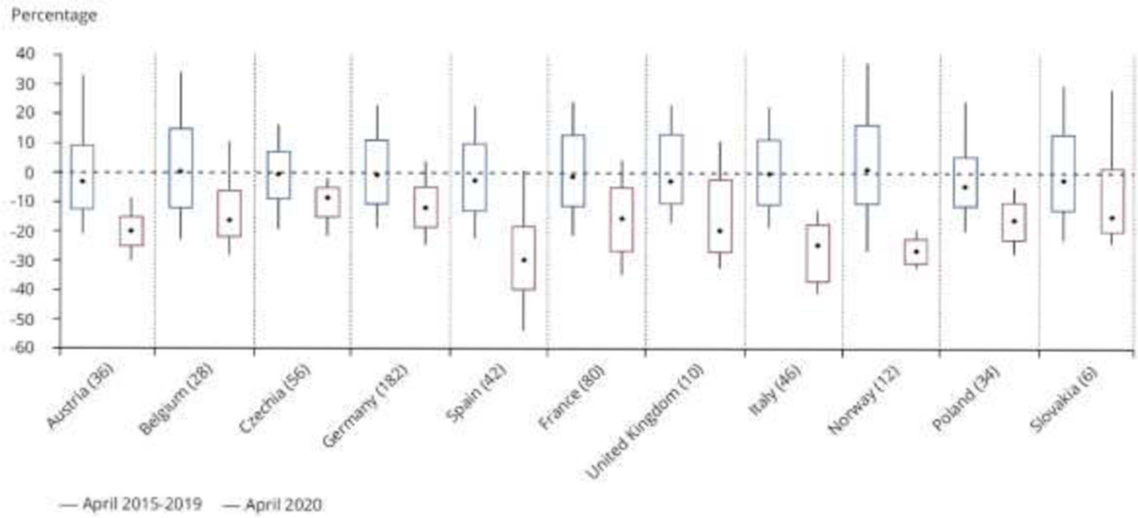
Cepeliauskaite et al. (2021) analyzed various intelligent mobility services in Berlin (Germany), Kaunas (Lithuania), Riga (Latvia) and Tartu (Estonia). In Kaunas, Riga and Tartu, people are highly dependent on private vehicles, while in Berlin, non-motorized means of transportation (walking, cycling) are favored. It also revealed that public transportation is one of the most common modes of travel. Based on the results, the example of mobile phone apps such as mobile ticketing app, smart bike-sharing and mobility point may help to transform mobility trends in a more environmentally friendly way.

The pandemic and its aftermath significantly changed the operation of sustainable mobility strategies. It affected the demand for transport modes; for example, although using public transport dropped sharply in urban cities, bike-sharing services were less affected and perspectives about the health safety of public transport have altered. In addition, free movement restrictions- within and between- districts had positive environmental impacts, enhancing regional air quality and lowering greenhouse gas emissions. These findings demonstrated both the environmental consequences of transportation and the ability of governments to respond quickly (Cepeliauskaite et al., 2021).

According to the EEA report (2020), regardless of meteorological parameters, $NO_2$ concentration were decreased dramatically across Europe in April 2020. The approximate relative reductions in $NO_2$ concentrations differed slightly inside cities and across continents. The relative reductions were more significant where lockdown restrictions were extreme such as in Spain, Italy and France, while in central-eastern Europe the reductions were lower. Traffic stations in Spain and Italy witnessed the maximum reduction, projected to be about 70%.
$PM_{10}$ concentrations were also decreased though to a minor extent than $NO_2$ across Europe because of lockdown measures. The relative reductions at traffic stations were considered 40% in Spain and 35% in Italy. Should be noted that in a few localized regions, $PM_{10}$ concentrations increased. Changes in $PM_{10}$ concentrations compare to the $NO_2$ concentrations are more difficult to determine. Despite the fact that the larger effect on $NO_2$ response is explained by lockdown restrictions limiting mainly road transport, which is a major source of $NO_x$ emissions, the lower effects on $PM_{10}$ reveals the other sources of air pollutant emissions lead to PM contamination(EEA, 2020). Figure 2.2 shows relative changes in countries with at least four traffic stations. In another study by Rossi et al. (2020), results confirmed that NO, $NO_2$ and $NO_x$ were positively correlated with traffic volumes during the COVID-19 pandemic, whereas no significant correlations for $PM_{10}$ and traffic levels were reported in Italy. They conclude that measurements to minimize traffic volumes, such as car-free days or odd-even number plate plans, seem to be successful in enhancing air quality if the aim of these policies is to minimize NO, $NO_2$ and $NO_x$ emissions (Rossi et al., 2020).




**(a)**




**(b)**

Figure 2.2. Relative changes (Percentage) per country during April 2020, (a) relative changes (%) per country in NO2 concentrations, (b) relative change (%) per country in PM10 concentrations (EEA, 2020)

## 2-5- Smart transportation in Prague

Based on the Smart City Index, Prague ranked 44th among 109 cities in 2020 (IMD, 2020). In 2017, The Sustainable Mobility Plan for Prague and its Surroundings (SMPPS) determined a list of solutions to the transport problems and introduces the vision for the development of mobility until 2030 in this city. Reducing the spatial intensity of transportation and carbon footprint, increasing quality and reliability, developing safety and financial sustainability, enhancing human health and transportation availability are among the strategic objectives. The idea of Smart Prague for Prague mobility is based on many pillars and presents a vision of modern, technologically advanced, cleaner, more secure and more effective transport. The key cornerstone is the desire to use public transportation more often, which offers more environmentally sustainable means of transport (subway, tram, electric bus, train). A constant increase in passenger satisfaction and awareness of using the new technology is connected to increasing willingness to use public transport. In mid-2018, a new passenger handling system was designed, offering passengers more payment options for buying tickets. Passengers can use smartphone applications to conduct entirely electronic passenger handling in the public transport system and use different means of transport including car sharing, bike sharing, etc. The development of shared mobility and electro mobility, preferably utilizing small urban electric cars, is another cornerstone. As part of the promotion of electro mobility, the conceptual design of a network of charging stations is being supported (Figure 2.3 shows the trend of electric vehicles in the city). Prague would also make greater use of real-time traffic data for adaptive traffic controls at intersections, allowing for more effective use of road capacity and active traffic management to minimize traffic jams and waiting times, particularly for public transport vehicles, and reducing pollution emissions. By analyzing data, relevant information must be provided to users through applications. The final pillar is support for the promotion of self-driving vehicles in terms of both modes of transport and transport infrastructure (Smart Prague Index, 2020).


Figure 2.3. the development of the number of registered electric vehicles in Prague (Smart Prague Index, 2020)

In the following paragraph, other relevant information indicators, which mainly focus on the quality of life and air pollution will be discussed (Smart Prague Index, 2020):

1. Premature deaths because of air pollution: this indicator expresses the number of premature death because of air pollution and assists in tracking the success of smart mobility in Prague. The implementation of electro vehicles and clean buses decreases the air pollution

caused by traffic. Smart mobility also has a direct impact on air quality by decreasing the effect of traffic and enhancing traffic flows.

2. Time spent in traffic congestion: the indicator calculates the wasted potential of the population in hours annually. Indeed, it is another indirect indicator showing the effectiveness of the implementation of smart mobility.
3. Age of registered vehicles: it is an indirect indicator to express the level of air pollution caused by vehicle technical conditions. This indicator is also affected by the current economic condition as well as future national policies. Poorly maintained cars with no particulate filters, for example, will increase pollution by hundreds of percent. Around two-thirds of the most toxic pollutants from transport, such as very small particulate and nitrogen oxides are generated by 10 percent of vehicles.
4. Cases when air pollution limits were exceeded: the indicator represents the relative value of cases when air quality levels were exceeded in terms of the number of measured days. It means value equals zero is the ideal situation, while value equals to one is the worse situation for the environment.

Table 2.9. Comparison of resulting indicator value in 2017, 2018 and 2019 in Prague (Smart Prague Index, 2020)

| Indicator | 2017 | 2018 | 2019 |
|---|---|---|---|
| Premature deaths because of air pollution | 518 | 693 | 807 |
| Time spent in traffic congestion (hours per person per year) | 119 | 119 | 128 |
| Age of registered vehicles (years) | 12.6 – 18.9 – 13.5 – 12.5 [2] | 11.6 – 17.3 – 12.6 – 11.8 | 10.6 – 17.3 – 11.4 – 11.1 |
| Cases when air pollution limits were exceeded (absolute number of days with exceeded limit values/number of measured days) | 0.1423 | 0.1437 | 0.1242 |

From the table, we can say that in human settlements, the most important causes of air pollution are the combustion process in the industry, energy supply and transportation. A rise of 10 $^{\mu g}/_{m^3}$ over 13.3 $^{\mu g}/_{m^3}$ in annual $PM_{10}$ concentration raises the estimation of overall premature death of the exposed individuals by 4.65%. In 2019, Praha ranked 136$^{th}$ out of 416 cities while in 2018 ranked 149$^{th}$ among 403 cities, with the congestion level of 29 and 27 percent, respectively. In

[2] This indicator is based on 4 category of cars (maximum eight passengers), buses (over eight passengers) and multi-purpose passenger vehicles (vans up to 3.5 tons)

comparison to 2018, traffic congestion in the capital rose by 2% and the citizens spent an average of 5 days in peak congestions. In 2018, the permitted air pollution threshold value was surpassed 12 out of 100 days. This seems an improvement from the previous two years, where it was around 14 days out of hundred days (Smart Prague Index, 2020).

# CHAPTER 3 METHODOLOGY

## 3-1- Traffic congestion reasons

In order to comprehend and overcome the traffic jam problems or reducing their consequences, there is a need to distinguish different type of congestion and their affect (Djahel et al., 2015):

### 3-1-1- Recurring congestion

Recurring congestion happens when a significant number of cars use the limited capacity of the road network at the same time (weekday morning and afternoon peak hours) (Djahel et al., 2015). Recurring congestion accounts for more than half of all traffic congestion, while non-recurring congestion accounting for 40% of all traffic congestion based on the United States Department of Transportation Federal Highway Administration (FHWA, 2005). The main reasons of recurring congestions are (Afrin & Yodo, 2020):

1. Bottlenecks and capacity: Obstructions are the most frequent source of this type of traffic. During rush hours, bottlenecks happen as the result of exceeding the number of lanes compare to the number of lanes converging on a highway, bridge, or tunnel. To put it another way, when the demand overreaches the road’s capacity. The maximum amount of traffic that a road can bear is indicated by its capacity. Capacity is defined by the number and widths of lanes, merging length at crossways, and highway adjustment.
2. Inadequate infrastructure: This factor is more tangible particularly in densely populated areas. By increasing the population rate, the number of vehicles will increase and the current system cannot accommodate the growing number of vehicles.
3. Variation in traffic flow: Due to the fluctuations of day-to-day traffic demands, some days have a higher density than others. If the fixed capacity does not adapt to the variable demands, a delay can happen.
4. Insufficient traffic controllers: Poorly traffic controls like traffic signals, stop signs, speed reductions or railway crossings can interrupt a daily traffic flow, resulting in delays and travel time variations.

