D 2020

U. PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

OPTIMUM ROAD NETWORK DESIGN FOR THE DEPLOYMENT OF AUTOMATED VEHICLES IN URBAN AREAS

LÍGIA CONCEIÇÃO PEREIRA
TESE DE DOUTORAMENTO APRESENTADA
À FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO EM
SISTEMAS DE TRANSPORTES

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OPTIMUM ROAD NETWORK DESIGN FOR THE DEPLOYMENT OF AUTOMATED VEHICLES IN URBAN AREAS

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DOCTORAL THESIS IN TRANSPORT SYSTEMS

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MAY 2020

DOCTORAL PROGRAM IN TRANSPORT SYSTEMS

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Co-funded by:

FCT
Fundação para a Ciência e a Tecnologia
MINISTÉRIO DA CIÊNCIA, TECNOLOGIA E ENSINO SUPERIOR

MIT Portugal

This research is supported by the Ph.D. scholarship grant PD/BD/113760/2015 awarded by the Portuguese Foundation for Science and Technology (FCT) under the MIT- Portugal Program.

To the following decades,

"Minds are like parachutes - they only function when open."

Thomas Dewar

“As in life, in sailing, you must believe in something you don’t see but feel (wind). You can even lose the tiler, but never your way. Direction is more important than speed.”

Anselmo Cassiano

O princípio da Sabedoria é o desejo autêntico de instruir, e desejar instruir-se é já amá-la.

Sb 6,17

DECLARATION OF ORIGINALITY

I hereby confirm that this thesis is my own work. Whenever published or unpublished work of others is used in any way, appropriate references are made.

ABSTRACT

Fully automated vehicles (AVs) are not yet a reality but already cast speculation on the future of urban regions. Several impacts are expected at different levels, mostly at traffic and mobility levels – which can disrupt the current transportation paradigm. Since the deployment of AVs will not happen from one moment to the next, a transition period must be considered to adjust the upcoming changes best ahead.

This study focuses on transport planning and traffic operation of AVs deployed in urban regions, as most of the existent research focuses on the technical features of driverless vehicles and their deployment in interurban environments. Specific urban transport policy shall be devised to leverage benefits from AVs and mitigate any adverse impacts. This thesis aims to contribute to this research gap.

The first part of the thesis aims to help city planners with a transport planning strategy. The main objective is to optimize the road network design of urban regions. In this complex transport planning problem, it is analyzed whether the segregation of mixed and automated traffic is valuable for the system and, if so, which roads within the urban network should be dedicated for connected AVs.

The second part of the thesis aims to help traffic engineers dealing with congestion. The main objective is to prove that a novel traffic control system centered on the network topology variation is viable. This strategy takes advantage of AVs connectivity to improve the traffic level of service.

The methodological objectives of this thesis are: 1) to develop an optimization model founded on mathematical programming that selects dedicated roads for AVs in urban networks; 2) to develop an optimization model to design the optimal lane layout of AVs dedicated roads; 3) develop a simulation-optimization model for solving road network design problems in large urban areas to maximize road capacity by making use of reversible lanes.

Two case studies are applied: a small-size city of Delft, the Netherlands, and a medium-size city of Porto, Portugal.

In summary, the general objectives of this thesis are:

1. to study whether the segregation of mixed and automated traffic through dedicated roads is valuable for the system;
2. to estimate the AVs' impact on traffic and congestion levels during the transition period;
3. to evaluate the benefits of having a dynamic reversible lane approach applied in AV dedicated roads;
4. to analyze the utility of centralized (system-optimal) AV paths on mitigating congestion.

KEYWORDS: automated vehicles, dedicated roads, reversible lanes, road network design, optimization, simulation.

RESUMO

Apesar dos veículos totalmente automatizados ou autónomos (AVs) não ainda serem uma realidade nas regiões urbanas e metropolitanas, existe uma imensa especulação sobre como será o futuro destas perante esta tecnologia. De acordo com a literatura, vários impactos em diversos níveis, principalmente ao nível do tráfego e da mobilidade, são expectáveis de ocorrer, podendo corromper com o atual paradigma de transportes. Uma vez que, nos centros urbanos, a circulação de AVs não aparecerá de um momento para o outro, um período de transição deverá ser considerado para adaptar o meio urbano da melhor maneira possível.

Esta tese incide no planeamento de transportes e controlo de tráfego para a circulação de AVs em regiões urbanas. A maioria da literatura existente concentra-se nas características técnicas de veículos e a sua circulação em ambientes interurbanos (autoestradas). Deste modo, esta tese prentende contribuir para o desenvolvimento de estratégias específicas a aplicar em meio urbano, de forma a tomar partido dos benefícios tecnológicos (conectividade) dos AVs e mitigar quaisquer impactos adversos, como o congestionamento.

A primeira parte da tese pretende dar suporte ao planeamento da cidade com uma estratégia de planeamento da rede de estradas. O principal objetivo é otimizar a circulação dos veículos na rede viária em meio urbano. O problema incide na segregação do tráfego de AVs dentro da rede viária de forma a ser globalmente benéfica para o sistema, reflectindo-se em estradas com tráfego misto e outras com tráfego automatizado, ou seja, dedicadas ao tráfego de AVs.

A segunda parte da tese pretende ajudar os engenheiros de tráfego a lidar com o congestionamento. O principal objetivo é testar um novo sistema de controlo de tráfego focado na variação topológica da vias ao nível da rede viária. Essa estratégia toma partido da conectividade dos AVs para implementar vias reversíveis e melhorar o nível de serviço das estradas.

Os objetivos metodológicos desta tese são: 1) desenvolver um modelo de otimização em programação matemática que decide quais serão as estradas dedicadas para AVs em meio urbano; 2) desenvolver um modelo de otimização para planear as vias reversíveis em estradas que já são dedicadas aos AVs; 3) desenvolver um modelo de simulação e otimização para resolver problemas de maior complexidade que maximize a capacidade das estradas usando vias reversíveis.

Dois estudos de caso são aplicados: uma cidade de pequena dimensão de Delft, na Holanda, e uma cidade de média dimensão do Porto, Portugal.

Em resumo, os objetivos gerais desta tese são:

1. estudar se a segregação do tráfego misto e automatizado é benéfica para a rede;
2. estimar o impacto dos AVs ao nivel do tráfego e congestionamento durante o período de transição;
3. avaliar os benefícios de implementar uma estratégia de vias reversíveis em estradas dedicadas aos AVs;
4. analisar a utilidade de centralizar (otimização do sistema) a decisão das rotas dos AV para mitigar o congestionamento.

PALAVRAS-CHAVE: veículos automatizados, estradas dedicadas, vias reversíveis, planeamento da rede viária, optimização, simulação.

ACKNOWLEDGMENTS

I would like to sincerely thank the MIT Portugal Program and Portuguese Foundation for Science and Technology (FCT) for financially supporting my studies (PD/BD/113760/2015). FEUP, where this work is developed and presented. The department of Civil Engineering, explicitly the transport infrastructures section, my second home over the last years. My supervisors: José Pedro Tavares who shared notorious insights with a solid traffic engineering perspective, always trusting and supporting my research; Gonçalo Correia who greatly contributed for this thesis with a perfectionist and challenging perspective towards the best outcomes, thank you. From TU Delft, I thank Bart van Arem who shared many insights in the first visiting period of my PhD journey. From MIT, Carolina Osorio, who stimulated my knowledge towards simulation and optimization in my second visiting period. Jorge Pinho de Sousa who supported this research. António Pais Antunes who supported the topic since the first proposal. Adalberto França and Carlos Rodrigues, who during my masters, initiated the spark on transportation. Alvaro Costa for the interest and curiosity. I also want to thank Rosaldo Rossetti for the informatic insight during my first year as a PhD student. Guilhermina Castro, Carla Monteiro, Flavia Cardarelli, Isabel Ribeiro and Leah Lovgren for administrative support.

I would like to thank FICO (Xpress software provider) for establishing a research agreement with the Department of Transport & Planning at TU Delft. Additionally, Mathworks Inc. (Matlab software provider) and PTV (VISUM software provider) for establishing a research agreement with the Faculty of Engineering of the University of Porto.

A very special word of thanks goes to my friends who accompanied me these years with advice and patience. Filipa Côrte-Real Beirão, the sister I always wanted, thank you. Claúdia Casal, for inspiring me on pursuing a Ph.D. when I was just a kid. Pedro Santos, my enduring friend. Ana Clara Lage, João Lage and family for the good energy and unforgettable memories. Christopher and Liliana Ribeiro, for the friendship and memorable moments in the US. My cousin, Carlos Costa, for the fruitful insights on ITS. André Carvalho, for the good and the worst, persistence, patience, all the books and all the random brainstorms. My wise friend, Diogo Catarino. FEUP or Ph.D. colleagues that are now friends for life: Ana Patrícia Oliveira, Anna Beatriz Espíndola; Catarina Cadima; Elis Silva, my dear; Joana Hora, my war companion; Mayara Monteiro; Melissa Mariana Silva; Rita Justo Silva; Sónia Soares; André Nóbrega; Alvaro Câmara; Aymen Boudebouz; Diego Neris; Francisco Soares; Guilherme Soares; João Neves; Marco Amorim; Miguel Pinto; Muhammed AH; Pedro Oliveira Ferreira; Samuel Matias and Thiago Sobral. Friends from Delft: Katerina Wojtaszekova, Afonso Ferreira; Jaime van Barros, Pedro Parreira. TU Delft lab colleagues: Xiao Liang and Freddy Antony. The MPP folks who were my family in the US: Cátia Salgado, Joana Abreu, Vanessa Tavares, António Alves de Campos, Fabian Heyman, Gonçalo Pereira. Valery Lyons, for welcoming me in the US. MIT CEE lab colleagues: Timothy Tay and Zhou Tianli. Friends from the MIT Sailing Pavilion: my dearest friend Anselmo Cassiano Alves, Conan Hom, and John Aleman, for sailing with me in the most beautiful sunsets on the Charles River and joyful sunrises at Boston harbor. My friend Francisco Assis who helped me in a critic moment.

Foremost, my beloved mother, Irene Conceição, the core of everything I am – my family, my rock, my safe port. *Obrigada Mãe, por todo o amor, paciência, presença e todas as vitaminas que compraste nos últimos anos por preocupação. Obrigada por todos os esforços que fizeste para me dar a melhor educação. Amo-te.*

Finally, my country, Portugal, whose society provided all the resources needed for my education and personal fulfilment. Thank you all.

Lígia Conceição

May 2020

Porto, Portugal

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Acronyms and Abbreviators

AV – Automated Vehicle

ACC – Adaptive Cruise Control

CACC – Cooperative Adaptive Cruise Control

CV – Conventional Vehicle

DS – Degree of Saturation

GA – Genetic Algorithms

IP – Incremental Planning

LTP – Long-Term Planning

MIP- Mixed Integer Programming

MIQP – Mixed Integer Quadratic Programming

NLP – Non-Linear Programming

ITS – Intelligent Transportation Systems

OD Matrix – Origin-Destination demand matrix

RNDP – Road Network Design Problem

RNDP-AVs – The Road Network Design Problem for the deployment of AVs

SO – Simulation-Optimization

SOF – Simulation-Optimization Framework

VTT – Value of Travel Time

V2I – Vehicle to Infrastructure Communication

V2V – Vehicle to Vehicle Communication

1

INTRODUCTION

1.1. CONTEXT

Over the last century, transportation systems have evolved primarily due to social and economic pressure, always alongside technology. As the core element of urbanization, its performance impacts several levels that describe both accessibility and mobility of cities, influencing citizens' lives. Back in the past, the main drive that increased road capacity was mostly done by improving and expanding infrastructure; for instance, through roadways expansion. Mobility has been improving gradually alongside with accessibility and technology that has had a particular role on advancing the modes of transport. Mobility is typically fostered by transport planning strategies, for instance, through public transport and transportation companies like carsharing and ride-hail systems – highly advanced by technology in the last century.

The idea of automated highways was firstly introduced in 1939 at the New York World's Fair, yet seen as futurist and science fiction. Over the past two decades, technological development has also been growing on the side of vehicle automation, focusing on automated driving systems. In 2004, the US Defence Advanced Projects Agency (DARPA, 2004) heavily promoted automated driving systems, after Eureka PROMETHEUS (Scholl, 1995), VaMP, ARGO (Broggi, 2001) research projects disclosed their first research results (Albanesius, 2010). Recently, research has shown that automated vehicles (AVs) will bring significant changes in transportation systems. However, while aiming to enhance mobility, AVs can disrupt the current transportation paradigm in urban areas in such a way that is still difficult to foresee nowadays (Correia et al., 2015).

Urban areas are gradually growing in population worldwide. In 1950, only thirty percent of the world's population lived in cities. In 2014 the rate was above fifty-four percent, and the forecast for 2050 is more than two-thirds of the world's population living in cities (Ilboudo et al., 2016). More population density promotes geographical expansion with land-use adjustments, new mobility patterns, and increased transportation demand, either public or private. Growth in private transport is forecasted, despite any competitiveness and quality improvement of public transport (Correia et al., 2015). In this sense, AVs are believed to naturally appear also in the form of private owned transport, given the benefits at the micro and macro level, e.g., the citizen quality-of-life from commuting door to door whenever they like, and the leverage of global economy.

However, more vehicles, mainly privately owned, overpressure cities that are already grappling with road traffic issues nowadays. For instance, in the last three decades (1987-2017), the annual cost of traffic delays per commuter has nearly doubled in the US (Schrank et al., 2019). According to INRIX Global Traffic Scorecard, in 2018, the average commuter spent in congestion in Paris was 237 hours, 7% more than the previous year. Similarly for the greater Boston area (US), in average, each driver lost 164 hours, almost a week (6.8 days), to congestion, costing each driver $2,291 on average a year – the entire area costs over $4 billion per year (Reed and Kidd, 2019). Besides, road accidents grasp more than 1.25 million fatalities every year (Toroyan et al., 2013). Transport infrastructure costs 20 to 30 percent of the land, on roadways, and parking lots (Litman, 1995). The Australian Bureau of Infrastructure, Transport and Regional Economics reported that the cost of congestion is growing in large cities alongside with population growth, leading to an infrastructure investment of US$600 billion over the next fifteen years (Bureau of Infrastructure, 2019). All these trends concern societies, and a new form of transportation without human intervention, i.e., AVs, must be well planned to alleviate or surpass these problems; otherwise it might worsen transportation systems in general.

1.2. THESIS RESEARCH

1.2.1. RESEARCH PROBLEM

Currently in the academy, AVs are a hot topic of research. Most of the existent research around driverless vehicles focuses on the technical features (e.g., adaptive cruise control systems) and traffic impacts in interurban traffic environments (e.g., road capacity). In urban areas, research is still scarce, though urban environments are the most prospected to have significant impacts from AVs deployment (Correia et al., 2015). The research gap in urban regions is mainly due to the complexity of modeling metropolitan areas with some kind of realism, given the number of variables (e.g., flow of pedestrians, bicycles, bus, among others) and the computational cost on modelling diverse types of roadways (e.g., highway hierarchy) and infrastructure (e.g., strict geometric features, intersections, roundabouts, parking lots).