### 3-1-2- Non-recurring congestion

Non-recurring congestion can cause new traffic jams in the off-peak hours and increase the delay because of recurring congestion. Unpredictable events such as traffic crashes (car accident), work zones, poor weather conditions and certain special events such as sporting events, Christmas, etc.

The following are few examples of non-recurring congestion (Afrin & Yodo, 2020):

1. Traffic accidents: vehicle accidents, breakdowns and debris in travel lanes are the most frequent type of traffic accidents. These occurrences interrupt the regular flow of traffic, normally by blocking the road, resulting in a decrease in capacity.
2. Work zones: Work zones are describes as areas where construction operations on the roadway are carried out by physically altering the roadway zone. These modifications

result in a decrease on the number or width of traffic lanes, lane shifts, diversions of lane, shoulder reduction or removal and short-term road blockage.

3. Weather: Changes in natural phenomena or weather may have an effect on traffic movement and driver response. Not only road conditions, but also the traffic control systems like traffic signals and railroad crossings can be affected. Around 28% of all highway accidents and 19% of all deaths occur as a result of poor weather related road conditions. Furthermore, strong wind gusts, heavy rainfall or snow may affect vehicle speed and volume.
4. Special events: Changes in traffic flow related to a specific occurrence that differ from the normal traffic volume. Sport competitions (game day), festivals or other social gatherings are examples of these events. During special events, a massive rise in traffic demand will overload the network and cause traffic congestion.

### 3-2- Traffic congestion measurement

Several congestion measures have been designed to calculate the extent of traffic congestion based on different performance criteria. These measurements can be classified into five categories (Afrin & Yodo, 2020):

1- Speed

- Speed Reduction Index (SRI): the ratio of the relative speed change between congested ($v_{ac}$) and free-flow conditions ($v_{ff}$). In order to maintain the SRI value in the range of 0 to 10, it is multiplied by ten. If the index value reaches 4 or 5, congestion happens, while a value of less than 4 indicates that the situation is not congested.

$$SRI = (1 - {}^{v_{ac}}/_{v_{ff}}) * 10 \qquad (1)$$

- Speed Performance Index (SPI): the ratio between average vehicle speed ($v_{avg}$) and the maximum legal speed ($v_{max}$)

$$SPI = \left({}^{v_{avg}}/_{v_{max}}\right) * 100 \qquad (2)$$

2- Travel time

- Travel rate is described as the rate of motion for a certain roadway segment or trip, which can be expressed by the ratio of the segment travel time ($T_t$) to the segment length ($L_s$). Travel rate is commonly expressed in units of seconds per meter. The inverse speed can also be used to calculate the travel rate.

$$Travel\ rate = {}^{T_t}/_{L_s} \qquad (3)$$

3- Delay

- Delay rate: The rate of time loss for vehicles functioning in a congested roadway segment or trip. The ratio of actual travel rate ($Tr_{ac}$) and the acceptable travel rate ($Tr_{ap}$)

$$Delay\ rate = Tr_{ac} - Tr_{ap} \tag{4}$$

- Delay ratio: Used to compare the relative congestion levels on different routes and can be measured by the ratio of delay rate ($D_r$) to the actual travel rate ($Tr_{ac}$)

$$Delay = {}^{D_r}/_{Tr_{ac}} \tag{5}$$

4- Level of services (LoS)

- Various traffic quantities, for instance, density, velocity, volume to capacity ratio (V/C) and maximum service flow rate can be used to calculate the LoS.
- V/C is the ratio between the spatial mean volume ($N_v$) and the maximum number of vehicles ($N_{max}$)

$$^{V}/_{C} = {}^{N_v}/_{N_{max}} \tag{6}$$

$$N_{max} = \left({}^{L_s}/_{L_v}\right) * N_l \tag{7}$$

$L_s$ is the spatial segment length, divided into the average vehicle length occupancy ($L_v$), and $N_l$ is the number of lanes

5- Congestion indices

- Relative Congestion Index (RCI): the ratio of delay time (difference between actual travel time ($T_{ac}$) and free-flow travel time) and free-flow travel time ($T_{ff}$)

$$RCI = {}^{(T_{ac} - T_{ff})}/_{T_{ff}} \tag{8}$$

- Road Segment Congestion Index ($R_i$): can be calculated by using the regular road segment state ($R_{NC}$) and the duration of non-congestion state ($t_{NC}$) in the length of monitoring time ($t_t$).

$$R_i = \left(\frac{SPI_{avg}}{100}\right) * R_{NC} \tag{9}$$

$$R_{NC} = t_{NC} / t_t \tag{10}$$

## 3-3- Traffic control strategies

Traffic management is the mechanism of designing, installing, evaluating and controlling the movements of vehicles in order to improve the use of available road systems. Many components used in traffic management can be adapted based on the road conditions including traffic signals, signs, speed limits, etc. (Małecki, 2016). Deploying a new signal control system by replacing both signal controller and detection system is expensive, thus determining an economical approach for enhancing the current signal control system becomes critical (Jin & Ma, 2017). As was mentioned before, the main goal of traffic control is to enhance traffic operation at intersections by reducing vehicle delays and optimizing the effectiveness of transportation networks in urban regions. Three main traffic control strategies are going to be discussed in this chapter (Ma et al., 2020).

### 3-3-1- Fixed time signal control

Recent researches have focused mainly on adaptive signal timing based on real-time traffic data obtained by infrastructure-based detectors. Because of the high cost of installing and maintaining such detectors, fixed-time traffic lights may continue to be the most commonly used method in the world (Ma et al., 2020). Fixed-time signal optimization has been divided into three categories: stage-based, group-based (phase based) and lane-based approaches.

1. The stage-based method is when compatible traffic movements are clustered and moved together in a defined time length, which is named a stage. Then, for each stage during a signal loop, green times are assigned (Ma et al., 2020). The aim of this method is typically to reduce total delay or to increase intersection capacity. This method is unable to manage mixed traffic flows with unbalanced volumes of motorized and non-motorized vehicles. Many safety concerns have arisen as a result of this approach, such as traffic conflicts between right-turning motorized vehicles and straight-through cyclists and conflicts at the change of stages because of cyclists failing to clear the intersection (Wang et al., 2019). Traffic conflicts due to stage-based signal control is illustrated in the figure 1.3.

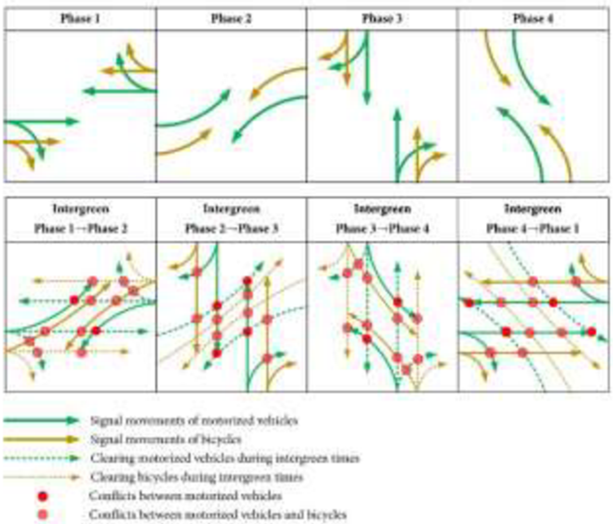



Figure 3.1. A stage-based signal control scheme and its resulting traffic disruptions (Wang et al., 2019)

2. A group-based signal control scheme is used to control a single or a group of turning movements (Figure 3.2). In several European countries, group-based traffic signal management is the most commonly used approach for traffic lighting.
The advantages of this approach are the allocation of green times, especially when the demands

on various turning movements at an intersection are unstable. Compare to the stage-based controls with pre-fixed phase sequence, group-based control allows compatible turning motions to be dynamically combined into phases (Jin & Ma, 2017). The ability to separate all the incompatible movements based on the inter-green duration, would enhance cyclists safety while preserving the intersections' operational performance (Wang et al., 2019).

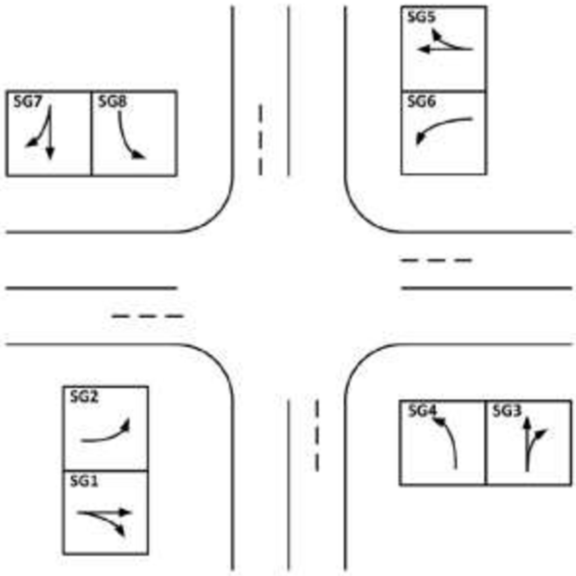



Figure 3.2. A group-based signal control scheme (Jin & Ma, 2017).

3. Lane-based method is employed to design signal-controlled crossroads. Lane markings are directional arrows drawn on the street that help drivers which way to turn at intersections (Figure 3.3).

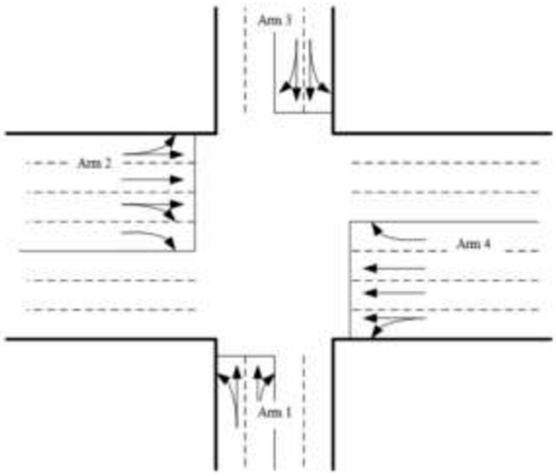



Figure 3.3. Optimized lane markings at an intersection (Wong & Lee, 2020)

Lane markings are described as binary variables that can be combined with traffic signal timings to improve the overall efficiency of an intersection. The original lane-based optimization approach uses the unrealistic point-queue technique, which considers unlimited capacities on road lanes by positioning all waiting vehicles vertically rather than horizontally along road lanes. (Wong & Lee, 2020). Minimizing vehicle delay or increasing intersection capacity is among the objective of this approach.

The majority of fixed-time signal timing methods depend on historical traffic data obtained by infrastructure-based detectors such as loop detectors. Nevertheless, those detectors are costly and have poor coverage. With the emergence of probe vehicles with GPS navigation devices, a large amount of trajectory data has become accessible. Not only trajectory data of probe vehicles are economical but also they have broad coverage and consistency in the spatial and temporal extents. Trajectory data as opposed to the traditional traffic volume data contains more accurate information regarding vehicle positions and speeds. Ma et al., (2020) focused on trajectory data for the optimization of traffic lights. Infrastructure-based detectors (loop detectors) are used to gather traffic volumes for the fixed-time traffic light optimization approaches. Considering the costs and coverage of infrastructure-based detectors, trajectory data by providing more information about traffic intersection and be used for signal timing are more applicable (Ma et al., 2020).

Ziemke et al., (2019) answered to the question of how to optimize fixed-time signals in reality. Simulation as a useful method is used for modeling real-world situations, evaluating case studies and predicting user behavior, while due to its difficulty, lacks optimization capabilities. On the other hand, mathematical methods such as cyclically time-expanded network can be used to utilize fixed-time traffic settings. Thus, two models were implemented in this paper: An analytical model for optimizing fixed-time schemes for massively extended network formulation and a coevolutionary transport simulation for evaluating the optimized fixed-time schemes for large-scale realistic traffic conditions. Despite all model inconsistencies, it was shown that coupling simulation and optimization could be used to provide enhanced fixed-time signal schemes in practice (Ziemke et al., 2019).

Cruz-Piris et al., (2016) figured out that for fixed time signal control strategy, autonomous vehicles can have a positive impact on reducing traffic congestions and related issues. This new idea is currently commercial solutions for semi-autonomous driving systems, while there are optimistic scenarios for a completely autonomous vehicle in the coming years. Intersections are the most conflict-generating elements, which must organize multiple traffic flow with different preferences and priorities. Therefore, the article concentrated on the optimization of intersections by presenting three different approaches. In order to simulate microscopic traffic flows, they used a Traffic Cellular Automata (TCA) simulator to realize the behavior of traffic in special circumstances like the behavior of the traffic crossing an intersection. Finally, they proposed a system that produces a lower degree of interference between inputs and outputs in the roads, developing and progressing intersection's operation and improving the arrival rate of vehicles using a Genetic Algorithm.

The result of the proposed model was compared with the traditional system and indicated the efficiency of 9.21% to 36.98% compared to the previous models. Other advantages of this model are that as a generic model it is compatible with any type of intersections and better results based on the traffic signals and priorities, high level of performance like calculating more than 80000 ways in less than 4 seconds. Generally speaking, a road network involves high number of intersections and an automatic optimization system can be beneficial (Cruz-Piris et al., 2016).

Costa et al., (2016) proposed a bi-objective optimization approach for the fixed-time traffic light in urban areas. Decision parameters for this algorithm are maximization of average speed and minimization of speed variance. The first function is concerned with the quality of traffic flow, while the second is concerned with traffic homogeneity (the network's flow equilibrium). In this paper, network signal optimization is modeled as a fixed-time challenge, which means that the signal plans are divided into time periods based on the predicted volume flow during the day. To boost efficiency, signal timing configurations can be varied over periods and for each day of the week. Thus, the key objective is to modify the operation parameters for each period to achieve near-optimal solutions for the whole network. The Memory-Based Variable-Length Nondominated Sorting Genetic Algorithm 2 (MBVL-NSGA2) optimizes this combination of functions by avoiding revaluation of candidate solutions. The study took into account two different peak times scenarios. The algorithm was able to discover drastic solutions similar to mono-objective techniques and much superior to the normal solutions. Furthermore, the approach generated sets of solutions to provide the authorities with a variety of options. The possible impact of these approaches can be significant, particularly when considering the current traffic conditions in medium and large cities. An improvement of twenty percent on average velocity could postpone the effects of increased traffic for several years without making systematic improvements to the transit infrastructure (Costa et al., 2016).

### 3-3-2- Vehicle-actuated signal control

In this approach, the timing scheme is created by the controller itself based on the parameters set for each phase. Detectors are installed on the entrance to an intersection in order to sense "actuations" (known as calls or demands) from the subject's motions. A controller collects detector actuations and then sets the subject cycle length to fulfill existing traffic demands using a gap-out, a phase skip or a max-out. The modification of a cycle length is controlled primarily by three signal control settings: minimum green, maximum green and vehicle extension (Ilsoo et al., 2006). As compared to fixed-time signals, vehicle-actuated coordinated systems have more flexibility in adapting to changes in traffic demand (Li et al., 2010).

Lu & Kim (2017) proposed an algorithm that allows the emergency vehicle to pass the intersection quickly with the least influence on the travel time of other vehicles. In the absence of emergency vehicles, the DTOT-based Intersection Control Algorithm (DICA) will be used to handle vehicles. Albeit when the emergency vehicle is present, finding the optimal vehicle sequence that assigns the highest priority to the emergency vehicle is challenging. In this regard, a new genetic algorithm-based approach called Reactive DICA (R-DICA) will be used to organize vehicles only when there is an EV within an intersection while the crossing traffic is monitored as before in regular situations.

In this algorithm, if EV enters an intersection, the model would give preference to EVs in autonomous traffic and optimize vehicle-crossing sequence. Simulation results stated that the proposed model confirms the hypothesis of reducing travel time of EV and better performance compared to the previous model. They conclude that there is no significant effect on the performance of the normal vehicles based on the analysis of DICA and R-DICA models (Lu & Kim, 2017).

Even if a vehicle-actuated signal enhances traffic conditions at an intersection, it does not result in system-wide benefits. When analyzing the results of signal control strategies, the second-order or network impacts should be considered as well. Network impacts include drivers' responses not only to route selection but also to schedule. The majority of microscopic traffic simulations concentrate on complex driver models that extend models in a specific way. Thus, driving behavior is precisely simulated, but in most situations, this is achieved for a single trip. Doing so, the information for capturing network impacts and time changes that have already been analyzed for other policies is lost. To capture such impacts in large-scale networks, Grether et al. (2011) employ a signal control simulation methodology. SYLVIA was used as a signal control strategy by focusing on one of its main characteristics of which is the traffic actuated phase length control. The findings show that as was expected, SYLVIA outperforms a fixed-time signal for all demand patterns. Aside from that, the system's stability is immune in all simulated scenarios (Grether et al., 2011)

Kumar (2011) stated that a well-designed actuated control paradigm that meets the traffic demands can greatly minimize delay and fuel consumption. This paper suggested many methods for implanting vehicle-actuated controllers in highly heterogeneous traffic situations with insufficient lane discipline. This involves adjusting the detector configuration and loop size, rational signal phase grouping and the use of dummy phase. By implementing the suggested solution in many Indian towns, the author also solved the complex phasing systems and free-queue parameters. He concluded that VA controllers outperformed the existing fixed-time signals. However, the sensitivity of cycle length, green time and gap standards must be investigated, usually using a robust simulator. Furthermore, using a good progression model, efficiency can be dramatically enhanced, especially along the corridor (Kumar, 2011).

Park et al., (2004) believed that signal timing plans for the fixed time signal controls during peak/off-peak hours must be different from each other. These time-of-day (TOD) breakpoints are often manually determined by engineers using one or two days' worth of traffic information. Archived data that was used in recent studies, has introduced statistical and heuristic methods for TOD breakpoints.

These methods calculated the breakpoints by minimizing within-cluster intervals and increasing between-cluster intervals. As a result, the clusters do not clearly represent timing scheme efficiency and often result in only local optimum TOD breakpoints. One approach uses a genetic algorithm (GA) to optimize TOD breakpoints by taking into account the efficiency of signal timing at a representative intersections. The proposed approach provides a two-stage optimization process: an outer loop for TOD breakpoints and an inner loop for timing setting of related intervals. The recommended method is installed on a network of three controlled actuated signalized intersection. The inner and outer loop optimization convergence graphs show that the GA-based algorithm receives breakpoints in a small number of times. According to the data based on a microscopic simulation application called SimTraffic, six breakpoints outperformed the other numbers of breakpoints. This technology could make traffic signals more sensitive to seasonal changes in traffic flow trends as well as saving resources used by local traffic authorities for finding the best TOD breakpoints to decrease total delay time(Park et al., 2004).

### 3-3-3- Adaptive signal control

Adaptive signal control has been widely used since the early seventies and has proven to be a more effective method of reducing traffic congestions than fixed-time and actuated control systems for signalized intersections. There are various methods including SCOOT, SCATS, PRO-DYN, OPAC, UTOPIA, RHODES, which all need a pre-specified model of the environment (Touhbi et al., 2017).

In this strategy, traffic signal timing parameters, for example, cycle length, phase split and phase period change depending on the traffic patterns and traffic density in order to fulfill a set of goals (reducing the total waiting time). SCOOT and SCATs are pioneers of the development of adaptive signal control in the 1980s. Many adaptive signal control systems use stage-based control, in which the sequence is predetermined. Recently, several novel approaches such as deep learning, artificial intelligence and reinforcement learning have been implemented in the mentioned strategy. While adaptive signal control methods are more effective than non-adaptive methods in reducing traffic congestion, the wide-scale deployment of such systems requires substantial long-term investment particularly in developing countries because of high cost of installation and maintenance. These methods often need a variety of inputs such as observed and predicted traffic density in each route, queue length, etc. To obtain these inputs, high-accurate detectors (cameras, GPS) are needed with additional procedures to analyze them. Adaptive control strategies are typically designed for oversaturated intersections or intersections during peak periods. However, during the peak-off hours, drivers can encounter delays especially if there are no cars in directions that would usually create conflict points with the current route. As a result, studying this strategy for crossroads during off-peak period is crucial. Zhu et al. (2019) suggest an adaptive traffic signal control that uses the detected green and red redundancy time of each route and based on the detected redundancy time, the signal planning is modified. As opposed to traditional adaptive techniques, the proposed solution has a lower deployment cost and is easier to install in practice since only two detectors are required to provide enough data for traffic management. In addition, the optimum position of each detector for low and high volume-to-capacity ratios is presented as follows. Detectors for the green redundancy period should be placed near the expected location of the last vehicle in the queue from the stop line, while red detectors should be established around the maximum distance a vehicle will drive during the green time before the stop line. To conclude, the total traffic delay based on the proposed method is the smallest (Zhu et al., 2019).