Urban areas are confined spatially, yielding land-use constraints and a high level of population density. As a consequence, congestion surges in peak hours from commuting patterns, hindering urban mobility. Over the last few decades, the current urban congestion problem was hardly handled by infrastructure expansion and current traffic management strategies. The inevitable coexistence between AVs and conventional vehicles (CVs) is expected to happen either in urban or interurban areas (Nieuwenhuijsen, 2015). GHSA (2016) foresees “a mix of autonomous and driver-operated vehicles on the road for at least 30 years”. According to recent research, the automated driving features will barely improve capacity of existent roads.

In this sense, the thesis problem is how to tackle urban congestion during this transition period by taking advantage of automated traffic and the existent road space. The aim is to optimize urban networks by strategically designing AV subnetworks with smart and optimized traffic management, as long as it does not substantially disturb the human-driven traffic (CVs), and the overall traffic system is improved. The thesis research focuses on optimum road network design for strategic transport planning in a transition period where both AVs and CVs coexist together, and smart traffic management optimized and applied to AV subnetworks.

1.2.2. GOALS AND CLAIMS

The goal of this thesis is to aid the transport planning of urban metropolitan regions to engage in AVs technology and tackle urban congestion by improving the overall traffic system. In other words, to propose a feasible transport planning for AVs traffic management of a smart city in the short and long-term of AVs' deployment. The research goal acts on two levels. At the upper level: supporting urban planners with a road network design for planning ahead the integration of automated traffic within urban areas. At the lower level: supporting traffic engineers with a lane traffic control to take advantage of the automated driving task and increase the level of service.

The claims of this thesis are the following:

1. The deployment of AVs in urban areas implies a transition period where AVs will coexist with CVs in urban areas.
2. The autonomy of AVs will play an important role in urban areas once AVs technology reaches level 4 that allows AVs to circulate autonomously.
3. Smart cities will be interested in controlling automated traffic to improve the overall traffic system, but also to articulate with other modes of transport.
4. Vehicle-to-infrastructure (V2I) communication will be the answer for controlling AVs and is an investment decision that municipalities will face at some point.
5. Automated traffic systems are more efficient than mixed traffic. The mixed traffic hinders the potential of boosting road traffic efficiency from AVs technology.

The reason that supports this claim (theoretical support) is the current infrastructure is shaped for CVs, and, at the beginning of the automated traffic operation, traffic efficiency may be compromised within mixed traffic from the technological side. There are prospects that congestion will get worse in urban areas as AVs get deployed and traffic flow increases. Therefore, in dedicated roads for automated traffic, the mitigation of congestion and travel time savings will be much more significant and easier to tackle (V2I technology).

1.2.3. Research Questions and Hypotheses

This thesis aims to answer three main research questions by testing the corresponding hypothesis:

RQ 1. Which approach can be used by policymakers to deal with the deployment of AVs in urban areas during the transition period?

H 1. Segregated traffic (mixed and automated) in urban centers optimizes the overall traffic system, reducing congestion. The overall road traffic will only be enhanced if AVs have dedicated roads to circulate automatically inside them.

RQ 2. In which way automated traffic can improve the existent capacity of urban roads?

H 2. Practical capacity can be improved through automated traffic through a dynamic lane management approach, i.e., reversible lanes.

RQ 3. Does control of AVs' paths towards a system optimal equilibrium solve the congestion problem inside AVs subnetworks?

H 3. Mitigating urban congestion is possible without a centralized system controlling AVs paths.

1.2.4. OBJECTIVES

The first part of the thesis aims to help city planners with a transport planning decision model of which roads within the urban network should be dedicated for connected AVs. The second part of the thesis aims to help traffic engineers dealing with congestion with a novel traffic control system centered on reversible lanes for automated traffic only.

The general objectives of this thesis are the following:

1. to study whether the segregation of mixed and automated traffic through dedicated roads is valuable for the system;
2. to estimate the AVs' impact on traffic and congestion levels during the transition period;
3. to evaluate the benefits of having a dynamic reversible lane approach applied in AV dedicated roads;
4. to analyze the utility of centralized (system-optimal) AV paths on mitigating congestion.

1.2.5. RESEARCH APPROACH AND METHODOLOGICAL OBJECTIVES

The philosophical stance of the following research is objectivism. This research is ontologically based on the objective side of reality – traffic and congestion can be measured and quantified in reality. Epistemologically, it is used scientific methods on observable and measurable facts (travel demand) to build a new strategy that will contribute to reducing congestion. In terms of methodology, a quantitative research strategy is adopted under available quantitative datasets in both case-studies. The specific term for the philosophical stance of this research is positivism.

The methodological objectives of this thesis are:

1. to develop an optimization model founded on mathematical programming that selects dedicated roads for AVs in urban networks;
2. to develop an optimization model to design the optimal lane layout of AVs dedicated roads;
3. to develop a simulation-optimization model for solving road network design problems in large urban areas to maximize road capacity by making use of reversible lanes.

1.3. THESIS OUTLINE

This thesis is structured in six chapters.

Chapter 1 herein provides background information for understanding the relevance of this topic in the global context and its contextual research perspective. Objectives, claims, and research approach are addressed, as well as the outline of the thesis.

Chapter 2 describes the state of the art, both at the industry and academy level. The AV concept and definition are debated, as well as its technological development overtime accompanied by forecasts.

Chapter 3 discusses the transport planning problem of designing AV subnetworks during a transition period where AVs coexist with human-driven vehicles (CVs) – AV penetration rate evolving from 0% to 100%. A road network design problem applied to the problem of selecting dedicated roads for AVs inside an urban network is presented. The road investment effect is discussed. The model is applied to a case study of the city of Delft, in the Netherlands. The design for the peak hour and the whole day is debated.

Chapter 4 discusses the traffic operation of AVs working in dedicated infrastructure that carries V2I connectivity – only possible in smart cities. An optimization problem of reversible lanes applied at the network level is presented. In addition, it is debated whether a centralized traffic control system should (not) control over AVs paths. The model is applied to a case study of the city of Delft, in the Netherlands, for a penetration rate of 100% of AVs.

Chapter 5 presents an approach that joins both simulation and optimization in a single framework to solve road network design problems in large-scale urban areas. The simulation-optimization framework solved the problem of desigining reversible lanes in a the case study of the city of Porto in Portugal.

Finally, Chapter 6 provides the conclusions, significant contributions, scientific publications from this thesis, and suggestions for future work.

2

STATE OF THE ART

2.1. INTRODUCTION

Technology has been evolving significantly since the industrial revolution. In the nineteenth century, a clear shift happened from vehicles pulled by animals to public rail transport pulled by electricity, in the form of omnibuses and electric trams. At the turn of the century, gas-powered vehicles rapidly emerged as fossil fuel became the primary source of energy. Nowadays, new forms of energy sources have been implemented like electric and hydrogen vehicles. During this technological advancement, people have always been responsible for the driving task and deciding the path. Driverless vehicles, departing from this human-centric perspective, will be the next shift in vehicular transportation.

Around the world, literature mentions different designations regarding AV that may overlap or be combined. Over time, several designations have appeared, leaving many questions unanswered regarding the implications of different contemplated deployment scenarios. Section 2.2 clarifies the concept of AV, explaining the established levels of automation in parallel with the current state of manufacturing (and technological development).

The assessment of the impacts of the deployment of AVs in urban networks is still unknown and difficult to determine. Section 2.3 discloses the literature review around the impacts of AVs that, according to Milakis, van Arem, and van Wee (2017) are divided into three levels that have a ripple effect amongst them: first, the traffic level that will have an effect on the mobility level, and consequentially on the societal level.

Section 2.4 is focused on the deployment of AVs in urban areas, explaining why it is mandatory to consider a theoretical transition period; then, why the need for transport policy, to regulate and control AV tests in real environments and to plan ahead the real deployment of AVs in urban areas; and at last, the state of research focused on network design for transport planning and traffic operation.

Finally, section 2.5 reports the main summary and conclusions of this chapter.

2.2. The Automated Vehicle

2.2.1. Definitions and concepts of autonomous and connected vehicles

“Smart” vehicles are often mentioned with different names that may even overlap or be combined, such as autonomous, automated, automatic, autopilot vehicle, cybercar, robotic, self-driving, or driverless cars. In order to choose a consensual designation, it is essential to clarify and distinguish features from its inherent attributes and specificities.

In all designations, the common feature is that driving is performed robotically and automatically, without human control. To do so, the external environments are imperative. Therefore, two distinct views emerge: the first reflects the autonomy and the second the cooperation.

Shladover (2009) schematized the relationship between automation, autonomy, and cooperation. Cooperation and autonomy are antonyms, and they are orthogonal to the level of automation. The highest level in both dimensions is attained with the so-called full advanced automated highway systems, which should be the ultimate stage of development and deployment.

The autonomy view entails an autonomous driving that is supposed to sense the external environments, and the vehicle is expected to drive with whatever the road and infrastructure conditions. In other terms, the vehicle has the ability to self-drive itself, e.g., driven autonomously, and senses the external environments whatever the road type and its conditions, without any internal (human) or external control/support. The decisions taken while driving are not influenced by external authorities – corresponding to the term of *autonomous vehicle*.

The term *autonomous vehicle* is still the most widespread and more familiar to the public (Chang et al., 2012). This concept was initially envisioned in the robotics and telecommunications fields, and thereafter traffic operators suggested that these vehicles should act linked to achieve traffic efficiency. Whereas autonomy implies no control or influence from outside, cooperation considers communication that relies on direct or indirect control of the driving task.

Connection is an analogous term to cooperation that denotes a vehicle that is able to establish communication with the infrastructure (V2I) or/and other surrounding vehicles (V2V) to perform decisions, like routing tasks. In this view, each vehicle might not be self-centered, and vehicles can act cooperatively to improve the traffic operation at the system level. This last reflects the term of *connected vehicle*, which assumes an exchange of information with other vehicles (V2V) and/or infrastructure (V2I).

Therefore, the aforementioned concepts, *autonomous vehicle* and *connected vehicle* form a distinct meaning or goal, and none of them forms a singular definition (Conceicao et al., 2016).

Whatever the degree of autonomy/cooperation, the driving task is expected to be performed robotically and automatically. The concepts of *robotic* or *automatic vehicle* gather intrinsic features of the vehicle no matter which controls it regards. First, automatization is not the same as automation. Automatization of the tasks improves the automation of the vehicles. Moreover, automation does not imply autonomy, as connected vehicles can be more automated than autonomous vehicles, gathering more sensors, communication and assistance controls. Similarly, when such automobile is called *autopilot vehicle*, the driving task is attributed to be performed automatically and robotically, somehow gathering independence while performing their mission.

Self-driving or *driverless vehicle* have similar definitions but are not equivalent. *Self-driving vehicle* implies that the driving task is done automatically, but does not guarantee that, in some parts of the route, there may exist a driver to control the operation. *Driverless vehicle* implies that there is no driver at all, e.g. no human control and therefore always acting alone, autonomously.

The term *cybercar* prompts the involvement of computers and information technology with automobiles. A *cybercar* can be seen as a new form of urban transport and a specific type of automated vehicle that is designed for short trips at low speed in small controlled urban environments (Parent and Fortelle, 2006). An example of cyber-car is the last mile taxis that are controlled by a central taxi management system. Moreover, a cybercar is a specific type of *connected vehicle*.

The often term *car* might lead to misinterpretation since this technology is expected to be applied to different types of vehicles (cars, heavy trucks, buses, vans and fire trucks). Therefore, the term *car* or even *automobile* is erroneous and, thus, *vehicle* appears to be the most appropriated designation because it encompasses several modes of transport.

Nevertheless, the term *automated vehicle* is not linked to autonomy nor cooperation. In fact, automated connotes control and operation by a machine. While *automatic*, *robotic*, *autopilot*, *self-driving* and *driverless* portray the driving task feature of these vehicles, *autonomous* and *connected vehicles* detail how the driving task is performed in general. The expression *automated vehicle* seems to be the most accurate definition for all of these expressions, and it aggregates both autonomous and connected vehicles (Conceicao et al., 2016).

Figure 2.1 summarizes the reasoning made afore. The rounded concepts represent common attributes with the concepts inside the rounded rectangle. The terms *autonomous vehicle* and *connected vehicle* culminate with *automated vehicle* concept. Moreover, the term *cybercar* is linked to the term *connected vehicle*. Henceforward, the designation of *automated vehicle* (AV) is the most advisable to use nowadays.

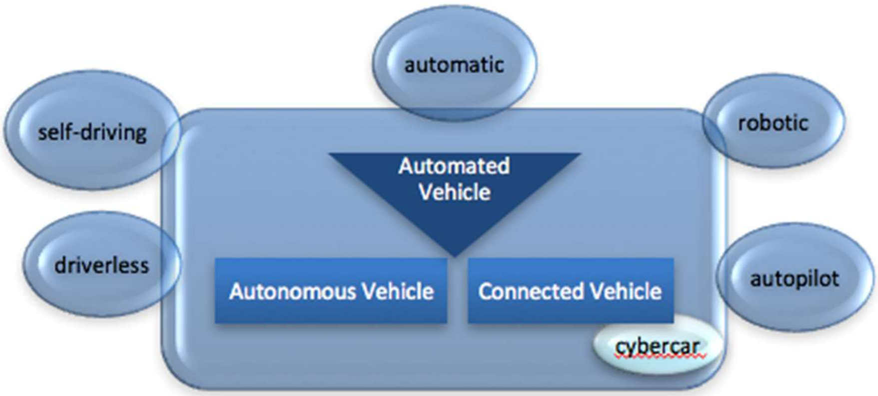


Figure 2.1 – Relationship of the concepts assumed for AVs

2.2.2. Levels of automation and the current state of manufacturing

Automobile original equipment manufacturer (OEM) companies are rapidly improving the technological side, with examples ranging from adaptive cruise control (ACC) to lane centering to parking helper systems. The NHTSA (2013) and the International Transport Forum / OECD (2015) were the first government directives that classified AV according to their automation level, United States of America and Europe respectively. These directives initially required a human operator to be present and capable of supervising the test drive and classified at the time three levels of automation (Level 0 – Level 3).

Nowadays, on a scale of six levels (0 to 5) of driving automation systems defined by the Society of Automotive Engineers International (SAE, 2018), vehicles with Level 3 have just started to be commercialized, and the so-called "autonomous vehicles" will only be seen once Level 5 of automation is reached. Meanwhile, Level 4 implies that the vehicle is capable of self-driving while performing all driving functions under certain conditions – a driver is needed inside the vehicle. Level 5 considers full autonomy – the vehicle might not have a steering wheel and does not need a driver/human inside.

Based on the SAE classification (SAE, 2018), Figure 2.2 shows the distinction between the six levels of AVs and details how automation progresses over time. The so-called semi-AVs are reflected in Level 3, whereas level 4 is considered an automated vehicle and level 5 reflects the fully automated vehicle or even autonomous vehicle. Only the last level can drive under all environmental and roadway conditions. It is important to denote that the *connected vehicles* only appear from Level 3 of automation onward. The so well-known term *autonomous vehicles* would only become possible in the latest level 5, although it might not be possible to have a fully autonomous vehicle capable of driving itself without connectivity (V2I and V2V) to assist its tasks. In fact, the balance between cooperation and autonomy is still not clearly defined in regulatory frameworks for AVs deployment, nor the level of connectivity/cooperation between V2I and V2V technologies. For example, the Google car is designed to comprise a high degree of autonomy, although governments intent that automated highway systems hold connectivity amongst vehicles and the surroundings (Gasser and Westhoff, 2012). This disparity reveals some detachment between governments and carmakers.