Rida et al., (2020) recommended using a wireless sensor network implemented on the road to collect data for optimization of cycle length and traffic signals. The purpose of this study is to produce a dynamic traffic timing scheme to decrease vehicle queues and increase vehicles trajectory passing an intersection during the green light. Metaheuristic ant colony optimization with several variants was applied in this regard. The consequences of simulation have confirmed that the proposed method is effective in reducing the waiting time of vehicles. Ant colony optimization system reduces average queue lengths for medium intensity traffic and saves time up to 57% in congested traffic situations (Rida et al., 2020).

Touhi et al. (2017) believed that because traffic is stochastic, a control approach that can respond to fluctuations in traffic and does not need a specific model for a specific environment will be easier. Reinforcement learning has the ability to adjust and self-learn from past events, thus, through continues interaction with the environment, has the ability to enhance the quality of service over time. The findings of reward definitions showed that the success of the reward function depends on the traffic density in the junction and the tools used to track the intersection, since certain measures, such as accumulated delay, require more advanced sensors (GPS equipped vehicles). In heavy traffic, queue length was found to be secondary but it is simpler to measure with normal sensors (loop detectors). Investigations can be conducted at the RL level by developing other reward models (delay squared) and their combinations in reality. Since traffic arrival patterns at a junction are strongly dependent on how traffic is managed at the upstream junction, it is essential to examine the alignment of multiple intersections (Touhbi et al., 2017).

Lawe & Wang (2016) presumed the goal of smart transport management is optimizing the traffic timing at intersections. Many existing methods are not adapted to the environmental variables like weather (raining), incidents that affected the traffic density. Deep learning neural networks as a practical tool in forming numerical regression were proposed in this paper. By using Multitask Learning (MTL) this model can foresee traffic flow and learn about the area at any given point. In the circumstances that normal patterns have been disordered, the algorithms observe it and implementing begins when similar patterns are expected. This algorithm helps the model to anticipate largely changes.

Historical details of all movements of an expected intersection, time series and environmental parameters were introduced to the model as inputs. The projected traffic volume was then applied to the delay equation in order to calculate the optimal green times to handle the traffic congestion. By comparing other methods including random walk, support vector machine and BP neural network the results declare that deep neural network does better than others in terms of optimizing the performance of traffic lights, however, the optimal operation of the model in low traffic volume is controversial. The proposed model also provides more precise predictions about traffic than other models (Lawe & Wang, 2016).

Roshandeh et al., (2014) focused on a new methodology that derives from kinematic wave theory for system-wide signal timing enhancement to minimize delays for vehicles and pedestrians using crowded roads. They realized that modifying splits of morning and evening peaks and the rest of the day timing schemes for each signalized intersection can optimize the traffic lights without changing the existing cycle length and signal coordination. By using pedestrian delay estimation approaches, this model overcomes vehicle and pedestrian delays. For comprehensive traffic assignments, both models are integrated into a high-fidelity simulation-based local travel demand forecasting models. Data was collected and used in a computational analysis from Chicago metropolitan area travel demand, traffic counts, geometric designs and traffic lights schemes for many intersections in the business region of Chicago.

After signal timing optimization, a sensitivity analysis was performed with the purpose of investigating the effects of assigning different weights to vehicle and pedestrian delays on vehicle travel time and delay decrement. According to the results, vehicle delays by considering only vehicle in the congested area of Chicago could be decreased by 13% and 5% reduction considering vehicle and pedestrian delays (M. Roshandeh et al., 2014).

### 3-4- Area of study

Olomouc as the cultural center of Moravia is located in the east of the Czech Republic and is the 6th largest city in the country (*Olomouc website*, 2021) by the population of 165,165 in 2020 (*Počet Obyvatel v Obcích* -, 2020). The presence of baroque fortifications influenced the town's development until the mid-nineteenth century. Another significant aspect is the city's transportation network, which includes a railway that divides Olomouc into two parts of the industrial eastern part and western residential part. Olomouc is on the verge of becoming a monocentric city with a centripetal transportation system. Olomouc's historic center is a pedestrian zone, which is surrounded by green landscapes (Burian et al., 2020). The city has an active Air Quality Management System (AQMS). It is able to describe the current state and long-term air pollution situation in the city, identify emission-pollution relations, determine causes of excessive air pollution, efficiently managing pollution load reductions and react to real local authority demands. The air pollution stations monitor $PM_{10}$, $NO_2$, $SO_2$ and $O_3$. ADMoSS system is used to measure the emission-pollution dependency. The Department of Environmental Protection in Industry at the Technical University of Ostrava developed this system. GIS software is used to prepare all relevant input data for modeling, break modeling tasks into smaller pieces and run them on a parallel supercomputer cluster. It also handles measurements, data storage and post-processing of results. The final outputs are provided in GIS format. The system's output is a realistic representation of pollution distribution in Olomouc city, allowing for extensive study of the impact of various pollution sources on air quality and pollution exposure of residents (Pavlikova et al., 2011). The monitoring stations of the city are presented in the table 3.1. Figure 3.4 shows air quality index at Olomouc-Smeralova station.

Table 3.1. Monitoring stations of air pollution in the Olomouc (Vysoudil & Jurek, 2004)

| Station | Location | Measured pollutants |
|---|---|---|
| Flora | City center | SPM, $NO_x$, $SO_2$ |
| Capka Choda | On the west side of the city | SPM, $NO_x$, $SO_2$ |
| OHES | On the south and south-east side of the city | SPM, $NO_x$, $SO_2$ |
| CHMI | On the north side of the city | SPM, $NO_x$, $SO_2$, CO, NO, $NO_2$, $PM_{10}$ + meterological measurements |
| Smeralova | Central part of the city | $PM_{10}$, $NO_x$, $SO_2$, $NO_2$, $O_3$, NO, heavy metals |
| City Hall | City center | $NO_x$, $SO_2$ |
| Hotelovy dum | On the south and south-east of outskirts | $O_3$, $NO_x$, $SO_2$ |
| Hodolany | On the eastern outskirts of Olomouc | $NO_x$, $SO_2$ |

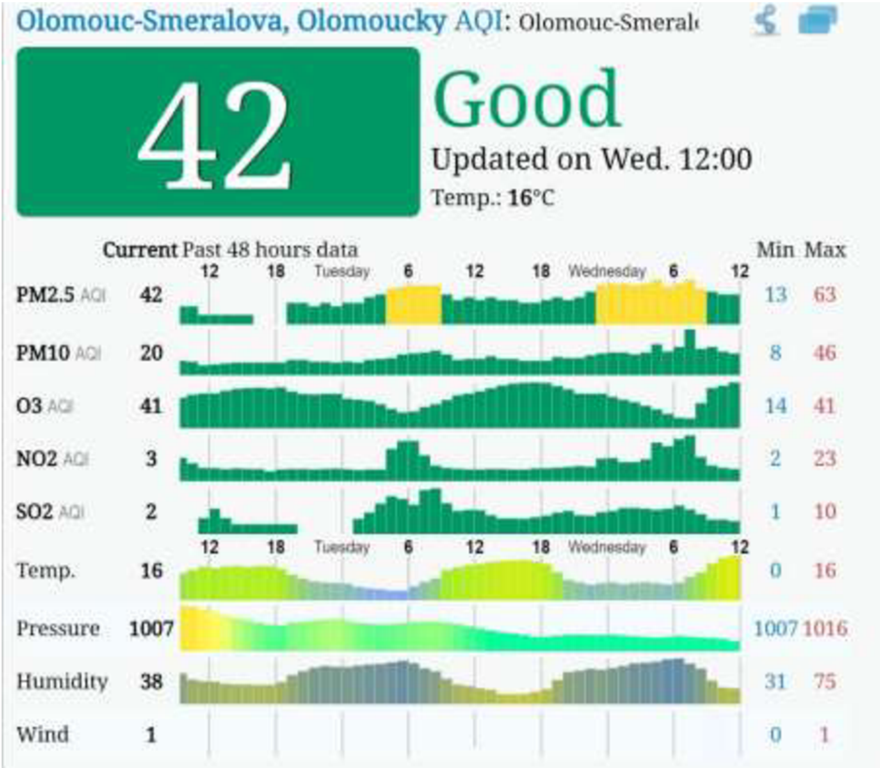



Figure 3.4. Olomouc- Smeralova, Olomoucky Air pollution: Real-time Air Quality Index (AQI) (World Air Quality Index project, 2020)

Transport in the city is covered mainly by trams and buses, which have a dense transport network. They operate seven days a week, with schedules available at all public transportation stations (*Olomouc website*, 2021).

In a quantitative research conducted by Burien et al. (2018) in the Czechia, they tried to learn about travelers' behaviors and motivations for using various modes of transportation. Based on the results, respondents prefer traveling to work or school using public transportation (Figure 3.5). The majority of roads in the city have concentric directions and most travel to and from the city center. The routes traveled by public transportation (Figure 3.6) are scattered across the city; major movements from the suburbs are also noticeable in the northeast and northwest. The main public transportation directions conform to the current public transportation network. A greater proportion of public transportation and less car traffic can be found in Olomouc's city center. It is critical to comprehend the most important service characteristics and what will encourage passengers to use public transportation. The travel time and related number of changes (on public transport) are the most significant considerations in determining the mode of transportation in this study. The departure and arrival times are both important. Employed people, in particular, do not want to lose time due to busy weekdays, and they want to be able to monitor the time and pace of their journey. To put it another way, public transportation's reliability is the most important factor. People are time-conscious and they expect fast and high-quality services (Burian et al., 2018).

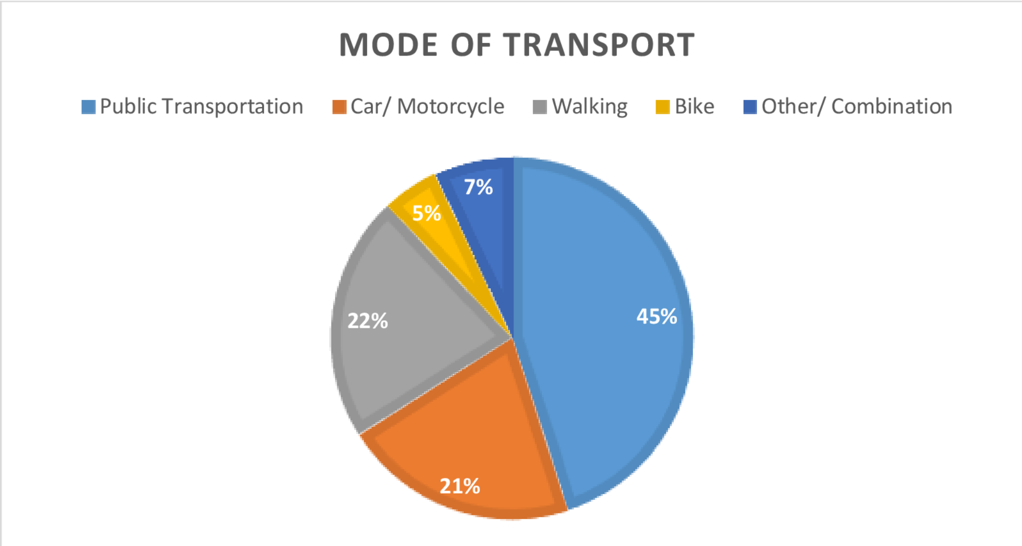



Figure 3.5. Mode of transportation in Olomouc (Burian et al., 2018)

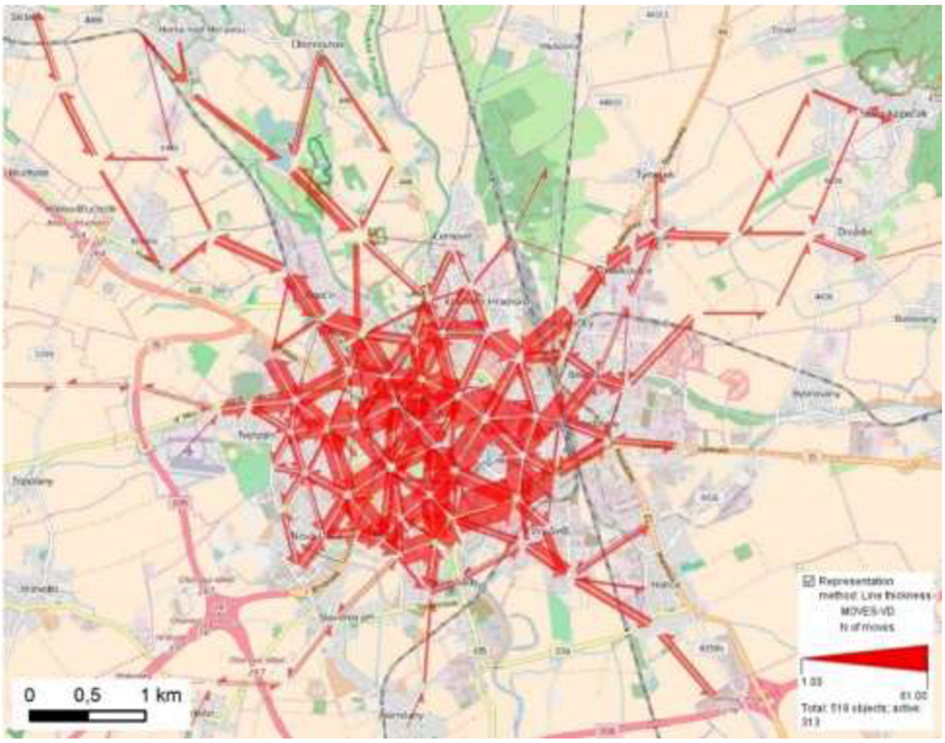



Figure 3.6 Main directions of movement according to public transportation in Olomouc (Burian et al., 2018)

One way of improving public transportation is by expanding and widening infrastructures in cities. Burian et al. (2020) found that prices grew in most of the priced parcels in Olomouc. The highest land prices were usually found in urban areas, these areas became the most costly regions, but rates steadily increased (Burian et al., 2020). Thus, expanding public transportation is not a reasonable solution due to the high price of land. It is more appropriate to optimize the current public transport by utilizing traffic signals.

The assessment of road traffic emission is based on traffic structure and frequency data estimation. The road Traffic Census, which is run by the Czech Republic's Road and Motorway Directorate, provides traffic structure and frequency data. The road traffic is expressed in AQMS by a network of linear sources that copies the road network. Road traffic emissions are affected by vehicle technical conditions, fuel type, road type and state, trip mode, traffic volume and other factors. Emission variables are used to define road traffic pollution (Pavlikova et al., 2011).

The most significant causes of air pollution in this city are traffic (particularly road traffic), Heating and Peak Heating Plant in Olomouc, local heating and construction projects. $NO_x$ emissions of which traffic is the primary cause have the greatest impact on the city's ambient air quality. The limit value of this emission exceeded especially in the city center and at congested intersections (Vysoudil & Jurek, 2004). To conclude, optimizing the traffic lights can play a positive role in the reduction of traffic-related air pollution in the city. The study was conducted for an imagined T-junction in Olomouc.

### 3-5- Optimization algorithms

We are always seeking to optimize something in engineering and industry, whether it is to reduce costs and energy consumption or to increase income, productivity, performance and efficiency. In the concrete, resources, time and money are often constrained; as a result, in practice, optimization is much more crucial. Since most real-world systems involve more complex variables and factors that influence how the system performs, making the best use of existing resources requires a fundamental change of scientific thinking. The optimization algorithm, an effective numerical simulator and a realistic representation of the physical processes are all interconnected components of the optimization process. After designing a decent model, the entire computing expenses are defined by the optimization algorithms used for search and the numerical solver used for simulation. The tools and approaches for reaching the optimality of the problem of interest are known as search algorithms. The fact that uncertainty is usually present in real-world systems complicate the search for optimality. As a result, we desire not only the optimal design but also robust design. Three fundamental concerns in simulation-driven optimization and modeling are; the efficiency of an algorithm, the efficiency and accuracy of a numerical simulator and assigning the proper algorithm to the right problem. The actual efficiency of an algorithm depends on a variety of variables, including the inner working of an algorithm, the information required and implementation considerations. The efficiency of a solver is determined by the numerical methods used and the difficulty of the issue. There are many empirical observations, but no agreed-upon standards for selecting the proper algorithm for the right problem. Accordingly, the decision may be influenced by a variety of elements, including the personal preferences of researchers and decision-makers. To apply an algorithm appropriately, the appropriate decision must be taken and sometimes a suitable combination of algorithms may generate significantly superior outcomes. (Yang, 2013).

### 3-6- Case Study of a T-junction

Based on the INIRIX reports, Olomouc is the 7th most congested city in the country which each citizen loses 12 hours a year in congestion. Below is an algorithm of how to optimize traffic light for a T-junction (Figure 3.7). The model is coded in MATLAB for a 24-h period. All algorithms are performed in a personal computer with an Intel 2.60 GHz CPU and 12.0 GB memory. The entire coding is written in appendix A.

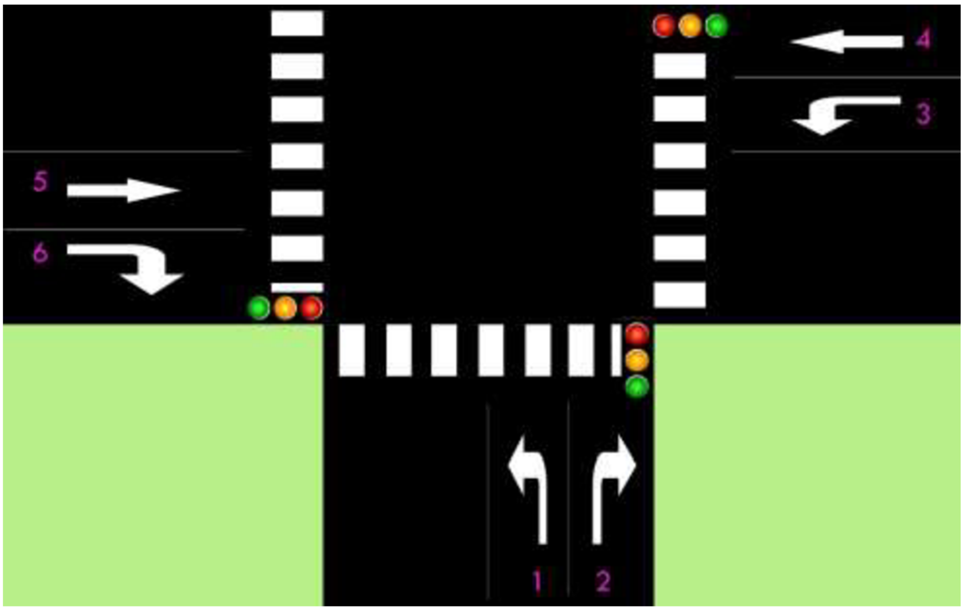



Figure 3.7. A typical T-junction in simulation (author)

Before getting into the codes, it is necessary to be familiar with two concepts; traffic volume (density) and throughput (capacity). Traffic volume is referred to the intensity of traffic on a specific road for a given period and can be measured using a variety of methods, like manually counting the number of vehicles or using an electronic instrument. Capacity is described as the maximum mean hourly rate and highest number of vehicles traveling through a point in a given road and traffic situation (Nor Aisyah, 2014).