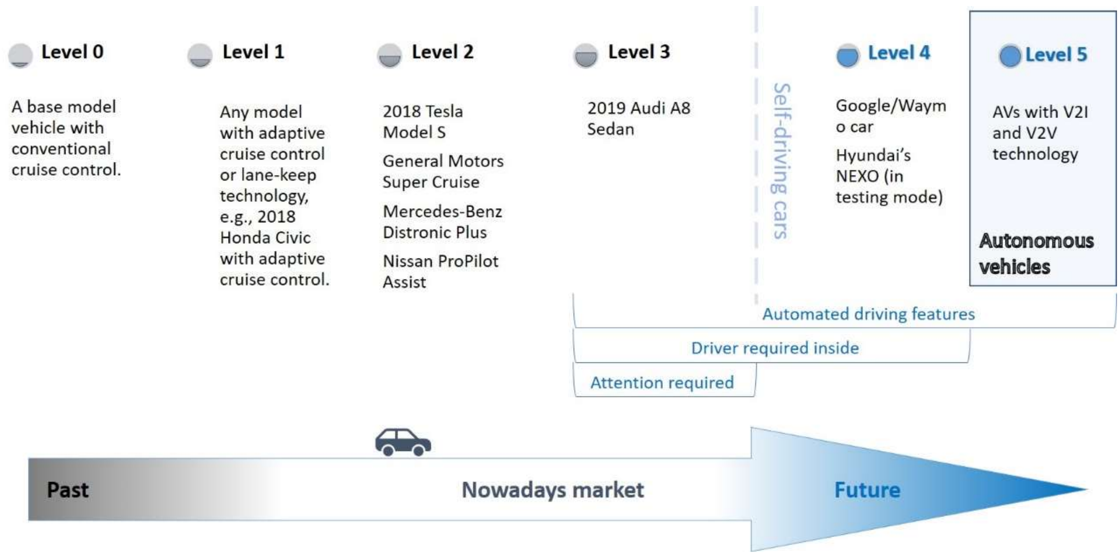


Figure 2.2 – SAE classification of AVs.

Automobile manufacturing has evolved much in the last ten years. Nowadays, carmakers are putting forward the idea of bringing automated highway systems to reality by developing and validating new automotive features.

Current vehicles available in the market are between levels 1 and 3 of automation. The Tesla Model S (level 2) has an autopilot function which, through “a combination of cameras, radar, ultrasonic sensors and data, automatically steers the vehicle down the highway”, still under driver supervision, and enables to “change lanes, and adjust speed in response to traffic” (Tesla Motors, 2016).

Vehicles with level 3 have just emerged in 2019 with Audi A8 (level 3) – the most advanced AV that is available to the public with a traffic jam pilot mode. The driver’s attention is required, and the driver can take the hands off the steering wheel and the feet away from the pedals, while the AV is on autopilot mode. However, the Audi A8 traffic jam pilot mode is still not activated in the US (and therefore, acts like an AV level 2) because of the lack of consensus in regulatory frameworks defining the responsibility on whether it is the human driver or the machine. Some OEMs say they’re going to skip Level 3 and do Level 4. (Automotive News, 2019).

A self-driving car (or a driverless car) – level 4 of automation – will be attained when the driver can perform other tasks, such as reading or playing with a mobile phone. Waymo one is currently the most advanced AV level 4, still requiring human driver inside to take over in case of a problem. Waymo began as the “Google Self-Driving Car Project” in 2009. Since 2017, Waymo started trials in some

USA states as a ride-hailing service (Engaget, 2018). Before making a trial in a new location, the corporation builds its own detailed three-dimensional maps that highlight information – road profiles, curbs and sidewalks, lane markers, crosswalks, traffic lights, stop signs, and other road features. Afterwards, during the trials, Waymo sensors and software scan constantly up to three football fields away in every direction for objects around the vehicle – pedestrians, cyclists, vehicles, road work, obstructions – and continuously read traffic controls, from traffic light color and railroad crossing gates to temporary stop signs (Waymo, 2019).

At this point, the beginning of a transportation disruption is foreseen, with the impacts of the first AVs incrementally appearing by citizens' behavior change. Level 5 unveils the reality of autonomous vehicles, i.e., when a driver (or a human) is not required inside the vehicle and possibly embedding vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) connectivity. This level represents significant changes in transportation, with impacts that are still difficult to foresee.

Jenn (2016) presents a roadmap with the evolution of automotive features. The evolution of the manufacturing sector in this topic occurred mainly since 2004. Zlocki (2014) presents an automated driving roadmap with projections towards the maximum level of automation, exhibiting three paths: the automated passenger vehicle, the commercial vehicle, and the urban environment systems. Urban environment systems comprise cybercars, high-tech buses, personal rapid transit, advanced city cars, and dual-mode vehicles. Zlocki roadmap estimates that cybercars will only become "real" automated taxis by 2028.

There are projections that "fully AVs that operate on public roads among other traffic are unlikely to be on the market before the 2030s" (European Transport Safety Council, 2016) and some forecast the 2040s (Toroyan et al., 2013). According to the ERTRAC (2019) driving roadmap, AVs level 4 will likely be on the market by 2022 and AVs level 5 by 2028. AVs level 4 will have an "urban and sub-urban pilot," as well a "highway autopilot including a highway convoy", while only AVs level 5 will be considered "fully automated passenger cars".

Nieuwenhuijsen et al. (2018) studied the diffusion of AVs using systems dynamics under a functional approach, by looking into the six levels of automation with different fleet sizes, technology maturity, and average purchase price and utility. The model was applied to the Netherlands both for a base and an optimistic scenario (strong political support and technology development). They found that market penetration of 10% of AVs level 4 will likely happen by 2027. AVs level 5 will be 90% of the market penetration somewhere between 2060 and 2080. Full deployment (100% of AVs level 5) will only occur after 2100.

In this section, the concept of AV was explained and described the evolution of the AVs levels of automation, concluding that AVs over level 4 will play an essential role in urban areas as self-driven cars, defying the current transportation paradigm (human-driven vehicles) – supporting the first and second thesis claim: "*The deployment of AVs in urban areas implies a transition period where AVs will coexist with CVs in urban areas.*" and "*The autonomy of AVs will play an important role in urban areas once AVs technology reaches level 4 that allows AVs to circulate autonomously.*"

2.3. IMPACTS OF AVS

Current literature describes the impacts of AVs as a ripple effect defined by Milakis, van Arem, and van Wee (2017), in three levels that can be liked to short, medium and long-term impacts.

The first level englobes travel costs (e.g., the value of travel time), travel choices (e.g., transport modes) and traffic implications (e.g., congestion and capacity). The second covers location choice and land-use implications (e.g., residential and employment), vehicle implications (e.g., ownership and sharing issues) and infrastructure (e.g., parking). The third encompasses societal implications (e.g., air pollution, safety, social equity, energy consumption, public health and economy issues). In the ripple effect model, each level influences the following level.

Research related to the first level is mostly focused on traffic in interurban environments (Calvert et al., 2011; Gora and Rub, 2016; Kesting et al., 2010; Talebpour and Mahmassani, 2016; van Arem et al., 1996; Zhang and Nie, 2018). The lack of studies in urban environments comes from the difficulty in representing a reality that involves other road users and modes of transport (e.g., pedestrians, bikes and buses).

Considering the value of travel costs, G. H. de A. Correia et al. (2019) looked at the expected changes on the value of travel time, through a stated choice experiment and found that the value of travel time of an AV with an office interior will be lower than the current value of travel time in a conventional time. Contrarily, an AV with leisure interior will not decrease, which corroborates with the theoretical insights from the microeconomics theory.

Considering travel choice implications, Yap et al. (2016) studied the user acceptance of AVs as last-mile public transport trips. Harper et al. (2016) analyzed the travel choices of non-driving, elderly and people with travel-restrictive medical conditions and the potential increase in their annual travel distances. Correia and van Arem (2016) proposed a mathematical model that details the impacts on traffic delays and parking demand if the family-owned CVs were to be replaced by AVs, including competition with public transport.

In the second level, i.e. in the medium-term of AVs deployment, research is still limited but gradually appearing. Concerning vehicle implications, the topic of vehicle sharing frequently relates to AVs in futuristic urban mobility scenarios, and in these studies, simulation plays an essential role in estimating the impacts (ITF, 2015; Zhang and Pavone, 2016). Concerning location choice and land-use implications, literature has just started to appear (Milakis et al., 2018).

In the third level (policy and societal implications), research embrace topics such as safety (IIHS, 2016), social equity, economy (Clements and Kockelman, 2017) and environmental issues linked to energy consumption savings and air pollution (Bose and Ioannou, 2003b; Mersky and Samaras, 2016; Wadud et al., 2016). These topics involve multiple interactions of complex estimation because there are many synergistic effects amongst automation levels, shared/private ownership, infrastructure communication, penetration rates, etc.; research is still being developed (Milakis et al., 2017).

2.3.1. IMPACTS ON TRAFFIC

As aforementioned, traffic impacts occur in the first level of the ripple effect model. Traffic research is mostly focused on interurban traffic environments. As AV are not yet a reality, mathematical and simulation tools are the only way to conceptualize the new paradigm and estimate the impacts of AVs on urban areas. The statements, variables' assumptions and simulation methods have a crucial role in the accuracy of the studies' conclusions. Additionally, simulation is a methodology that is continuously under computational and artificial intelligence areas of research.

Few studies have really distinguished the driving behavior of AV and CV. It is challenging to model the exact characteristics of automated traffic flows because it is not a reality yet and the few experiments in real-life are scant, or data is private. Most of the research is focused on the effect that driver assistance systems have on traffic flows which regard the intermediate level of automatization, SAE level 3 of automation.

Gora and Rub (2016) developed a microscopic traffic simulation software for self-driving connected vehicles, with a robust protocol for exchanging information. Their tool visualizes traffic flow in roadmaps from which the transport infrastructure includes multiple junctions, traffic lights, travel lanes.

The AV decisions, such as acceleration or turning maneuvers, are headed by communication tools to collect data and perform negotiations.

One of the main traffic research topics is the effect of AVs on road capacity. The majority of the studies use ACC and/or cooperative adaptive cruise control (CACC) models to test its influence on traffic capacity and stabilization. The ACC was the first step towards the automatization of vehicles. The delay due to driver reaction is eliminated, and a control system automatically adjusts the vehicle speed and keeps a desired headway with the following vehicle. The CACC is the subsequent level and improves the traffic roadway system since vehicles act collaboratively with a certain degree of connectivity (V2V or V2I).

The first authors to study the impact of ACC on traffic flow were van Arem et al. (1996). Their simulation model called MIXIC defined lane-changing, longitudinal car following, and interaction with the ACC (on/off). Their study varied the ACC penetration rate (20 and 40 percent), the ACC target headway setting (time gaps of 1.0 and 1.5 seconds), the traffic flow levels, and traffic compositions. In three of the four scenarios, there was a deterioration of the average travel times, between 1 to 4 percent, denoting a slight decrease of free-flow capacity. However, the conclusions state that vehicles' ACC systems stabilize traffic flow without sacrificing much capacity.

In 2010, Kesting et al. conducted a similar simulation study concerning the effect of ACC vehicles on traffic-flow efficiency by including a higher level of detail on vehicle dynamics through a car-following behavior model. Parameters such as desired speed, acceleration, comfortable deceleration and desired minimum headway time, were considered. Their results stated that an increase of 1% of ACC vehicles leads to an increase of 0.3 % of the capacity of the link.

Tientrakool et al. (2011) suggest that, for a 100% of AVs with V2V and sensors for collision avoidance, in highways, a capacity gain of 43% for AVs but that gain can become 270% if V2I is present (i.e., AVs with ACC systems).

In 2009, Yuan et al. studied a hybrid modeling approach to assess the effect of ACC vehicles on traffic flow efficiency. The behavior of the driver for CV was defined by a cellular automaton model with three traffic states (free flow, synchronized flow, and jam) and a probabilistic phase transition among them. For ACC vehicles, the behavior of the driver was defined by a car-following model, comprising a fixed time headway and no artificial speed fluctuations from the randomization in the cellular automaton model. The authors evaluated how the penetration rate and headway variations reflected on capacity. The authors concluded that the introduction of ACC improves traffic stability of synchronized flow and it can be further enhanced by an increase of the headway. The authors found that given a specific headway, a critical value of penetration rate exists to avoid jam (congestion). Likewise, given a penetration rate, free flow stability is enhanced with a decrease of the headway. Therefore, the primary inference found respects to the stability of traffic that can be either enhanced or weakened, depending on the penetration rate and the fixed headway.

Regarding the topic of introducing vehicles that incorporate ACC systems in highway systems, there is not a solid conclusion for a positive or negative influence on free-flow capacity and traffic efficiency. In fact, it is concluded that low penetrations rates of ACC vehicles do not have any effect on traffic flow, even in the most favorable conditions, the impact is minor (VanderWerf et al., 2002).

Calvert, Schakel, and Lint (2017) suggested through an empirical study and validated by simulation, that a low penetration rate of AVs with ACC in the vehicle fleet will have a negative effect on traffic flow and road capacities due to higher gap times in early stages of deployment, and any improvement in traffic flow will only be seen at penetration rates above 70%.

Other studies suggest an improvement of traffic-flow efficiency in vehicles that function in the cooperative following, the so-called CACC systems. These CACC vehicles might function in platoons for which share information cooperatively with external vehicles and/or infrastructure (Ioannou, 1997). Several studies suggest traffic solutions that seem to highly improve traffic performance. Regarding the methodological approach, the major part of the literature considers traffic simulation models with the agent-based approach.

In 2006, Van Arem et al. adapted the MIXIC simulation model to incorporate the CACC system features. The scenarios engaged a highway merging from four to three lanes and considered a closer distance between vehicles due to wireless communication restrictions. The results reinforced the traffic-flow stability conclusion and revealed a slight increase in traffic-flow efficiency when the CACC-penetration rate was above 40%, compared with the previous study (van Arem et al., 1996).

One of the first authors that studied the effect of CACC on traffic flows through an agent-based approach were Hallé and Chaib-draa (2005) through a hierarchical driving agent architecture based on three layers: guidance, management, and traffic control layer in centralized and decentralized platoons (STEAM multiagent architecture). The comparison of these two approaches enhanced safety, time efficiency, and communication efficiency aspects.

In 2008, Van Middlesworth et al. proposed a system that simulated autonomous vehicles through an agent-based approach in thousands of unmanaged intersections. The results revealed that, for low-traffic intersections, the vehicles with a CACC system significantly outperformed traditional stop signs.

Arnaout and Bowling (2011) conducted a flexible agent-based simulator of traffic (FAST) to model a roadway with 4 lanes, with and without an entry slip road. Their results revealed that CACC influences positively capacity when there is a high CACC-penetration rate. When the CACC-penetration rate is 100 percent, capacity increases by up to 60 percent. These results followed a parametrization of the headway about 0.5 seconds if they followed a CACC AV and between 0.8 and 1.0 seconds if they followed any conventional vehicle.