In order to show the potential of mathematical modeling and optimization, we present a simplified version of a T-junction. Designing simple models of complicated intersections needs the use of simplifying assumptions. By using simplifying assumptions in our T-junction model, we eliminate some of the complexities of the real world. Simplifications of our model include:

1. Constant influx density in each direction
2. Constant throughput in each direction
3. No adaptivity or interaction between vehicles

We begin the coding by presenting a function with parameters that takes an input and produces an output. Hard-coded parameters in the function are; (a). Density of incoming vehicles in each direction (in cars per minute), (b). Throughput in each direction (in cars per minute), (c) offset (in minutes) and (d). Total time of the simulation (one day). The input in this setting is the duration of the green light (in minutes) in each direction group and the output will be the total waiting time. That is to say, the sum of waiting time of all the vehicles that had to stop at the crossing during the modeling period. The state of crossing is given by six numbers, of which numbers are either zero (red light) or one (green light). The valid states are the states that the trajectory of no two cars with a green light across, in other words, valid states are those that no collision occurs in them. In this regard, three valid states in our simulation are (Figure 3.8):

$S_1 = [1\ 1\ 0\ 0\ 0\ 1]$

$S_2 = [0\ 1\ 1\ 1\ 0\ 0]$

$S_3 = [0\ 0\ 0\ 1\ 1\ 1]$

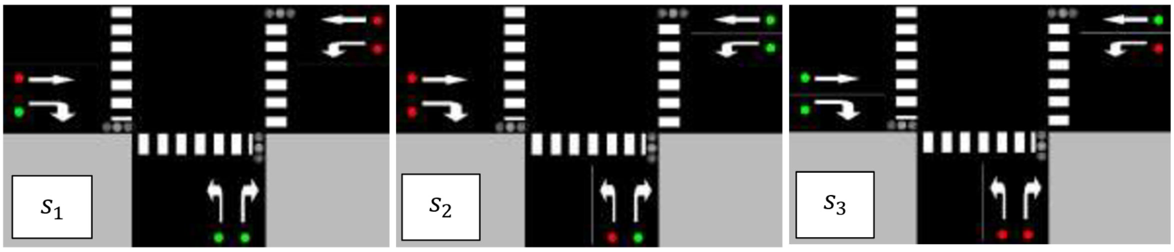



Figure 3.8. Valid states configuration in a T-junction (author)

Each state will last for a period, which means the crossing will be at state $s_1$ for $t_1$ minutes, then at state $s_2$ for $t_2$ minutes and then at state $s_3$ for $t_3$ minutes and then it will be repeated. In order for optimization to work, there is a need for an offset in minutes. Whenever there is a transition from any state to any other state, there is a penalization for everyone. The declaration of the function is described as bellow:

Function waiting_time = crossing (timetable)

> Timetable is defined as $t_1$, $t_2$ and $t_3$, which is the duration of the three states in minutes. $t_1$ is the duration of the first state ($s_1$), $t_2$ is the duration of the second state ($s_2$) and $t_3$ is the duration of the third state ($s_3$).
>
> Waiting_time is the total amount of time that all cars stop at the crossing during the simulation period.

The function gets the timetable and returns the total waiting_time. Finally, the pseudo-code is drafted as:

- Prepare admissible states; $s_1$, $s_2$ and $s_3$
- Prepare the timetable; $s_1$ for $t_1$
  $s_2$ for $t_2$

$s_3$ for $t_3$

- Set the state of the crossing to 0
  Cars = [0 0 0 0 0 0]
  Set the waiting_time to 0
- While time $<$ total model time
  State = current state
  Cars = cars + duration * density
  Cars = cars – cars that pass the intersection
  Waiting_time = waiting_time + cars * duration + offset
  End

We continue our simulation by coding optimization (appendix B). Switching lights in a timetable which are less than 0.2 and more than 1.5 minutes is too often, so the minimum and maximum allowed duration of a state is 0.2 and 1.5 minutes, respectively.Then we initialize the situation and increase the time for each state by 0.1 minutes. In a case that the new configuration is better than the current value, the current optimum and current times for the optimum will be updated.

Finally, the simulation will look at all the possibilities of $t_1$, $t_2$ and $t_3$ for the minimum total waiting time which is the optimum and displays it as the waiting time at the optimum. For a better comparison, the model also displays waiting time at the particular state, where the duration of each state equals one minute.

## CHAPTER 4 DISCUSSION & RESULTS

### 4-1- Methodology application

The result of our simulation is given in the three scenarios. We run our entire algorithm with the initial condition of zero vehicles at the beginning of the simulation. The duration of each state is allowed to be between 0.2 to 1.5 minutes, which will be increased by 0.1 minutes during a 24-h simulation. In addition, for the simulation to work properly, after each state changing, all the cars must wait at the intersection for 0.3 minutes. The last assumption for the simulation was a constant flow of cars (incoming cars) and capacity in unit of cars per minute. It should be noted that exceeding the capacity results in linear growth of queues, because the capacity is not enough for every vehicle to pass. Figure 4.1, illustrates the evolution of the number of cars in y-axis and time (minute) in x-axis in different directions. The lines from 1 to 6 are assigned to the number of cars waiting at each minute of the day. Based on the figure, directions 1 and 5 become progressively more and more congested and the queues grow during the whole day. In order to avoid linear growth of queues, we try to model situations where the capacity is not exceeded. In addition, for a better understanding, we compare the results of our simulation for all the three scenarios with the fixed time duration of each state equal to 1 minute.

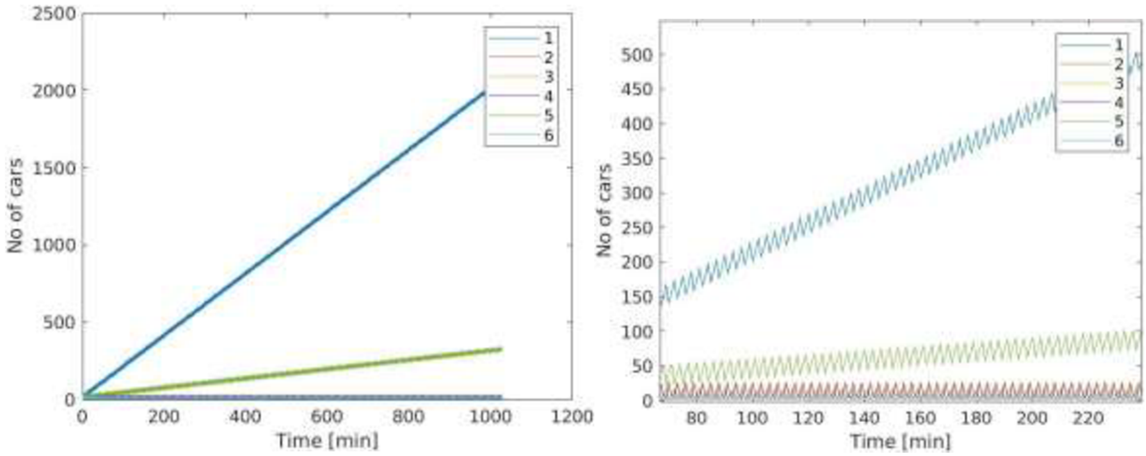



Figure 4.1. Exceeding the capacity leads linear queues in directions 1 and 5 (author)

### 4-2- The off-peak scenario

In the first scenario, the number of cars per minute in each direction is equal or less than 5 ([3 2 3 5 5 4]) and the capacity of all the directions is constant and equals 30 cars per minute. Comparing the result from the off-peak scenario and the pre-timed scenario, the total waiting time has improved from $3.69 \times 10^4$ to $2.03 \times 10^4$ in minutes at the optimum situation. According to the point that almost 30,000 cars arrived at the crossing during the modeling period, the total waiting time per single car would be 0.6 minutes in this scenario. The optimum duration of each state and total waiting time per single car is given in table 4.1.

Table 4.1. Comparison of fixed-time and off-peak scenario regarding the duration of each state and total waiting time per single car (author)

| Scenario | Duration of $s_1$ (min) | Duration of $s_2$ (min) | Duration of $s_3$ (min) | Total waiting time (min) per single car |
|---|---|---|---|---|
| **Fixed-time scenario** | 1 | 1 | 1 | 1.16 |
| **Off-peak scenario** | 0.2 | 0.2 | 0.3 | 0.6 |

The duration of each state in this scenario (12 seconds) is too short, which could be changed into flashing mode operation or turning the signals off. Based on Adbelghany & Connor (2006) report, the shorter cycle length is a potential approach for low volume off-peak traffics in order to minimize unnecessary stopping time at empty intersections. It is suggested that when traffic volumes are low, flashing mode traffic signal controls can be a cost-effective way to reduce delays, fuel consumption, vehicle emissions and electricity use. As a result, setting flashing traffic lights during non-peak hours could be used as a delay-reduction approach but it needs careful implementation and additional monitoring (Adbelghany & Connor, 2006).

Unjustified stops evoke contempt among drivers, who either dismiss the red light or simply slow down without stopping. Unoptimized off-peak signal timing often causes operational issues such as wasting fuel, increased pollution and delay and in some cases, more catastrophic outcomes (Amanzholov et al., 2009). It is assumed that as the signal stopping time is decreased, signal violations will decrease as well. By achieving the minimum waiting time in this scenario, it is expected that off-peak operations can be enhanced. It is believed fuel consumption, pollutant emissions and travel time all will improve in this regard. Figure 4.2, on the left side, shows that if the capacity is not exceeded we have a periodic graph because there is a periodic pattern and constant density of cars. On the right side, the single period and the switching points are illustrated.

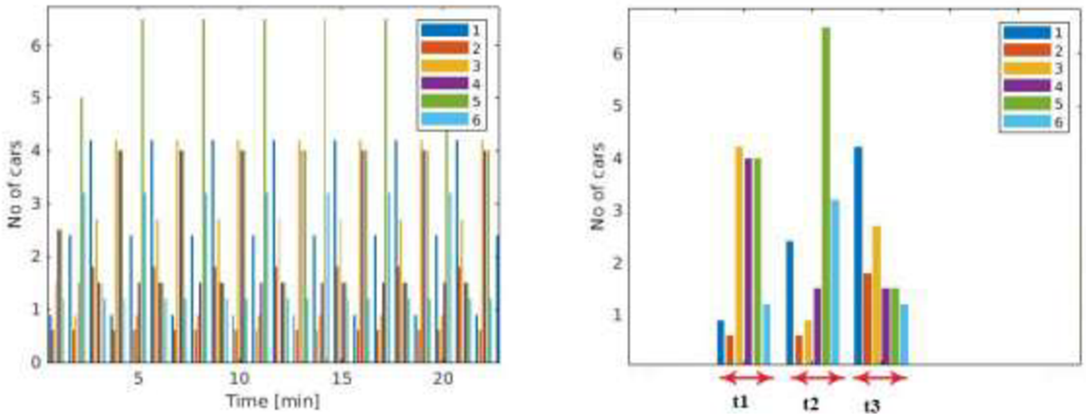



Figure 4.2. Number of cars waiting at each minute of the day for the off-peak scenrio for a single priod (right side) and periodic graph (left side) (author)

**4-3- The peak hours scenario**

During this scenario, the number of cars per minute increases in each direction ([5 8 6 12 9 5]) while the capacity has not changed (30 cars/min). Peak times are describes as times when vehicular demand is at its highest, resulting in the longest queues and waiting time (Ezzat et al., 2014). Traffic jam at peak hours is a major problem that must be tackled. This problem affects drivers in a variety of ways, including loss of productive working hours due to traffic congestion. It also results in the depletion of natural resources such as fossil fuel, which is used by the vehicle engine when it is running but stuck in traffic (Prasad et al., 2020).