In the meantime, Calvert et al. (2011) simulated the effect of different CACC-penetration rates on shockwaves in an Amsterdam freeway. For a penetration rate of 10 percent, the increase in the total number of arrivals (indicator for flow) was about 3 percent. For 50 percent, the increased throughput was 22 percent, and at 75 percent of penetration rate, the increase was 39 percent. When the CACC-penetration rate is 100 percent, traffic throughput can increase up to 68 percent, not much different than in the Arnaout and Bowling (2011) study. Regarding the occurrence of congestion shockwaves, above a penetration rate of 50 percent, the shockwaves were significantly reduced, then when it was 100 percent, there were no shockwaves at all.

Fernandes and Nunes (2010) and Brownell (2013) studied platooning through CACC systems and suggest a capacity gain of up 270% for highways and 80% for urban roads if AVs work within cooperative systems (Meyer et al., 2017).

Friedrich (2015) suggests road capacity gains of up to 80% on highways and up to 40% on urban roads compared to today if all vehicles turned into AVs, acknowledging the same time gap to the next car (0.5s) as nowadays for CVs.

Regarding mixed traffic studies, Kala and Warwick (2013a) simulated autonomous vehicles in mixed traffic through specific micro-simulation software, which was specially created in Matlab. The scenario embraced an infinite straight road without speed lanes defined. The driver behavior considered a restriction vision of every vehicle, as well obstacle avoidance, overtaking, giving way for vehicles to overtake from behind, vehicle following, adjusting the lateral lane position, among others. The proposed planning algorithm within mixed traffic revealed that driver aggression plays a vital role in overall traffic dynamics. However, the influence on traffic performance was not tested. In 2014, the authors proposed a heuristic approach (a real-time genetic algorithm with Bezier curves) for the coordination of autonomous vehicles in the absence of speed lanes (Kala and Warwick, 2014). Later, they proposed an intelligent transportation system framework for vehicles with diverse levels of automation (Kala and Warwick, 2015).

Bailey et al. (2015) published a work in which they used a microscopic traffic simulator to model AV and CV with distinct behavioral models for car-following. For the CV, they used a variant of the Gipps car-following model while for AV, the enhanced intelligent driver model. They simulated in two scenarios with mixed traffic the effect of a traffic signal and a lane merge. Their conclusions were similar to the previous studies: with a high penetration rate of AV, it is expected that lane capacity increases, and the average travel time in traffic signals decreases.

Talebpour and Mahmassani (2016) analyzed the individual influence of connected and autonomous vehicles on traffic flow stability and throughput. The simulation model analyzed scenarios contemplating CV and a penetration rate of either connected or autonomous vehicles in platoons placed in a one-lane highway of infinite length. The triple interaction of these vehicles (conventional, connected, and autonomous) was not contemplated. Their framework distinguishes the driver behavior models that entail different communication capabilities and, therefore distinct deployment scenarios. Results confirmed that both connected and autonomous vehicles improve traffic stability, regardless the penetration rates. Another interesting finding from this study revealed that autonomous vehicles are found to be more effective in preventing shockwave formation and propagation under their model's assumptions when compared with connected or conventional vehicles. In addition to stability, the effects of these vehicles suggest a potential throughput increase under higher penetration scenarios.

Yang et al. (2016) proposed a signal control strategy, considering three categories of vehicles: conventional vehicles, connected vehicles, and autonomous vehicles. Simulations were conducted for different flows, demand ratios, and penetration rates. The results revealed a decrease in the number of stops and delay when using the connected vehicle algorithm with an information level of about 50 percent.

Olia et al. (2018) did an analytical framework for quantifying and evaluating the road capacity impacts from mixed traffic (AVs and CVs). They found that, for an AV penetration rate of 100%, road capacity can increase up to 109% if AVs are fully autonomous (i.e., without cooperative systems), and 315% if AVs are connected and driven in a cooperative automated manner.

Regarding driving simulators, they can be particularly useful to assess the effect on traffic by studying the CV drivers' reactions towards AVs. One of the first driving simulators was developed by StSoftware (van Wolffelaar and van Winsum, 1992), which consisted of three screens placed at an angle of 120 degrees, a driver's seat mock-up and software interfacing it to a central computer system.

In 1997, Chang and Lai had also proposed an automatic vehicle control system, called ADVANCE-F, to be equipped with conventional vehicles which the authors considered an alternative to the earliest ACC systems. Their findings were similar: the stabilization of the traffic flow; and a significant increment when the penetration rate was above 50. For a penetration rate of 100 percent, the capacity benefits would reach up to 33%.

In 2014, Gouy et al. investigated the influence of vehicle platoons with short time headways on non-platoons drivers within mixed traffic. They state a reduction in time headway for CV that was then examined through driving simulation. Three scenarios were tested: one where AV platoons respected a short time headway of 0.3 seconds; another with large following distance with a headway of 1.4 seconds; and the last scenario without platoons. Their results point out some possibly negative behavioral effects of mixed traffic due to the reduction of time headway in CV, below the safety threshold of 1 second. However, they suggest that this effect is not lasting in time because there was no carryover effect from one platoon condition to the other.

Regarding the real-life experiments, considering cooperative and connected vehicles, one of the first cooperative driving experiments was conducted in 2003. Bose and Ioannou simulated mixed traffic flow with an early definition of vehicle dynamics (Pipes, 1953) and then validated the theoretical and simulation results through experiments with instrumented vehicles. This validation allowed to evaluate the effects on traffic-flow characteristics and environment within a mixed traffic scenario. Their traffic findings infer that these semi-AVs do not contribute to the slinky effect phenomenon when the lead manual vehicle performs acceleration/deceleration maneuvers. However, semi-AVs helped to stabilize traffic flow because they absorbed the response of rapidly accelerating lead vehicles.

In 2011, Alonso et al. conducted experiments to test an autonomous intersection control system. A real scenario was created, comprising a connected vehicle, equipped with sensors and actuators, and two CVs. Two decision algorithms were tested for priority conflict resolution at intersections to help the AV decide whether to cross. The system demanded the position, speed and turning intentions of the vehicles involved in the crossroad. It was not contemplated V2I communication, and therefore no infrastructure costs. Whereas the first algorithm considers priority tables, the second assigns priority levels to vehicles dynamically which was considered the most reliable algorithm. The results of both methods were similar, and the authors state that the selection of one or the other should be based on the need to modify intersection priorities.

Rastelli and Peñas (2015) proposed a framework to model the behavior of autonomous vehicles in roundabouts. The entrance and the exit can be handled as an extension of the intersection, whereas inside the roundabout this study designed and simulated a fuzzy logic system for the steering control of autonomous vehicles. Their experiments have been conducted in different speed profiles (up to 24 km/s) and lane change maneuvers inside the roundabout which revealed satisfactory results.

In this section, the leading research focused on AVs' traffic implications. Overall, it is consensual that in a scenario with AVs, road capacity can only be improved if cooperative systems (like V2I and V2V) are present in the system. This review supports the fifth and fourth thesis claims that "*Automated traffic systems are more efficient than mixed traffic. The mixed traffic hinders the potential of boosting road traffic efficiency from AVs technology.*" and that "*Vehicle-to-infrastructure (V2I) communication will be the answer for controlling AVs and is an investment decision that municipalities will face at some point.*". The following Table 2.1 summarizes the literature around the traffic impacts, ordered by text reference.

Table 2.1 – Literature summary regarding the traffic impacts.

Reference	Topic	Effect	1st author Affiliation
Gora and Rub (2016)	Connected self-driving traffic model		University of Warsaw Warsaw, Poland
Bart van Arem, Hogema, and Smulders (1996)	ACC systems	Headway Capacity Traffic flow stability	TU Delft Delft, The Netherlands
B. van Arem and Jacob Tsao (1997)	AV guidance systems		TU Delft Delft, The Netherlands
VanderWerf et al. (2002)	ACC systems	Capacity Environmental Benefits	University of California Berkeley, USA
Yuan et al. (2009)	ACC systems	Headway Capacity Traffic flow stability	University of Science and Technology of China Anhui, China
Kesting (2010)	ACC systems	Capacity	TU Dresden Dresden, The Netherlands
Tientrakool et al. (2011)	ACC systems V2V	Capacity	Columbia University New York, USA

Reference	Topic	Effect	1st author Affiliation
Calvert, Schakel, and Lint (2017)	ACC systems	Capacity	TU Delft Delft, The Netherlands
Ioannou (1997)	Full-platooning concept		University of Southern California Los Angeles, USA
Van Arem (2006)	CACC systems	Headway Capacity Traffic flow stability	TU Delft Delft, The Netherlands
Hallé (2005)	CACC systems	Highway safety Traffic flow stability	Universite Laval Sainte-Foy, Canada
Van Middlesworth (2008)	CACC systems		Harvard University Cambridge, USA
Arnaout (2011)	CACC systems	Capacity	Old Dominion University Norfolk, USA
Calvert (2011)	CACC systems Mixed traffic	Capacity Traffic flow stability	Netherlands Organisation for Applied Scientific Research TNO Delft, The Netherlands
Fernandes and Nunes (2010)	CACC systems AVs platooning	Capacity	University of Coimbra Coimbra, Portugal
Brownell (2013)	CACC systems Shared AV taxis network	Capacity	Princeton University New jersey,USA
Friedrich (2015)	CACC systems	Capacity	Institut für Verkehr und Stadtbauwesen Germany
Kala and Warwick (2013)	CACC systems Mixed traffic		University of Reading Reading, UK
Kala and Warwick (2014)	CACC systems Mixed traffic		University of Reading Reading, UK
Kala and Warwick (2015)	CACC systems Mixed traffic		Indian Institute of Information Technology Allahabad, India
Bailey et al. (2015)	car-following, Mixed traffic	lane capacity average travel time	Massachusetts Institute of Technology Cambridge, USA
Talebpour (2016)	ACC and CACC effect Mixed traffic	Capacity Traffic flow stability	Texas A&M University Texas, USA
Yang (2016)	ACC, CACC, Mixed traffic	Capacity Traffic flow stability	ETH Zurich Zurich, Switzerland
Olia et al. (2018)	ACC, CACC, Mixed traffic	Capacity	McMaster University Ontario, Canada
van Wolffelaar (1992)	Driving simulators	StSoftware	Traffic Research Centre Haren, The Netherlands
Correia (2015)	Literature review		TU Delft Delft, The Netherlands
Chang (1997)	Driving simulators	Capacity Traffic flow stability	Tamkang University Taipei, Taiwan
Gouy et al. (2014)	Driving simulators	Headway	TRL (Transport Research Laboratory) Berkshire, UK
Baber (2005)	Real Experiments		Griffith University Queensland, Australia
Bose (2003)	Real Experiments	Traffic flow stability slinky effect phenomenon	Real-Time Innovations, Inc. Sunnyvale, USA
Pipes (1953)	Vehicle dynamics theory		University of California Los Angeles, USA

Reference	Topic	Effect	1st author Affiliation
Alonso et al. (2011)	Real Experiments	Capacity Traffic flow stability	Universidad Politécnica de Madrid Madrid, Spain
Rastelli and Peñas (2015)	Real Experiments	Capacity Traffic flow stability	INRIA Le Chesnay, France

2.3.2. IMPACTS ON MOBILITY

Traffic performance is determinant to the users' opinion as they will have a significant influence on the mobility system itself. The mobility impacts can be organized in three main subjects: travel cost implications (cost of vehicle, travel time, value of travel time) which influence the travel choices implications (vehicle use, public transport, walking, and cycle use); and vehicle implications (vehicle ownership and sharing). These topics are part of the first and second levels of the ripple effect model introduced before. The literature is growing but still highly limited.

Regarding the topic of the value of travel cost implications, Steck et al. (2018) studied the impacts of AVs on the value of travel time and on mode choices for commuting trips, either in privately owned or shared AVs, through a stated choice experiment. The results show that travel time and costs play a crucial role in mode choices. They found that AVs reduce value of travel time for commuting trips. In a privately-owned vehicle the reduction goes up to 31% compared with CVs; in shared AVs the reduction goes up to 10%.

Correia et al. (2019) looked at the expected changes in the value of travel time from a stated choice experiment (de Looff et al., 2018) and confirmed their results with the theoretical insights from the microeconomics theory. They found that the value of travel time of an AV with an office interior (between 4.99€/h to 6.26€/h) will be lower than the current value of travel time in a CV (between 7.91€/h to 8.37€/h). Contrarily, an AV with leisure interior will not decrease (between 9.94€/h to 10.82 €/h). This study revealed that AVs have the potential of reducing 25% if AVs are an office and increase up to 29% if AVs are used as a leisure place.

Regarding the topic of travel choices implications, Yap et al. (2016) explored the preferences of travelers for using AV as last-mile public transport of multimodal train trips. Their stated preference study analyzed the user perception towards the utility of using AV as an egress mode of train trips. The estimated discrete choice model considers two classes of travelers (the ones that traveled by train in 1st class and the others) and, for each class, four-mode alternatives of transport after the train trip (bus/tram/metro, bicycle, shared cybercar, AV, cybercar). Additionally, in alternative to the public transport choice, a private car alternative was incorporated which resulted in 9 transport mode alternatives. The preference results, on average, revealed AVs as egress mode rather than bicycle or bus/tram/metro regarding the 1st class train travelers. The preference results indicate that 2nd class train travelers, on average, prefer the use of bicycle or bus/tram/metro as egress mode. The authors concluded that there is a potential use of AV as last-mile transport mode from train stations to the final destination. They suggested that the VTT might not go lower as expected thus that some travelers may not see a great interest in, for example, performing other tasks while traveling which can be explained because travelers did not have any real experience of traveling in a (semi-) AV thus blurring somehow their perception. The authors also found that the two critical factors contributing to a successful deployment of AV are through strengthening the travelers' trust regarding safety perception; and also, the possibility of the AV increasing mobility sustainability.

Also, in 2016, Harper et al. analyzed the travel choices of non-driving, elderly and people with travel-restrictive medical conditions and the potential increases in travel with autonomous vehicles. They assumed that: non-drivers travel as much as the drivers within each age group and gender; the driving elderly (over 65) without medical conditions travel as much as a younger population within each gender;

working-age adult drivers (19–64) with medical conditions travel as much as working-age adults without medical conditions within each gender; the driving elderly with medical any travel-restrictive conditions will travel as much as a younger demographic within each gender in a fully AV environment. Their results concluded the increase of annual vehicle miles traveled about 14 percent. However, they admit that this was an initial study to give a perspective on possible future challenges.

Regarding the topic of vehicle implications, i.e., private and shared vehicles evaluation, Fagnant and Kockelman (2014) used an agent-based model to analyze the implications of having shared AV (3.5 percent of the trips) in the mobility system of a mid-sized city such the city of Austin, Texas. Although the results pointed to a travel distance increase of 11 percent, it was concluded that a shared AV could replace eleven CV currently on the network.

Similarly, the International Transport Forum (ITF, 2015) designed a model to analyze the introduction of automated taxis to satisfy the transport demand besides the metro transport system, in a mid-sized European city (Lisbon, Portugal). Results showed that, in a scenario that includes metro, each AV could replace ten CV, given a maximum five-minute waiting period. In a scenario without metro, e.g. only shared AV satisfy the mobility demand, each AV can replace six CVs of the current network traffic flow.

Spieser et al. (2014) did an analogous study when they considered the substitution of all CVs for AV for the city of Singapore. The authors used an analytical mathematical formulation to find the minimum fleet size of vehicles, given minimum waiting time and vehicle availability. The results showed that each AV replaces 3 CVs to satisfy the total personal mobility needs.

Recently, Zhang and Pavone (2016) studied the replacement of the taxi demand in Manhattan for a fleet of AV through the queuing theory approach. The results concluded that, if automated, 60 percent of the existing fleet would satisfy the current mobility demand.

Correia and van Arem (2016) studied the impacts on traffic delays and parking demand if private-owned CVs were replaced by AVs. Their method dynamically assigns the family trips in AV, and the vehicles might travel empty to satisfy multiple household trips or park themselves in any of the network nodes. The problem considers two modes of transport: AV and public transport, for which the model considers a ticket cost and a penalty for choosing public transport. It was first formulated by minimizing the total transport costs of all families in the city (system-optimal approach) and afterward by minimizing each individual household transport costs, which best adapts to reality. This non-linear problem, due to the traffic congestion equations, was applied to a very small network and a quasi-real case of study in the city of Delft, the Netherlands. Nine scenarios were created by changing parking policies and value of travel time (VTT). The results revealed that traffic congestion increases up to 5.04% when the existence of empty vehicles is significant. The percentage of empty kilometers along the scenarios ranged between 10.3% and 87.4% of which the last regards a scenario where there is paid parking everywhere. In scenarios with lower VTT, e.g. with higher comfort while traveling, the car mode share increased, and congestion actually was reduced. Overall, vehicle automation reduced generalized transport costs and satisfied more trips demand.

In this section, the existent and scarce research focused on the impacts of AVs in mobility. Overall, it is consensual that AVs will likely reduce the value of travel time, but then again, according to microeconomy theory, that value will depend on the occupants' comfort and use inside AVs. According to literature, AVs will likely become a reality regardless the ownership mode (private or shared). This review supports the second and third thesis claims, that "*The autonomy of AVs will play an important role in urban areas once AVs technology reaches level 4 that allows AVs to circulate autonomously.*" and that "*Smart cities will be interested in controlling automated traffic to improve the overall traffic system, but also to articulate with other modes of transport.*". The following Table 2.2 summarizes the literature around the mobility impacts, ordered by text reference.

Table 2.2 – Literature summary regarding the mobility system effects.

Reference	Topic	Effect	1st author Affiliation
Steck et al. (2018)	*Travel Cost Implications:* VTT in privately owned and shared AVs	Value of Travel Time Mode Choice	German Aerospace Center, Institute of Transport Research Berlin, Germany
Correia et al. (2019)	*Travel Cost Implications:* VTT inside AVs and theoretical microeconomy	Value of Travel Time	TU Delft Delft, The Netherlands
de Looff et al. (2018)	*Travel Cost Implications:* VTT inside AVs as work or leisure place	Value of Travel Time	TU Delft Delft, The Netherlands
Correia and van Arem (2016)	*Travel Choices Implications:* VTT and parking policy analysis	Congestion Average total travel time Generalized Transport Costs	TU Delft Delft, The Netherlands
Yap et al. (2016)	*Travel Choices Implications:* User acceptance and opinion	Preference for AV as last-mile trips	TU Delft Delft, The Netherlands
Harper et al. (2016)	*Travel Choices Implications:* Non-driving people challenges	Annual travel distance	Carnegie Mellon University Pittsburgh, USA
Fagnant and Kockelman (2014)	*Vehicle Implications:* Shared AV in Austin	Demand Travel distance	The University of Texas at Austin Austin, United States
ITF (2015)	*Vehicle Implications:* Shared AV in Lisbon	Demand	International Transportation Forum Europe
Spieser et al. (2014)	*Vehicle Implications:* Shared AV in Singapore	Demand	Massachusetts Institute of Technology, Cambridge, USA
R. Zhang and Pavone (2016)	*Vehicle Implications:* Shared AV in Manhattan	Demand	Stanford University California, USA

2.3.3. Impacts on Urban Environments

These aforementioned topics influence the whole urban environment itself – the second and third levels in the ripple effect model. The deployment of AV in urban and regional networks will first influence traffic, then mobility, and at that point urban environments at the macro and the micro-scale. At the macro scale, accessibility changes can accrue from ex-urbanization waves with a low value of time and a reasonable high market penetration rate of AV. At the local level, changes are expected in land use and streetscape if parking space is eliminated, and traffic solutions such as automated intersection management are a reality. These waves of accessibility changes are a result of mobility effects that accrue from the AV adoption. Topics such as location choice, land use, and infrastructure are still relatively unexplored. The societal impacts, e.g., safety and environmental issues, are still in the early stages of research. As Yap et al. (2016) concluded in their stated preference study, the safety perception and the sustainability matter of AVs are the two major factors that might have a significant contribution to a successful deployment of AV.

Meyer et al. (2017) were one of the first studying accessibility impacts from the presence of AVs in urban environments. They state that AVs favor urban sprawl as accessibility in rural areas increases. Therefore, public transportation will be rendered to only some urban agglomerations, except in dense urban areas.

Following, Papa and Ferreira (2018) discuss the critical decision process that will emerge shortly after AVs deployment concerning accessibility. They argue that AVs have great potential to aggravate and alleviate accessibility problems, in which stakeholders and governments should consider avoiding a dystopian mobility future. Transport network design (which is the topic of the thesis) is mentioned as one of the critical decision themes.

Milakis et al. (2018) developed a conceptual framework to estimate the accessibility impacts based on expert opinion. Three viewpoints were extracted: accessibility benefits stemming from AVs will be highly uncertain, mainly because of induced travel demand that will likely cancel out travel time and cost savings of AVs in the long term; then, accessibility changes because of AVs will have two opposing implications for urban form: densification of city center and further urban sprawl; finally, those who can afford an AV will mainly enjoy AVs benefits; thus AVs will have more negative than positive implications for social equity.

On the safety topic, IIHS (2010) estimates a reduction to one-third of the crashes and fatalities if all vehicles on the road were AVs level 1 – equipped with safety functions such as forward collision and lane departure warning systems, side view assistance and adaptive headlights. Farmer (2010) analyzed the effectiveness of electronic stability control (ESC) in reducing the risk of fatalities. According to data collected during 10 years in the United States, it was conclusive that the ESC reduced the crash risk by 33 percent on average. Afterward, Cicchino (2016) studied the effect of forward collision warning (FCW) and a low-speed autonomous emergency breaking (AEB) system. Poisson regression was used to compare the rates of police-reported crash reports in twenty-two U.S. states during 2010-2014. The results reflected a reduced rear-end striking crash involvement rates of about 23% and 39% for the FCW and AEB, respectively.

Anderson et al. (2014) infer that AVs classified as NHTSA's level 3 or 4 might improve traffic safety because they will substantially reduce human error, distraction, and alcohol-related crashes and fatalities. AVs are believed to reduce crashes and fatalities, but not 100 percent. Like airbags systems, these technologies are not perfect. It can prevent thousands of fatalities but sometimes happens failures. Nevertheless, airbags systems are still regulated, and their functioning is scrutinized (Atiyeh and Blackwell, 2017).

With respect to environmental issues, the studies about the AV deployment are still scarce and inconclusive, allied with a lack of methods. Nonetheless, the vision of connected and shared AV is that it will be beneficial for the environment since their technology will work automatically towards the road traffic improvement that, consequently, will reduce fuel consumption and emissions. Electric and connected shared AVs surely will bring many more benefits in terms of emissions, fuel consumption, and environment (cleaner sources).

In 2003, Bose and Ioannou simulated mixed traffic flows with an early definition of vehicle dynamics (Pipes, 1953) and then validated the theoretical and simulation results, through experiments with instrumented vehicles, to evaluate the effects on traffic-flow characteristics and the environment within a mixed traffic scenario. Their environmental findings suggest that the speed tracking and t\he smooth response of these vehicles reduce fuel consumption and levels of pollutants of following vehicles. Their results indicate that with an AV penetration rate of 10%, fuel consumption and monoxide pollution levels are reduced up to 3.6% and 19.2%, respectively. CO2 emissions are reduced up to 3.4%.

BhAVar et al. (2014) studied hybrid electric connected vehicles in three strategies: one with signal timing information, other with headway information, and a last with both signal timing and headway information. Their results suggest energy savings ranging between 60 and 76 percent for a full penetration rate. For a 30-penetration rate, the emissions ranged from 31 to 35 percent of energy savings.

G. Wu et al. (2014) analyzed the benefits of semi-AVs with connectivity deployment at signalized intersections. They compared speed profiles with the CV ones. Their results reflected on average: a fuel economy and CO2 reduction about 5 to 7 percent; a CO emissions reduction ranging from 15 to 22 percent; HC emissions reduction up to 7 percent; and between 9 to 13 percent of travel time savings, for AV when compared with CV.

In 2016, Mersky and Samaras tested the fuel economy of AVs (2010 Honda Accord) through a method that simulated automated following cycles. In order to estimate fuel consumption, they used the Virginia Tech Comprehensive Fuel Consumption Model (Rakha et al., 2011). Their findings suggest that the impact of AV on fuel economy can return losses of up to 3% to gains of up to 10%, depending on the efficiency-focused control strategies towards fuel economy.

The expectable benefits from the deployment of such novelty are attractive to governments and citizens. At a macro level, the societal implications include the efficiency of traffic systems, safety by collisions and fatalities avoidance and performance of dangerous tasks in inaccessible locations, leverage of local economy, amelioration of environment by air pollution reduction and a decrease of energy consumption. At a micro level, vehicle automation can also transcend former restrictions as to provide mobility to non-driver citizens, improve the quality of life by easing congestion time and making the time spent while driving productive, increase road safety through driver assistance systems, amongst other potential unproven benefits (Stevens and Newman, 2013).

The following Table 2.3 summarizes the literature around the urban environment impacts, ordered by text reference. This review evidences the impacts that AVs may have in urban areas: urban sprawl, higher road safety, lower emissions, for instance – which supports the third claim that "*Smart cities will be interested in controlling automated traffic to improve the overall traffic system, but also to articulate with other modes of transport.*"

Table 2.3 – Literature summary regarding the urban environment impacts.

Reference	Topic	Effect	1st author Affiliation
Meyer et al. (2017)	Transport modeling	Accessibility	ETH Zurich Zurich, Switzerland
Papa and Ferreira (2018)	Exploratory study	Accessibility	University of Westminster London, UK
Milakis et al. (2018)	Expert opinion	Accessibility	TU Delft Delft, The Netherlands
IIHS (2010)	Report	Road Safety	Insurance Institute for Highway Safety Virginia, USA
Farmer (2010)		Road Safety	Insurance Institute for Highway Safety Virginia, USA
Cicchino (2016)		Road Safety	Insurance Institute for Highway Safety Virginia, USA
Anderson et al. (2014)		Road Safety	RAND Corporation California, USA
Bose and Ioannou, (2003a)	Mixed traffic flow simulation	Fuel consumption Emissions	Real-Time Innovations, Inc. California, USA
BhAVar et al. (2014)	Hybrid electric connected vehicles	Energy savings Emissions	Clemson University South Carolina, USA
G. Wu et al. (2014)	AVs with connectivity at signalized intersections	Fuel consumption Emissions	University of California at Riverside California, USA
Mersky and Samaras (2016)	Simulation of automated following cycles	Fuel consumption	Carnegie Mellon University Pennsylvania, USA

2.4. The Deployment of AVs in Urban Areas

2.4.1. A transition period

The deployment of this technology in urban areas is uncertain upon the interaction with pedestrians, cyclists, and other automobiles. Nevertheless, the deployment of AVs will occur in urban areas in a transition period where AVs (over level 4) will coexist with CVs driven by humans that have different range of levels of automation. Theoretically, the deployment was primarily defined in interurban environments (Shladover, 2000; van Arem and Jacob Tsao, 1997), but a similar analogy can be made in urban environments.

In 1997, van Arem and Tsao identified the factors that could affect the development of AV guidance systems in interurban environments and defined two approaches. The geographical approach states that full automation will be implemented in one step and expand geographically. The functional approach states that the deployment cannot be realized suddenly as difficulties may be encountered and, therefore, intermediates steps must be identified in a "transition period" and optimized to best adjust the technology in reality. Currently, these intermediate steps can correspond, for instance, to the distinct levels of automation; or be characterized by the diffusion of AVs in the networks (penetration rate) (Correia et al., 2015).

Shladover (2000) stated different paths for functional deployment in interurban environments, noticing that this deployment can occur differently over regions. This analysis was focused on achieving fully automated highway systems. The author defends that in some regions, the deployment can be introduced with V2V communication and ACC that perform CACC systems without dedicated lanes. In other regions, the deployment can be led through the introduction of dedicated lanes before V2V communication entirely exists, which is suitable for trucks' operation. The author states that the combination of these two instances (CACC + dedicated lanes) corresponds to partially automated highway systems. It is stated that to accomplish fully automated highway systems, network control (V2I communication), cooperation amongst vehicles (V2V communication), and lane-changing control (to perform dedicated lanes) are required.

According to the European Transport Safety Council (2016), this transition period can be divided into two stages: the first focused on automated and non-automated vehicles, and the second focused on automated vehicles and vulnerable road users. Therefore, in the first stage of this transition period, a functional deployment will occur in urban regions as AVs over level 4 will be deployed in reality amongst other vehicles. At the operation level, the technology installed (V2I) and protocol cooperation (V2I) will rule out if such deployment will occur successfully in urban areas. Some parts of the network might have V2I connectivity, others might not. This confirms the first claim of the thesis: "*The deployment of AVs in urban areas implies a transition period where AVs will coexist with CVs in urban areas.*".

2.4.2. The need for transport policy

Self-driving cars (level 4 onwards) are primarily envisioned to gradually appear in the next decade in urban areas through a period of transition within mixed traffic. According to the previous review, studies indicate that this level will bring both positive and negative impacts. From citizens-perspective, the fact that the driving task is no longer an obligation is seen as bringing more traveling comfort, increased road safety, efficient energy consumption, etc. From government-perspective, AVs are envisioned to bring less congestion, less pollution, less mortality rate, improve economic leverage from small ride-hailing and car-sharing businesses, among others. However, AVs technology may influence citizens' behavior on increasing the willingness and predisposition for traveling, which might go against government expectations, for example, on less congestion and less pollution.

When AVs technology reaches level 5, AVs might eventually drive empty throughout the network, which ultimately will increase traffic flow. For instance, after dropping off the passenger and then drive towards a parking spot or ultimately home. Also, citizens that were not able to drive previously, e.g., the elderlies, will increase travel demand. These individualistic behaviors mean additional trips, i.e., more traffic flow and increased overall congestion, energy demand, and consumption. Air pollution might eventually become a problem if such vehicles are not electric.