Peak hours are usually from 6 a.m. to 10 a.m. and from 4 p.m. to 7 p.m. However, there are no fixed guidelines for calculating peak hour times. It is debatable that midday to 2 p.m. is another, less chaotic peak hour, with employees driving during lunch break. The comparison of the fixed-time and peak hours scenario has shown that although the duration of each state has decreased, the total waiting time can be improved from $1.83 \times 10^6$ to $5.93 \times 10^4$ minutes at the optimum condition. During peak hours more cars communicate in each direction, near 60,000 cars arrived at the intersection, which the total waiting time per single car equals to 0.9 minutes a day. The table 4.2 states the duration of each state and total waiting time per single car for both scenarios.

Table 4.2. Comparison of fixed-time and peak hours scenario regarding the duration of each state and total waiting time per single car (author)

| Scenario | Duration of $s_1$ (min) | Duration of $s_2$ (min) | Duration of $s_3$ (min) | Total waiting time (min) per single car |
|---|---|---|---|---|
| **Fixed-time scenario** | 1 | 1 | 1 | 27.20 |
| **Peak hours scenario** | 0.5 | 0.6 | 0.9 | 0.9 |

One of the concerns during rush hours is the rising number of car accidents. This accidents are most common in areas near congested roads when drivers prefer to drive faster before or after encountering traffic jams to compensate for the time lost (Djahel et al., 2015). When drivers observe long queues, they tend to drive faster or change their routes, which increase the probability of crashes. The following are some of the considerations that influence the waiting time at the traffic light intersections (Harahap et al., 2019):

1. Red light duration
2. Period of one traffic light loop
3. Number of cars joining the queue
4. Length of the queue

In this scenario as the duration of each state has been decreased compared to the pre-timed scenario, the drivers tend to be more patients, waiting for green lights. Based on figure 4.3., everyone is able to cross during one impulse, which avoids long queues during rush hours.

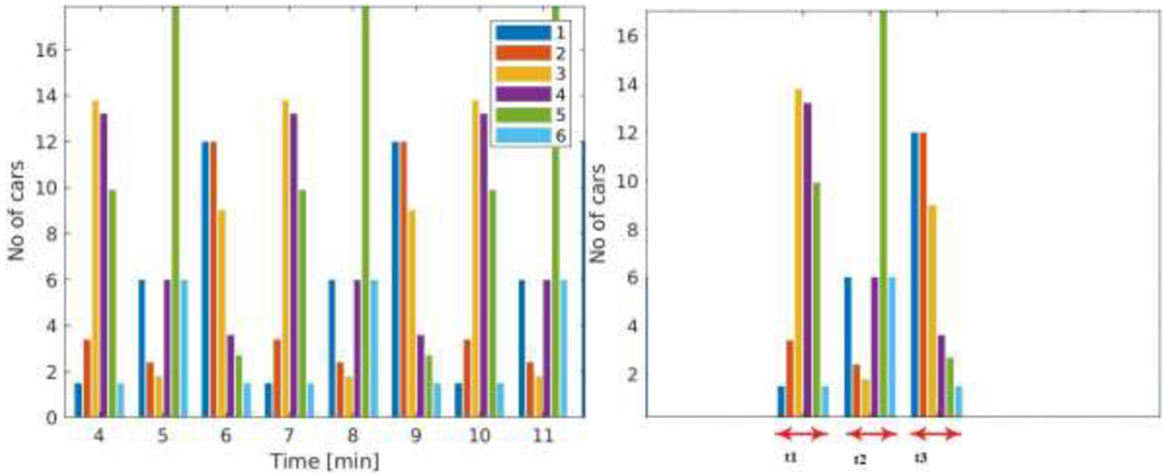



Figure 4.3. Number of cars waiting at each minute of the day for the peak hours scenario for a single priod (right side) and periodic graph (left side) (author)

Furthermore, the long red light duration will increase the probability of red-light running. Red-light running is a dangerous traffic violation that can result in fatalities or serious injuries at intersections. Traffic density, cycle length, green light duration, speed, signal coordination, presence of heavy vehicles, delay, intersection width, the position of other cars and signal visibility have all been found to affect frequency for car drivers. Right-angle and left turn-opposed are the two most frequent forms of road safety conflicts caused by red-light running.
Right-angle crashes happen as a result of the signal changing to green and drivers travel into the intersection. As a result, after few seconds of red have passed, the right-angle conflicts are more likely to happen. Left turn-opposed conflicts happen, when left-turning vehicle drivers accidentally turn in front of an opposing vehicle, assuming that driver will stop for the red light. These kinds of conflicts are likely to arise shortly after the start of red light (Goldenbeld, 2017). By shortening the duration of each state, we will decrease the chance of these two conflicts during peak hours.

Another issue regarding the traffics during the rush hours is a significant change in the air quality index (AQI). AQI is due to pollution caused by cars waiting in lines during peak hours or emergencies. AQI is a number used by government agencies to inform the public about the amount of pollution in the atmosphere. Traffic conditions, vehicle characteristics, vehicle's production year and its efficiency and road intersections influence the rate of harmful gasses emitted by vehicles. As a result, the quality of air in urban areas is largely determined by vehicular emissions, which are influenced by traffic patterns, road design or vehicle characteristics (Anjum et al., 2019). The mentioned simulation did not consider the pollution rate however, it is believed due to shorter waiting times and queues in the intersection, harmful emissions will decrease.

### 4-4- Increasing the capacity scenario

In this scenario, we decided to increase the capacity of each direction to 50 cars per minute. Building new roadway or managing existing roads can increase the capacity. Increasing the capacity by adding more lanes to the existing road or building new highways can reduce the congestion, on the other hand, is a significant construction project. As a result needs a large financial investment and often takes a long time to complete (*Urban Mobility Report*, 2011). Therefore, managing the existing infrastructure is more recommended. For a better understanding, this scenario has been compared with the same density of incoming cars of off-peak and peak hours scenario at the optimum situation. The result is reported in the table below.

Table 4.3. Comparison of the total waiting time in case of increasing the capacity (author)

| **Density of incoming cars per minute** | **Total waiting time (min) per single car** | |
|---|---|---|
| | capacity = 30 cars/min | Capacity = 50 cars/min |
| **[3 2 3 5 5 4]** | 0.6 | 0.6 |
| **[5 8 6 12 9 5]** | 0.9 | 0.64 |

By increasing the capacity, the density of incoming cars increased as well ([12 7 9 16 15 11]), in this regard total waiting will be improved in cars per minute. The optimized duration of each state and total waiting time is given in table 4.4. By increasing the capacity, the total number of cars that arrived at the intersection during the simulation increased to 100,000 cars, and the total waiting time per single vehicle will be 1.03 minutes a day. Similar to the other scenarios, we have a periodic graph due to the fact that our pattern is periodic and densities of incoming directions and capacity are constant (Figure 4.4).

Table 4.4. Comparison of fixed-time and increasing the capacity scenario regarding the duration of each state and total waiting time (author)

| Scenario | Duration of $s_1$ (min) | Duration of $s_2$ (min) | Duration of $s_3$ (min) | Total waiting time (min) per single car |
|---|---|---|---|---|
| **Fixed-time scenario** | 1 | 1 | 1 | 29.04 |
| **Increasing the capacity scenario** | 0.8 | 0.6 | 1 | 1.03 |

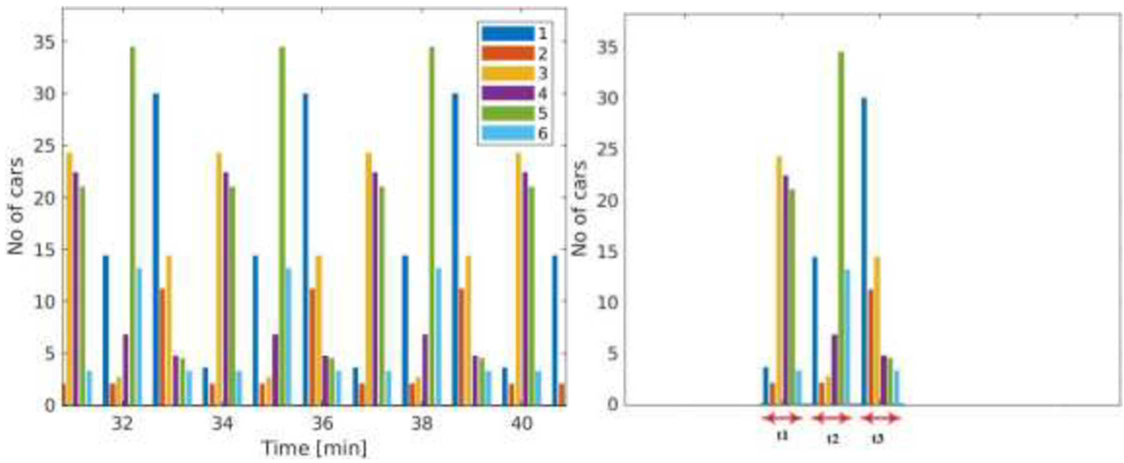



Figure 4.4. Number of cars waiting at each minute of the day for the increasing capacity scenario for a single priod (right side) and periodic graph (left side) (author)

According to Klibavičius & Paliulis (2012), improvements in traffic control may increase the capacity of street intersections. For instance, at the non-signalized junctions, suitable road surface markings, modifications in the traffic light duration at signalized crossings and coordinated traffic control at all junctions might assist accomplish these improvements. Under some circumstances, additional traffic lanes might be employed to alleviate oversaturated traffic problems at signalized junctions. As buildings are located at varying distances from street boundaries, streets have a restricted width that makes it impractical to create an additional lane across the length of the street between two intersections. In such a scenario, using short traffic lanes, which could bear a limited number of cars, is recommended (Klibavičius & Paliulis, 2012).