More travel demand and empty trips are two of the biggest challenges once AVs reach levels 4 and 5, respectively. Besides these, the unchecked growth in ride-hailing services will possibly threaten road traffic congestion. On the one hand, the ride-hailing services ease congestion by taking drivers off the road, but, on the other hand, these shared systems complement mass transit and induce a change of behavior in detriment to public transportation. Nowadays, even without AVs, a recent study in Boston area revealed that 42 percent of passengers would have used public transit for their trip if ride-hailing services were not available, meaning travelers are dropping public transportation (Boston Globe, 2018). This means that irrespective if they are privately-owned or shared vehicles, AVs deployment has the capability of deteriorating congestion – and transport policy is an important key to mitigate its issues.

The need for transport policy usually occurs due to loss of efficiency, equity, regional development, and employment. Policies must be outlined together with both manufacturing and research development in a proactive way, anticipating and trying to manage a technological disruption that can be both a crisis and an opportunity. AVs will be a reality sooner or later and planning ahead design or planning strategies is a way of studying transport policy that can come from a scientific, professional and political view, either reactively or proactively. Reactive policy focus on solving negative implications, whereas the pro-active politics defines objectives and plans focused on prevention and problem-solving. In transportation, congestion usually foments transport policy which normally is devised in a reactive manner.

The timeline of policy actions is very critical in the case of AVs. The issues are notorious with implications for transport planning (Yasin et al., 2015). Policymakers must be aware of strategies that attain the expectable impacts of AVs (Karlsson and Pettersson, 2015).

As abovementioned, the first directives are mostly focused on the levels of automation (SAE, 2018), and they are constantly updated along with the technological evolution. Regulatory frameworks for testing and deploying self-driving cars are currently being settled. In 2011, Nevada was the first state of the USA with legislation for that purpose, allowing the operation of limited and full self-driving autonomous vehicles on public roadways for research and testing purposes. Since then, other US states such as California, Florida, Michigan, Columbia endorsed similar legislation for that purpose.

In 2016, the NHTSA enacted the first policy guidance for testing and deployment of AV. Alongside the European Union (2016) enacted the necessary first steps for the development and deployment of AV technology in Europe. This regulatory framework was signed by EU member states and the transport industry pledge and deliberated the first regulations to allow AV to travel on public roads. Germany is the front-runner regarding the regulatory frameworks allowing the transfer of driving tasks to the vehicle – AVs level 3 of automation (Gauck et al., 2016).

Governments around the world are trying to understand what infrastructure changes are needed to support AVs' operation in rural and urban areas (Austroads, 2019). Currently, the existent regulatory enacted (European Committee for Standardization (CEN), 2018; International Organization for Standardization, 2017) is focused on establishing performance requirements so that AVs are able to read the roads, e.g. line marking recognition, lane support systems, and traffic sign recognition (EuroNCAP, 2020a, 2020b, 2019, 2018).

However, according to the American Association of Motor Vehicle Administrators (2018), most of the US stakeholders can only speculate on what are the road requirements to best adapt roads to AVs, as their technology has been developed in the absence of collaboration between the infrastructure owners and technology developers. Moreover, it has been stated that some states are not as willing to modify their lane striping widths because it is seen as significant investments (Austroads, 2019). Contrariwise, it has been stated that V2I should be the next priority of investment in addition to traditional infrastructure (markings, signage, etc.) (American Association of Motor Vehicle Administrators, 2018).

Meanwhile, a first report focused on dedicated lanes was developed under the National Cooperative Highway Research Program (National Academies of Sciences and TRB, 2018). They describe the benefits of dedicated lanes in terms of safety, mobility, and environmental and societal considerations, the conditions amenable to dedicating lanes for priority and exclusive use by connected AVs, and a review of laws and regulations regarding dedicating lanes. Still, the existent regulatory framework is focused on AVs level 3.

In this thesis, it is aimed to support transport policy from a scientific and proactive vision. Planning strategies are lacking on how the automated traffic should be conducted in cities, mixed together with CV or jointly. This subsection assessment supports the third claim of the thesis: "*Smart cities will be interested in controlling automated traffic to improve the overall traffic system, but also to articulate with other modes of transport.*".

2.4.3. Network design in an urban context to plan the traffic operation of AVs

The network design problem in the context of urban transportation systems has been continuously studied in the last five decades and involves complexity and multidisciplinary topics. In transportation planning, the network design problem covers decision-making situations in three hierarchical levels at a long, medium and short term respectively (Magnanti and Wong, 1984):

1. *Strategic Level* when problems regard the design of new streets, bus routes, existing routes expansion, etc.
2. *Tactical Level* when problems cover the determination of the orientation of one-way streets, the allocation of lanes in two-way streets and exclusive bus lanes, etc.
3. *Operational Level* when problems are related to the scheduling of traffic lights, transit, and repairs on urban roads.

Two classical problems stem from urban transportation networks: the Road Network Design Problem and the Transit Network Design and Scheduling Problem (Farahani et al., 2013). The first is usually related to the strategic and tactical levels, e.g., for decisions of upgrading or expanding the capacity of roads. The second usually comprises the operational level that deals with new transit network configurations, i.e., the mobility improvement of the network, such as the optimal transit routes, frequencies, or timetables. Table 2.4 details the most significant reviews on this topic.

Table 2.4 – Literature reviews in the context of urban transportation network design problems.

Problem	Reviews				
Road Network Design Problem	Boyce (1984)	Magnanti and Wong (1984)	Friesz (1985)	Migdalas (1995)	H. Yang and H. Bell (1998)
Transit Network Design Problem	Desaulniers and Hickman (2007)	Guihaire and Hao (2008)	Kepaptsoglou and Karlaftis (2009)		
Both Problems	Farahani et al. (2013)				

However, the network design typically involves two perspectives: the decision-maker (e.g., the municipally) regarding the planning of roadways; and the users (e.g., the travelers) whose behavior (paths) depends on the network design and influences the performance of the transportation system. On one level, authorities aim to devise a policy to optimize the traffic system with cost-efficiency, and on the other level, each user holds an individual travel pattern, which depends on their travel choice and the road network solution tested.

Accordingly, network design problems are typically formulated as a bi-level to embrace both perspectives. Each level regards a general mathematical formulation that can be more or less difficult to solve linearly. Even if each level can be solved by exact solution methods, e.g., linearly, the problem is NP-hard and very difficult to solve because the convexity of the bi-level problem might not be guaranteed (Ben-Ayed et al., 1988; Luo et al., 1996). In order to deal with this issue, heuristics or metaheuristics are usually proposed to deal with this optimization problem, yet the optimum is not guaranteed, and a local optimum may be found instead.

Regarding the upper-level problem, based on the nature of the decisions considered (discrete, continuous or mixed), the literature defines several typical problems for each one in the context of urban transportation (Farahani et al., 2013):

▪ for the Road Network Design Problem (RNDP)

i. *Discrete Network Design Problem*, such as the decision to build new roads or determining the direction of one-way streets (Wu et al., 2009).

ii. *Continuous Network Design Problem*, such as the maximization of the capacity of streets and scheduling traffic lights.

iii. *Mixed Network Design Problem*, which is a combination of discrete and continuous decision variables, such as (Cantarella et al., 2006) (Yang and H. Bell, 1998).

▪ for the Transit Network Design and Scheduling Problem

iv. *Transit Network Design Problem* designs the routes of the transit lines, including the links, nodes and sequence of the links visited.

v. *Transit Network Design and Frequency Setting Problem* determines the service frequency besides the route design.

vi. *Transit Network Frequencies Setting Problem* determines the frequency setting, given the route structure.

vii. *Transit Network Timetabling Problem* deals with the timetable issues, given the service frequency and routes.

viii. *Transit Network Scheduling Problem* considers decisions about the frequency and timetable, given the route structure.

Regarding the lower-level problem, there is a major distinction between the Road Network Design Problem and the Transit Network Design and Scheduling Problem. While in the first, vehicles count as flow units, in the second, units reflect on passengers. In both, the lower-level problem comprises the assignment of trips into the network links. In the first, the traffic assignment, and in the second, the transit assignment.

Theoretically, there are two approaches for the traffic assignment (Sheffi, 1985):

▪ the user-equilibrium, which is more realistic regarding current traffic (CV) as the equilibrium is reached when traffic arranges itself in congested networks that no individual trip maker can reduce its path costs by switching routes – a selfish behavior and aims at decreasing his own travel time to a point that there are no better alternatives (Wardrop, 1952) ;

- and the so-called social equilibrium, which represents a system-optimal approach as the equilibrium is reached when, in congested networks, the total travel cost is minimized (Newell, 1980).

The most popular method to do the traffic assignment of car flows to a road network is the Wardrop (1952) principle, which considers capacity constraints and may also consider stochastic effects. For a time-dependent dynamic traffic assignment, Ziliaskopoulos (2001) presents an excellent literature review.

The transit assignment approaches are similar to the traffic assignment, with methods that deal with capacity constraints and stochastic effects. Different criteria and passenger behaviors are assumed, which leads to different approaches to allocating passenger demands to transit paths.

The RNDP is typically focused on a single transit mode; however multiple modes of transport coexist together in the network (bus, vehicle, and railway networks). Multi-Modality comprises at least two modes of transport and the interactions of the different flows can be captured in three cases (Farahani et al., 2013):

- the flows of the different modes do not interact, such as the case of railway and highway networks. Regarding AVs deployment, this case happens when they circulate exclusively in dedicated infrastructure only (lanes/roads);
- the flows of different modes interact, such as the case where buses and vehicles share the road, or in when AVs and CVs share the roadway (mixed traffic roads);
- the flow and decision interrelations, i.e., when decisions affect the flow interactions and vice-versa, such is the case where the decision of converting a two-way street into a one-way street affects itself the distribution of the AV flow.

Similarly, in the transit assignment, the passenger can travel in more than one mode of transport. The so-called combined-mode trips problem usually involves mode choice models, which substantially increase the complexity of the formulation (Farahani et al., 2013).

In addition, the multi-class trip assignment considers different demands and travel costs (multinomial) functions for each user class (e.g., AVs, CVs, bus, trucks). When such problem considers various travel choices other than route choices, there are three main types of assignments (Farahani et al., 2013):

- the trip distribution-assignment problem when both destination and route choices are considered;
- the modal split-traffic assignment when mode choice and route choice are considered;
- and the combined travel choice problem when destination, mode, and route choices are considered together with the alternative to travel or not.

In network design problems, there are problems that consider network changes over the planning horizon that reflect time-dependent extensions of the problems above. In mathematical programming, this extension of the network design problem, where the decisions at each stage will influence/limit the following stages, is called dynamic programming (Bradley, Stephen P.; Hax, Arnoldo C.; Magnanti, 1977).

The higher the complexity of the problem, the higher the probability that the problem is not linear and becomes difficult to solve mathematically. Therefore, the solution methods can be classified in three major categories: the mathematical and exact methods, such as branch-and-bound; heuristics that are usually developed methods from the insights of the problem; and metaheuristics, such as Simulated Annealing, Genetic Algorithm, Tabu Search, Scatter Search, Ant Colony, among others. In both last two categories of the solution search process, the convergence and convexity of the method are not guaranteed, and therefore, the optimal solution is not assured, but a near-optimal solution is found.

The nature of this thesis fits into a network design problem for a decision-support process on planning the deployment of AVs in terms of traffic improvement at the network level. Network design problems are a useful policy-making tool as it allows the decision-maker to evaluate and simultaneously forecast the network user-behavior in response to the formulated design policies – and it may be considered itself as a sort of a proactive transport policy approach.

In a scenario with AVs and human-driven vehicles, this is a way of testing transport strategies while estimating the impacts of AVs circulation and diffusion during the transition period. As automatisms are in constant advancement, the deployment of AVs level 4 onwards might imply traffic segregation (automated or mixed traffic roads) by implementing dedicated roads/zones for AVs (first thesis problem); and then such environment would allow the implementation of a dynamic reversible lanes management (second thesis problem).

Concerning the upper-level of the network design problems, the first thesis problem can be summarized in terms of the decision of which road links of the network should be dedicated for AVs traffic-only, while the rest of the road links engage mixed traffic. The second thesis problem can be summarized in terms of the decision to choose how many lanes should be assigned to each road link, where each link has a single direction associated.

In both problems, the lower-level problem is to assign the traffic flow to each road link, given the upper-level decisions that influence the link availability and the road capacity for each class. The traffic assignment, however,

A typical RNDP is composed of three main elements:

- The discretization of the road network in a graph composed by links and nodes;
- Each link is a road type, defined by speed, length, capacity, for instance;
- Each node is associated with a trip demand, i.e., each node is an origin and/or destination;

An objective function of the problem: to maximize the performance of the network given the impacts (costs) of road improvement, or to minimize the costs of the road network improvement for a given trip distribution.

In transport planning, the performance of the network is a complex and significant concept, since it can be addressed to maximize efficiency, equity, robustness, safety, environmental quality, among others. These performance aspects have been intensely studied in the last decade.

Jenelius et al. (2006) quantitatively assess the reliability and vulnerability of critical infrastructures. They calculated the indices derived from the increase in generalized travel cost when links are closed. Moreover, they analyzed the ‘‘equal opportunities perspective’’ and the ‘‘social efficiency perspective’’.

Santos et al. (2008) reviewed the equity concerns in transportation planning. They studied three equity measures and incorporated them into an accessibility-maximization road network design model. They concluded that there are different perspectives on equity that must be carefully analyzed according to the main planning objectives for each problem. Subsequently, Santos et al. (2009) also evaluated the robustness aspect in a multi-objective approach to long-term interurban road network planning. In 2010, three network robustness measures were studied together with accessibility concerns to evaluate different robustness concerns: network spare capacity, city evacuation capacity, and network vulnerability. They proved that the results obtained with or without robustness objectives vary considerably, regardless of the size of the network (ten centers). It was also concluded that the differences mainly depend on the measure used to assess robustness (Santos et al., 2010).

In this thesis, the RNDPs are founded on the claims of this thesis in Chapter 1.2.2. The RNDP in smart cities is conceptualized in a perspective of minimizing costs, including travel time and investment costs at a macro/social perspective. Micro/user perspective would evaluate, for example, how much each trip costs and that would depend, for instance, on the energy source. Accordingly, in this thesis, travel time costs evaluate how much time vehicles spend on traveling in the road network – either if they behave in a user-equilibrium (minimizing individual trips time, i.e., selfish behavior) or not. Investment costs evaluate how much society/municipalities will spend on turning roads suitable for AVs traffic with V2I communication. These are the two network "performance" aspects addressed in the RNDPs presented this thesis.