Xie & Jiang (2016) suggested an approach that does not need more land space and is simple for vehicles to follow. In this method, two different types of incompatible movements, which are strictly incompatible and potentially incompatible, are distinguished. Strictly incompatible movements are pairs of motions that proceed in opposite directions and whose trajectories cross in the intersection's center. These two movements cannot pass through the junction at the same time, and their green times must fulfill the clearance time requirement. Potentially incompatible movements are those that go to the same destination arm. In our simulation any pair of movements among movements (2,5), (1,4) and (6,3) in Figure 3.7 are potentially incompatible as they are heading to the same arm. By properly allocating exit lanes, there is the possibility to overcome the conflict between potentially incompatible movements, which reduced the requirement to separate their green lights duration by a clearance period. Therefore, these two movements can travel through the junction at the same time, thereby increasing the utilization of the exit lanes on the destination arms and creates the possibility for potential capacity improvement (Xie & Jiang, 2016). In our algorithm, by allocating appropriate exit lanes (figure 4.5) we would have different valid states that could enhance our simulation.

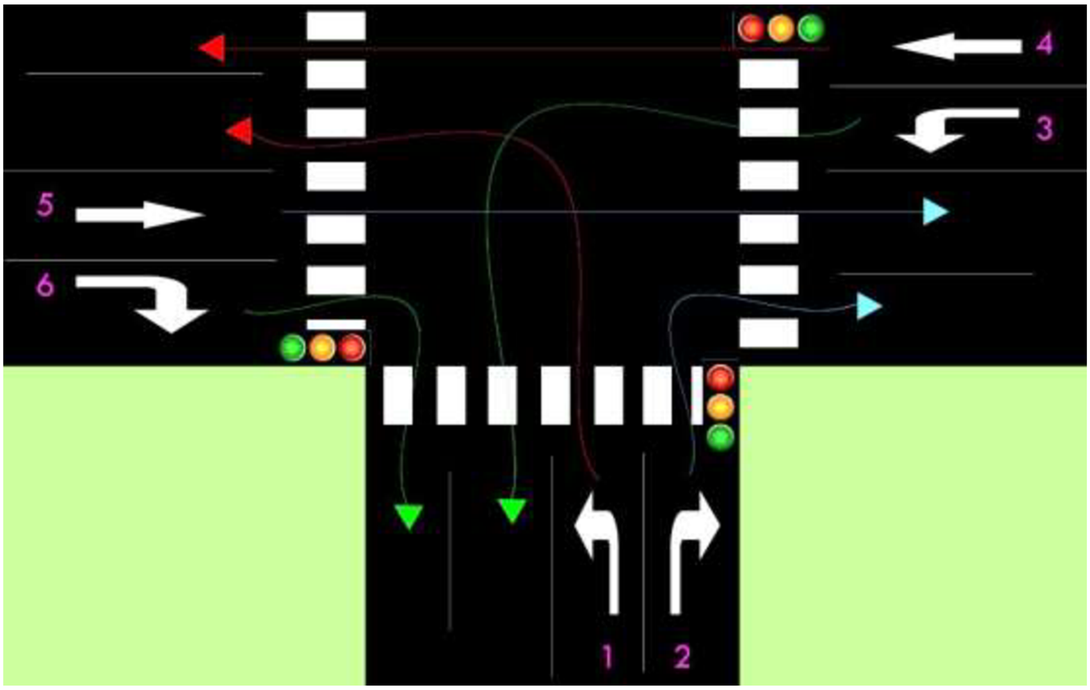



Figure 4.5. Movements (2,5), (1,4) and (6,3) are made compatible of each other by allocation of existing lanes (author)

# CHAPTER 5 CONCLUSIONS & RECOMMENDATIONS

## 5-1- Conclusion

Smart mobility is an intuition, based on the smart city idea that could lead to a more prosperous future. One of the main objectives of introducing smart mobility in urban areas is reducing traffic congestion and total traveling time, which could be achieved by optimizing the traffic light setting. This study aimed to take a step to transform Olomouc into a smart city by utilizing fixed-time traffic signals at intersections. Normal pre-timed traffic lights are inefficient and often result in traffic jams at peak hours, while people are forced to wait unnecessarily longer during off-peak periods. Based on the results that were obtained from programing in MATLAB, three main scenarios were proposed for three valid states.

As was reported in Ma et al. (2020), the cost of installing and maintenance of vehicle-actuated and adaptive signal controls, which collect data by loop detectors are more than fixed-time signals. Thus, in this study we focus to optimize the current pre-timed signals in the city to be more economical.

According to Park et.al (2004), traffic engineers create several signal timing plans to manage changes in traffic demand over time, particularly by the time of the day. A signal timing schedule for the morning hours will differ from the afternoon peak so it is preferable to use two separate signal timing schemes. This strategy is noted as TOD mode control, which is the most frequent traffic control solution for nonadaptive signals. Along with this paper, one of the main goals of this investigation was identifying optimal TOD plans for intersections with considerable changes in traffic volume. In this regard, two scenarios were introduced for peak and off-peak periods, based on the density of incoming cars in different directions. The key idea behind proposing time-of-day schemes is to try to maximize the duration of green light for routes that suffer from traffic jams during peak hours, particularly along routes where citizens conduct their daily routine activities. To put it another way, the key goals are reducing the average waiting time during peak times and increasing the number of cars passing through the intersection every day.

Comparison of the pre-timed scenario of 1 minute for each state and the optimum conditions, stated that the total waiting time for both scenarios (off-peak and rush hours) decrease to a considerable amount. The total waiting time during peak hours improved significantly from 27 minutes per single car to 0.9 minutes, while non-peak hours improved less significantly from 1 minute to 0.6 minutes per single vehicle a day at the optimum condition, respectively.
It was found that by increasing the capacity from 30 to 50 cars per minute, the intersection could hold more number of cars and the total waiting times in cars per minute will improve in this scenario. The total waiting time per single vehicle enhances from 29.04 minutes in the fixed-time scenario to 1.03 minutes at the optimum state for a day.

Theoretically, the waiting time for drivers during rush and non-rush hours could be decreased, making the system more efficient than it is now. The relationship between the mentioned model and air pollution was not investigated but based on similar researches there is a chance of $CO_2$ reduction in the long term. Also along with Borkar and Jenekar (2012), due to the cycle length duration for green and red light, it is expected that vehicle speeds become more uniform, since there is no reason to drive at unnecessarily high speeds to pass the intersection within a green light. In addition, the slow driver is urged to accelerate in order to stop at a red light (Borkar & Jenekar, 2012).

Finally, back to our research questions, based on the results that were discussed we figured out that the mentioned mathematical modeling can be optimized if it changes during peak and non-peak periods. Furthermore, it was shown that the algorithm has the potential to reduce total waiting time and delays. Due to the fact that engines are running while vehicles are waiting to pass the intersection, by reducing the total waiting time, there is the possibility to reduce air pollution as well. By validating the current algorithm on real data, it can be used in practice as the beginning step towards smart mobility.

### 5-2- Recommendations

Based on the experiments of this research and other similar researches, the following points are recommended to improve the algorithm:

- It is better to get the real time traffic data and use a random process (not constant density) with the correct characteristics for more intersections in the Olomouc
- Modeling and optimizing algorithm for changes during the day as they are not constant.
- Modeling and optimizing traffic light setting for continuous-time modeling, as traffic crossings are continuously evolving throughout the time.
- Adding pedestrians for improving the simulation. Pedestrian flow and volume in urban areas can influence the total waiting time for vehicles.
- Type of the vehicle including heavy and light vehicles must be considered as well. This is due to the fact that the kinds of vehicles on the road at any given time are very diverse, which can decrease the capacity value. Heavy vehicles (trucks, buses) take up more space and they often have a lower speed than light ones, causing traffic to flow more slowly.
- In more advanced models, human factors including driver's impairment, frustration or speed of reacting to incidents could be considered.
- Considering a relation between the amounts of GHGs each engine produces while waiting at the crossing could improve the algorithm in accordance with the air pollution concerns.

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**Appendix A**

```
% main coding

function argout = Crossing_fce(argin)

times = argin; % duration of the states
% times(i) is the duration of state(i,:)

% Admissible (and intelligent) states of the crossing: 0 for red light and 1 for green light
states = [1 1 0 0 0 1; ...
   0 1 1 1 0 0; ...
   0 0 0 1 1 1];
% state(i,:) lasts for times(i) minutes
% then it repeats..
offset = .3; % [min] penalisation for each state change

day1 = repmat([1;2;3], [100000 1]); % many cycles of state1, state2, state3
day2 = times(day1); % duration of the states [min]
day3 = cumsum(day2); % cumulative sum (= minute in the day)
day = [day3 day1]; % [time of day, programme]
% between minutes day(i-1,1) and day(i,1) programme day(i,2) is running

cars = [0 0 0 0 0 0]; % intial state of queues (at minute=0)
density = [x x x x x x]; % density of incomming traffic [cars/min] in each direction
capacity = [x x x x x x]; % throughput of the crossing in each direction [cars/min]
zero = 0*capacity; % technical (all zeros)
wait_time = 0; % total waiting time allocation
i=0; % index in the 'day' field
perform = true; % while not the end of the day

while perform % during one day

   i = i+1;
   state = day(i,2); % this programme is now on
   duration = times(state); % for this long it lasts
   cars = cars + duration*density; % these many cars arrived at the crossing
   maygo = states(state,:).*capacity*duration; % as many as these cars can pass
   cars = max(cars - maygo, nuly); % current state
   cars = cars + offset*density; % penalisation for all red lights
   pom = sum(cars)*duration; % waiting time during this period
   wait_time = wait_time + pom; % total waiting time
   perform = day(i,1) < 24*60; % until the end of the day

end

argout = wait_time; % total waiting time
```

**Appendix B**

```
% optimization

tmin = 0.2; % [min] minimum for a duration of a state
tmax = 1.5; % [min] maximum for a duration of a state

%initialization
N = 1e6;
wait_time = nan(N,1);
times = nan(N,3);
pos = 0;

step = 0.1; % [min]

for t1 = tmin:step:tmax
   for t2 = tmin:step:tmax
      for t3 = tmin:step:tmax

         pom = Crossing_fce([t1;t2;t3]);
         pos = pos+1;
         wait_time(pos) = pom;
         times(pos,:) = [t1,t2,t3];


      end
   end
end

pos = pos+1;
wait_time(pos:end)=[];
times(pos:end,:)=[];

kde = find(wait_time == min(wait_time)); % index of the optimum
wait_time(kde) % disp wait time at the optimum

kde1 = find(times(:,1)==1 & times(:,2)==1 & times(:,3)==1); % find a particular state
wait_time(kde1) % disp wait time at this state
```