2.5. SUMMARY

The analysis of the state of the art has revealed a vast potential of research around AVs. This chapter can be summarized in five main inferences:

- The first denotes the opportunity of research related to the deployment of AVs and their upcoming impacts. Over the last decades, automated driving technology has developed at a fast track, and several levels of automation distinguish AVs. The conclusions have been somewhat consensual on AVs over level 3, positively impacting the traffic system from their platooning and efficiency skills. However, the mobility impacts revealed that once AVs reach levels 4 and 5, increased travel demand is likely to happen that would eventually worsen congestion. The urban environmental impacts are highly vulnerable to these previous effects (traffic and mobility), although recent studies show that AVs might help road safety and reduce carbon emissions in urban areas.
- The second inference denotes that it must be assumed a transition period to outline the best deployment until the full dissemination of AVs (levels 4 and 5). The level 4 of automation reflects the most likely automation level in this "transition period" and that means that this would be the turning point when AVs might drive automatically yet requiring a human driver inside the vehicle. The place of non-AVs (human-driven vehicles) cannot be forgotten.
- The third inference relates to the need to study this topic of research in urban areas at the network level to improve mobility and tackle the congestion problem accrued by higher travel demand and high population density.
- The fourth inference relates to the lack of regulations that promote the deployment of AVs in urban areas, especially at a transport planning with a smart traffic operation perspective. As AVs level 4 and 5 are not yet a reality, academia represents the opportunity to study and evaluate future transport policy alternatives to help the governments state proactive directives for policy actions in the future.
- The fifth and last inference denotes that network design is a feasible methodology to study transport policy in the context of AVs. Two levels are embedded in this methodology, the municipality decision (policy action/strategy) and the consequential network performance that accrues from the citizens' behavior (traffic assignment).

Optimizing urban road networks integrated with intelligent transportation systems will be an effective alternative to deal with the congestion from the use of AVs. Nonetheless, it is only possible to optimize traffic and manage congestion. Intelligent transportation systems are the most promising solution for dealing with the deployment of AVs in urban areas, both at transport planning and traffic operation level, with automatic real-time traffic control. Nevertheless, such a policy strategy in the transition period must also contemplate the existence of human-driven vehicles that have connectivity incompatibilities and might not be "easily controlled." V2I and V2V will play an essential role in the traffic control of AVs. Still, a technological investment is demanded throughout the network, and V2I might only work within automated traffic (AVs). Therefore, at the beginning of the transition period, a segregation of the road infrastructure and must be well designed considering CVs in the system. Dedicated roads to deploy the first AVs level 4 in the urban environment are explored in Chapter 3, for future implementation of reversible lanes that are explored in Chapter 4, that for large-scale urban areas must be implemented in a methodology explored in Chapter 5. Given the fact that each chapter talks about a specific research topic and methodological approach, a comprehensive literature background is firstly introduced in each chapter.

3

SUBNETWORKS FOR AUTOMATED VEHICLES

3.1. INTRODUCTION

Transportation systems, particularly road networks, are fundamental for modern societies because their performance has a significant impact on social and economic development. As AVs enter the scene, understanding their role in the future is a challenge to be faced all over the world. A functional deployment is first envisioned of AVs gradually emerging over time, with incompatibilities solved throughout this process (van Arem and Jacob Tsao, 1997). Shladover (2000) stated that this functional deployment would happen with some regions having Vehicle-to-Infrastructure (V2I) communication and other separate dedicated lanes. ERTRAC (2015) projects the segregation of lanes for AVs by 2020 and mixed traffic by 2028.

However, dedicated lanes encompass numerous practical problems, and its implementation might not be that simple. Nowadays, for example, bus and taxis dedicated lanes experience unauthorized circulation and illicit parking from human-driven vehicles – the so-called conventional vehicles (CVs). In a futuristic scenario, such situations would create unpredicted traffic conflict points and compromise the automated driving feature. Besides, the physical segregation of lanes would also reduce free-flow speed for both lanes (automated and mixed traffic) and decrease road capacity (Melo et al., 2012).

D. Chen et al. (2017) developed a theoretical framework to study how the macroscopic capacity in equilibrium traffic changes in the function of the AV penetration rate. They found that strict lane segregation of AVs and CVs can lead to lower capacity, while a mixed-use lane and an exclusive lane either for AVs or CVs would lead to a higher capacity.

A scenario with regular (mixed traffic) and dedicated roads (automated traffic) might be a stronger solution than dedicated lanes in terms of traffic efficiency. Yet, problems of equity, human-driven traffic detour must be contemplated. The implementation of dedicated roads would not reduce congestion just by themselves, but rather segregate congestion that would indirectly foster/hinder AVs circulation and diffusion.

At some point, the deployment of AVs will happen in dedicated infrastructure, with dedicated traffic zones to deploy the first driverless vehicles, i.e., AVs level 4 – a specific level of automation in which a vehicle drives automatically under certain conditions (SAE, 2018).

Henceforward, in this thesis, CVs are considered all the human-driven vehicles, i.e., vehicles under level 3 of automation inclusive.

Restricted driving zones are not a new practice; for instance, many urban centers ban old vehicle circulation (except residents) from reducing air pollution. Legal aspects are involved, and traffic control in city centers might still be needed for pedestrians and bikes. In fact, from city authorities and other stakeholders' perspectives, AV traffic zones will allow better traffic control, managing safety aspects and improving efficiency on network elements such as traffic intersections. From AV private owners' perspective, AV subnetworks could be appreciated for convenience and comfort, which could potentially motivate buying such vehicles. Although, from the CV owners' perspective, AV subnetworks could be unwelcomed if they represent fewer route choices, destinations hindrance and extra travel times.

The challenge of this chapter is translated through the following research questions: Is the creation of AV traffic zones a viable strategy in urbanized regions? How should AV subnetworks be designed without excessively affecting CVs? Which is the best planning approach throughout this transition period?

Section 3.2 presents a background focused on the analogous studies that studied this subject and the methodological.

Section 3.4 introduces a new road network design problem for AVs deployment (RNDP-AVs) through non-linear programming (NLP) mathematical model. The challenges faced while conceptualizing this problem into a mathematical formulation are debated. The RNDP-AVs model assigns road links to fully AVs circulation in the function of the percentage of AVs on the fleet (market penetration rate). During the transition period, as more AVs enter the vehicle fleet, AV subnetworks will progressively expand and three planning approaches are introduced: incremental, long-term and hybrid planning.

Section 0 sets up the dataset and the conditions in which the case study is based – the city of Delft, in the Netherlands. Two main scenarios are tested, with and without road investment, under several planning strategies to evaluate the AV subnetwork creation throughout the transition period.

Section 3.6 presents the application to the Delft case study, showing the results that mitigate congestion of the peak hour. The experiment envisioned the long-term for a ratio between AVs and CVs of 90%, therefore still considering a 10% presence of CVs in the network, which according to current literature, that may happen between 2060 and 2080 (Nieuwenhuijsen et al., 2018). Finally, the consequences in the remaining part of the day from the peak hour design are debated.

Subsequently, in section 3.7, the RNDP-AVs model is applied for the whole day in the same scenarios and strategies as the previous section. Here, the long term was envisioned for a penetration rate of 100%, which will likely happen in the year 2100 (Nieuwenhuijsen et al., 2018).

Finally, Section 3.8 reports the main summary and conclusions of this chapter.

3.2. BACKGROUND

Hitherto investigation has looked to potential scenarios that involve the progress from mixed traffic through separate lanes that in the future, will evolve to dedicated roads throughout the network. Current literature is focused on dedicated lanes to first deploy AVs in urban environments (National Academies of Sciences and TRB, 2018).

Chen et al. (2016) published a mathematical approach that defines when, where, and how many AV lanes should be deployed. The objective function minimizes the social cost, given an AV penetration rate. Dedicated AV lanes in the network produce a net benefit (e.g., reduced travel cost). Their study merges a multi-class user-equilibrium model (Wu et al., 2006) and a diffusion model describing the evolution of AV market penetration in a time-dependent deployment model, which is solved by a heuristic algorithm (Zhang et al., 2009) as a bi-level model. They applied to the south Florida case study, and the results showed that AV lanes should be deployed progressively when the AV market penetration rate reaches above 20 percent.

On the topic of AV subnetworks/zones (AV dedicated roads), Z. Chen et al. (2017) proposed a bi-level framework for the optimal design of AV zones in a general transportation network, solved through a simulated annealing algorithm. However, their equilibrium analysis ignores CV trips that start or end in AV zones for simplification purposes, in a deterministic mixed routing problem that considers system optimal inside AV zones and user equilibrium outside. They did a numerical example with 55% of AVs and found that AV zones can reduce social cost by up to 21.4%, assuming that road capacity triples in AV roads.

Recently, Madadi et al. (2019) proposed a framework for AV subnetworks through a modified static multiuser class stochastic user equilibrium traffic assignment with a path-size logit model with Monte-Carlo labeling for a priori route-set generation. Their solution algorithm consists of a linear approximation type algorithm, which uses a step size based on the method of successive averages. They did an experiment in a hierarchical network (freeways, regional, and urban roads) in the city of Delft, in the Netherlands. They used a single Passenger Car Unit (PCU) for penetration rates above 50% of 0.90, which means an 11% of capacity gain, and they found that AVs can reduce travel time cost between 7.16% and 11.02%, and travel times could be reduced between 0.45% to 1.5%, depending on whether dedicating the main variant or everywhere. The total distance of all users increases already when AVs reach a penetration rate of 50%. They also calculated the total travel costs savings if the value of travel time decreased (AVs and CVs) 30% for an AV penetration rate of 90% and the travel costs would be reduced by 11.72% while total travel time would reduce 0.43% for a 0.08% of distance increase.

The RNDP-AVs model that will be introduced in this chapter is instead formulated on a single-level formulation of a RNDP to evaluate all the possible combinations of the problem, with a multi-class traffic equilibrium assignment that does not have any route and mode choice algorithms or path flow constraints, while evaluating simultaneously the increasing comfort and traffic efficiency from AVs. The proposed formulation guarantees that all travelers reach their destination while covering all links characteristics, i.e., individual link performance (travel time) functions. Besides, in this study upgrading costs are considered to transform a regular road (mixed traffic) into a dedicated road for AVs, e.g., for V2I connectivity, are also introduced in this chapter. Furthermore, this chapter also initiates the debate around progressive AV subnetworks on whether designing incrementally or limiting the planning to the solution that will be optimal in the long-term.

3.3. METHODOLOGY

As aforementioned, a RNDP involves two perspectives, i.e., two levels of decision:

- The stakeholder (in this case municipalities) decide which roads should be assigned for AVs traffic-only while allowing mixed traffic in the remaining part of the network – meaning that this decision problem is binary.
- The passengers at the lower level, involving the traffic distribution of each class of vehicle (AVs and CVs) throughout the network – this problem is integer or continuous.

The traffic assignment problem is a highly combinatorial problem, involving two dimensions: a demand (trips) and supply background (network). Thus, the complexity of the problem is proportional to the size of the graph, e.g., the number of road links, and the number of O-D pairs to be satisfied. The trips reflect the travel pattern of the travelers and they must be assigned across the network that involves numerous links.

Forcing the traffic distribution on reaching an equilibrium turns the problem even more complex and quite hard to express it on mathematical programming (non-linearity). In theory, there are two types of traffic assignment in equilibrium: the user-equilibrium and the so-called social equilibrium (Sheffi, 1985).

The user equilibrium, also known to be ruled by the Wardrop principle (Wardrop, 1952), assumes that traffic arranges itself within congested networks so that no individual trip maker can reduce its path costs by switching routes. Two main assumptions persist in equilibrium: first, all users have identical behavior; second, users have full information (i.e., travel time on every possible route), meaning that they consistently make the correct decisions regarding route choice. The user equilibrium is quite hard to express linearly as a traffic assignment problem.

The so-called social-equilibrium represents a system-optimal solution whose equilibrium reaches when, in congested networks, the total travel cost of all travelers is minimum. The social-equilibrium distinguishes itself from the user-equilibrium because, in this case, vehicles are assumed to choose their paths in order to benefit the whole social system (Newell, 1980). Here, the main advantage is the linear formulation of this traffic assignment.

Additionally, each link has individual road properties, e.g., capacity limit, that defines its performance (travel time) function. The most accurate travel time functions are polynomial, exponential, and even time-dependent (Akcelik, 1991). The classical function is the BPR (Bureau of Public Roads) parabola. For mathematical programming, this is an issue because of the intrinsic non-linearity (Ortuzar and Willumsen, 2011).

Therefore, the equilibrium in the traffic assignment and the travel time functions used as link performance are the two aspects that turn this model challenging to simplify. The typical non-linearity is the major drawback of setting the RNDP-AVs model a useful tool to plan networks properly.

On a first approach, a mixed integer programming (MIP) model was formulated (see Appendix A-A.1). A system-perspective allows the necessary simplifications to obtain a static linear model in MIP. Here, the minimization of the average travel time in every road link of the network is computed instead of the minimization of all passengers' travel times, which is necessary for traffic equilibrium (i.e., no traffic assignment equilibrium). A linear travel time function is used in this initial study. The MIP formulation is not aware of the length of the trips but instead focused on the link flows. Also, the traffic efficiency coefficient, i.e., the capacity benefit gave by AVs, is constant (25%) regardless of the penetration rate in both regular and dedicated roads. It should vary alongside with AV penetration rate and be higher in dedicated roads (Conceição et al., 2017).

In the experiments, the minimization of the link travel times (see Figure 3.1) revealed that at the beginning of the transition period, the sum of link travel times would drastically be reduced, meaning that a wide traffic flow distribution would happen, mostly caused by AVs that would minimize the link travel times. That tendency rapidly changes, after 10% of AV penetration rate. For an AV penetration rate, 39% of the network would be already dedicated for AVs (19 dedicated roads). When road cost was introduced, AV subnetworks were limited to 28% (14 dedicated roads) throughout the entire period (Conceição et al., 2017).

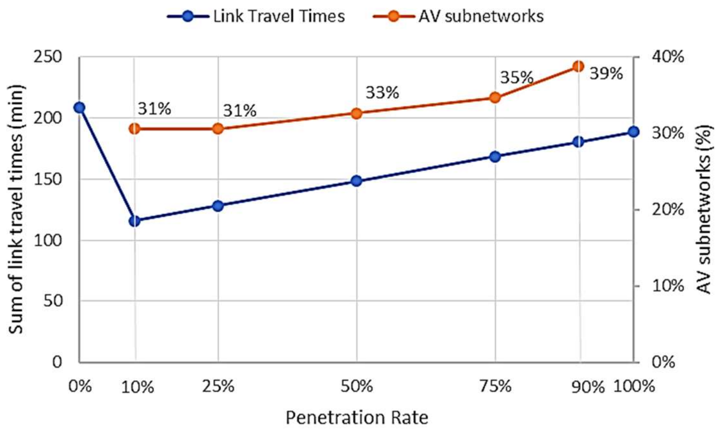


Figure 3.1 – MIQ experiments.

Despite the limitations of the MIP model, it is noticeable that even for a given 25 % of the capacity benefit, dedicated roads can help to reduce the travel times all over the network. Nevertheless, the traffic assignment was not replicated in equilibrium conditions, so it is difficult to measure how much that benefit would be.

Subsequent, a second model was formulated to solve the RNDP-AVs by performing a traffic assignment equilibrium in mixed-integer quadratic programming (MIQP) (see Appendix A-A.2). In this case, the social equilibrium was tested, as its mathematical formulation is more straightforward than the user-equilibrium (that implies an integral). The MIQP model minimizes the travel times of all vehicles – which can only be realistic if AVs are connected and their routes are given by a centralized infrastructure system. The MIQP formulation is now aware of the length of the trips, with variables that are in function of the link and O-D pair. Once again, a linear driving travel time degradation function is used, which is a straight simplification of reality. The traffic efficiency coefficient, i.e., the capacity benefit given by AVs, is a parabolic function upon the AV penetration rate, and differentiated in dedicated roads (AVs circulate with more efficiently in dedicated roads than in regular roads that have with mixed traffic).

In the MIQP model, there was given an alternative to the model for the CV drivers that needed to reach the destination, when such destination was inside AV subnetworks. In such cases, CV users would park and walk towards destination when walking is more cost-efficient than detouring. Mathematically, the flow of CVs is kept for equilibrium purposes and the walking flows represent a change of mode, which is associated with extra costs in the objective function.

Experiments were performed in a numerical network for an AV penetration rate of 50% (see Appendix A-A.2). Three scenarios were evaluated, AV subnetworks with and without road investment and a base scenario that didn't include AV subnetworks. According to these experiments, AVs subnetworks could reduce congestion by up to 60% (from 4.6% to 1.8%). The road investment highly constrained the creation of AV subnetworks. Walking trips occurred in both scenarios that considered AV subnetworks and represented a significant portion of the total costs.

Nevertheless, such a conceptual MIQP model was only possible to be formulated by introducing some simplifications and assumptions, and further complexity needed to be added to approximate to reality. The final formulation was possible in non-linear programming (NLP), by including the BPR function as travel time performance and is presented in the next subsection.

Given the current paradigm of transportation, the user-equilibrium is considered the most accurate traffic assignment because it considers the selfish behavior of the drivers and the driver/AV passenger "free will" on the route decision. A centralized system might be possible in shared systems, or even inside AV subnetworks commanding AVs reach level 5 – which seems utopian.

When considering AVs and CVs in the same model, a multiclass traffic assignment can quickly turn into an asymmetric assignment if each class is distinguished (Dafermos, 1980; Florian and Hearn, 1995; Sheffi, 1985). Problems concerning multi-class traffic assignments are summarized in two types of incoherence: behavioral or mathematical (Toint and Wynter, 2001). The behavioral incoherence happens if each class holds an individual travel time function or if links amongst the network have travel time functions that depend differently on each class. In order to reduce the complexity of the multiclass problem, a new variable is defined combining both classes, so that AVs and CVs share a joint link travel time function all over the network. This variable (total flow) embeds an automated traffic efficiency (e.g., PCU) that distinguishes AVs traffic benefits from CVs. However, in some situations, a mathematical incoherence might appear because of the dependencies in the singular Jacobian matrix that implies a linear relationship between each class cost function and the weights used in the single variable grouping the classes (Toint and Wynter, 2001). In other words, mathematical incoherence happens when each class is distinguished by different costs (e.g., toll pricing) or has a unique value of travel time. In this thesis problem, the effects of such linearity were tested and such a linear relationship depicts recent findings on AVs reduced value of travel time (Correia et al., 2019).

Still, designing dedicated infrastructure for one of the classes recognizes a natural asymmetric user equilibrium amongst classes that only happens when part of the network becomes restricted to one class (network segregation), i.e., when dedicated roads are added. This means that, in OD pairs whose AVs encountered dedicated roads, their efficiency will allow them a reduction of value of travel time (and cost), which will naturally be dissimilar to the value of travel time experienced by CVs. Therefore, in such cases, each class is under a user-equilibrium traffic assignment. Contrariwise, in OD pairs in which AVs circulate amongst CVs in regular roads, a simple user-equilibrium traffic assignment occurs.

The following study addresses a transport planning strategy (AVs subnetworks) that is aimed to be static throughout the day, also because each dedicated road for AVs holds an investment cost. The method acknowledges an hourly static traffic equilibrium throughout the day.

Table 3.1 summarizes the mathematical models formulated to conceptualize the RNDP-AVs.

Table 3.1 – Mathematical Models formulated for the RNDP-AVs

	Traffic Assignment	Link Travel Time Function	Objective Function	Type
MIP	No equilibrium	Linear	(A.1) – page 168	Static
MIQP	System Optimal Equilibrium	Quadratic	(A.19) – page 173	Static
NLP	User-Optimum Equilibrium	BPR function	(3.1) – page 38	Static

3.4. THE ROAD NETWORK DESIGN PROBLEM FOR THE DEPLOYMENT OF AUTOMATED VEHICLES (RNDP-AVS)

The problem addressed is how to design, on top of an existing road network, AV subnetworks to start the deployment of the first driverless vehicles (level 4 of automation). During this transition period, the network will be composed of regular roads (mixed traffic) and dedicated roads (automated traffic). Dedicated roads will have V2I connectivity installed, while regular roads won't. This single-level optimization problem combines discrete and continuous decision variables, where both the dedicated roads decision and the traffic flow assignment problems are formulated in a binary non-linear programming model.

All travelers reach their destination, according to a user-optimum equilibrium, meaning that every passenger of each class (CV or AV) minimizes their own travel time. I believe that, during this transition period, user equilibrium will still be the most realistic because the system-optimum routing would be even more challenging to implement, and its assumptions are somehow inadequate for nowadays reality. The objective function minimizes the generalized costs that include travel time costs and road investment. The decision making occurs at every AV design stage, based on the AVs' market penetration rate. Such a progressive process is solved by mathematical optimization (also called dynamic mathematical programming). The global evaluation is not trivial, because dedicated roads infer a travel time reduction for AV passengers but imply an increase of CVs' travel times (detour). The model evaluates the CV detour problem, as the formulation includes a penalty variable to restrict CVs driving inside dedicated roads. The model respects all road links characteristics, ensuring link performance (travel time) functions.

3.4.1.THE RNDP-AVS FORMULATION IN BINARY NLP

The assumptions of the problem are:

- AVs are assumed to be Level 4 (SAE, 2018), meaning they can be driven manually outside dedicated roads but will assume autopilot mode inside AV zones;
- AVs circulate everywhere, whereas CVs circulation is prohibited in AV traffic zones;
- A constant trip matrix exists for AV drivers and another one for CV drivers;
- Each trip is assigned to an AV or a CV;
- Public authorities invest in each dedicated road to make it fit for AVs;
- A dedicated road comprises both directions dedicated to automated traffic;

To formulate the problem, the following notation is introduced:

Sets:

$\boldsymbol{I} = (1, \dots, i, \dots, I)$:	set of notes in the network, where I is the number of nodes.
$\boldsymbol{R} = \{\dots, (i,j), \dots\}\ \forall i,j \in I \cap i{\neq}j$:	set of arcs of the road network where vehicles move.
$\boldsymbol{P} = \{\dots, (o,d), \dots\}\ \forall o \in O \cap d \in D \cap o{\neq}d$:	set of origin-destination pairs that represent the trips demand in the network.
$\boldsymbol{V} = \{AV, CV\}$:	type of vehicles (mode) in the network: AV and CV
$\boldsymbol{H} = \{1, \dots, h, \dots, 24\}$:	hours of the day

Parameters:

ρ:	the penetration rate of AVs on the vehicle fleet, between 0 and 1.
α_{mixed}:	the coefficient that reflects the efficiency of automated traffic that benefits road capacity, in mixed traffic roads, i.e., the number of CVs to which an AV corresponds to. Defined between 0 (an AV has no effect on traffic) and 1 (an AV is as efficient as a CV).
$\alpha_{automated}$:	the coefficient that reflects the maximum efficiency of automated traffic in dedicated roads, also between 0 and 1.
$VOT^{driving}$:	value of travel time while driving in monetary units per hour.

VOI: value of investment for road upgrade in each dedicated road link, in monetary units per kilometer.

$D_{od}^{v\ h_i h_f}$: trips from an origin node o, towards a destination node d, from period h_i to period h_f, $\forall\ o, d \in \boldsymbol{D}\ \cap\ h_i, h_f \in \boldsymbol{H}$.

t_{ij}^{min}: minimum driving travel time in free-flow speed at each link $(i, j) \in \boldsymbol{R}$, expressed in hours.

L_{ij}: length of each link $(i, j) \in \boldsymbol{R}$, expressed in kilometers.

C_{ij}: road capacity of each link $(i, j) \in \boldsymbol{R}$, in vehicles for the period of analysis.

M: big number.

Decision variables:

x_{ij} : binary variable equal to 1 if link $(i, j) \in \boldsymbol{R}$ is assigned for AV only driving.

$f_{ijod}^{v\ h_i h_f}$: continuous variable that corresponds to the flow of vehicles $v \in \boldsymbol{V}$ in each link $(i, j) \in \boldsymbol{R}$ and each pair $(o, d) \in \boldsymbol{P} \cap D_{od}^{v\ h_i h_f} > 0$, from period $h_i \in \boldsymbol{H}$ to period $h_f \in \boldsymbol{H}$.

$p_{ijod}^{h_i h_f}$: continuous variable that acts as penalty factor to avoid CV flow in dedicated roads, defined per link $(i, j) \in \boldsymbol{R}$ and pair $(o, d) \in \boldsymbol{P}$, from period $h_i \in \boldsymbol{H}$ to period $h_f \in \boldsymbol{H}$.

$z_{ijod}^{h_i h_f}$: continuous variable that represents the flow of AVs when a link $(i, j) \in \boldsymbol{R}$ is dedicated for AVs only ($x_{ij} = 1$), regarding each O-D pair $(o, d) \in \boldsymbol{P}$, from period $h_i \in \boldsymbol{H}$ to period $h_f \in \boldsymbol{H}$. This variable distinguishes AVs benefits in mixed or automated traffic.

The main decision variables are x_{ij} and f_{ijod}^{m}.The remaining variables depend on the first ones through constraints.

Objective Function:

$$\text{Min(Cost)} = VOT^{driving} \sum_{(i,j)\in \boldsymbol{R}} \int_0^{f_{ij}^{h_i h_f}} t_{ij}^{h_i h_f} df + \text{M} \sum_{(i,j)\in \boldsymbol{R}} \sum_{(o,d)\in \boldsymbol{P}} p_{ijod}^{h_i h_f} + VOI \sum_{(i,j)\in \boldsymbol{R}} x_{ij}\, L_{ij} \tag{3.1}$$

The objective function (3.1) minimizes the generalized costs of all travel times costs, penalty costs if CVs circulate in dedicated roads, and a road investment cost (for example, for V2I infrastructure), expressed in monetary units. The first component of the objective function computes the driving travel time costs under a user equilibrium traffic assignment formula (Sheffi, 1985) that works for each class of vehicles and according to the BPR function (3.2) to compute each link travel time function. The second component of the objective function works as a penalty term to induce the detour evaluation nature of the model. The third component of the objective function computes the total cost of road investment through the number and length of the dedicated road links.

$$t_{ij}^{h_i h_f} = t_{ij}^{min}\left[1 + \alpha \left(\frac{f_{ij}^{h_i h_f}}{C_{ij}}\right)^{\beta}\right] \tag{3.2}$$

Constraints

The objective function is subject to the following constraints (3.3)-(3.17).

$$\sum_{j\in \boldsymbol{I}} f_{ojod}^{v\ h_i h_f} = D_{od}^{v\ h_i h_f}, \forall\ (o, d) \in \boldsymbol{P}, v \in \boldsymbol{V}, D_{od}^{v\ h_i h_f} > 0 \tag{3.3}$$

$$\sum_{j \in \boldsymbol{I}} f_{jdod}^{v\, h_i h_f} = D_{od}^{v\, h_i h_f}, \forall\, (o,d) \in \boldsymbol{P}, v \in \boldsymbol{V}, D_{od}^{v\ h_i h_f} > 0 \tag{3.4}$$

$$\sum_{j \in \boldsymbol{I}} f_{ijod}^{v\, h_i h_f} = \sum_{j \in \boldsymbol{I}} f_{jiod}^{v\, h_i h_f}, \forall\, (o,d) \in \boldsymbol{P}, i \in \boldsymbol{I}, v \in \boldsymbol{V}, D_{od}^{v\ h_i h_f} > 0, \mathrm{i} \neq o, d \tag{3.5}$$

$$f_{ij}^{h_i h_f} = \sum_{(o,d) \in \boldsymbol{P}} \left[\left(\alpha_{automated} * z_{ijod}^{h_i h_f} + \alpha_{mixed} * (f_{ijod}^{AV\ h_i h_f} - z_{ijod}^{h_i h_f}) \right) + \left(f_{ijod}^{CV\ h_i h_f} \right) \right] \forall\, i, j \in \boldsymbol{I} \tag{3.6}$$

$$p_{ijod}^{h_i h_f} \geq f_{ijod}^{CV\, h_i h_f} - M * \left(1 - x_{ij}\right), \forall\, (i,j) \in \boldsymbol{R}, (o,d) \in \boldsymbol{P}, D_{od}^{CV\ h_i h_f} > 0 \tag{3.7}$$

$$p_{ijod}^{h_i h_f} \leq f_{ijod}^{CV\, h_i h_f}, \forall\, (i,j) \in \boldsymbol{R}, (o,d) \in \boldsymbol{P}, D_{od}^{CV\ h_i h_f} > 0 \tag{3.8}$$

$$p_{ijod}^{h_i h_f} \leq C_{ij} * x_{ij}, \forall\, i, j \in \boldsymbol{I}, (o,d) \in \boldsymbol{P}, D_{od}^{CV\ h_i h_f} > 0, i \neq o, d \tag{3.9}$$

$$z_{ijod}^{h_i h_f} \geq f_{ijod}^{AV\, h_i h_f} - \mathrm{M} * (1 - x_{ij}), \forall\, (i,j) \in \boldsymbol{R}, (o,d) \in \boldsymbol{P}, D_{od}^{AV\ h_i h_f} > 0 \tag{3.10}$$

$$z_{ijod}^{h_i h_f} \leq f_{ijod}^{AV\, h_i h_f}, \forall\, (i,j) \in \boldsymbol{R}, (o,d) \in \boldsymbol{P}, D_{od}^{AV\ h_i h_f} > 0 \tag{3.11}$$

$$z_{ijod}^{h_i h_f} \leq C_{ij} * x_{ji}, \forall\, (i,j) \in \boldsymbol{R}, (o,d) \in \boldsymbol{P}, D_{od}^{AV\ h_i h_f} > 0 \tag{3.12}$$

$$x_{ij} = x_{ji}, \forall\, i, j \in \boldsymbol{I} \tag{3.13}$$

$$x_{ij} \leq f_{ij}^{h_i h_f} + f_{ij}^{h_i h_f}, \forall\, (i,j) \in \boldsymbol{R} \tag{3.14}$$

$$x_{ij} \geq \sum_{(o,d) \in \boldsymbol{P}} f_{ijod}^{AV\ h_i h_f} \Big/ M, \forall\, (i,j) \in \boldsymbol{R} \cap \rho = 1 \tag{3.15}$$

$$x_{ij} \in \{1,0\}, \forall\, (i,j) \in \boldsymbol{R} \tag{3.16}$$

$$f_{ij}^{h_i h_f}, f_{ijod}^{v\, h_i h_f}, p_{ijod}^{h_i h_f}, z_{ijod}^{h_i h_f} \in \mathbb{N}, \forall\, (i,j) \in \boldsymbol{R}, (o,d) \in \boldsymbol{P}, D_{od}^{AV\ h_i h_f} > 0 \tag{3.17}$$

Constraints (3.3)-(3.5) assure that, for each O-D pair, both AVs and CVs flows ($v \in \boldsymbol{V}$) are generated in the origin node $o \in \boldsymbol{O}$ (3.3), absorbed in the destination node $d \in \boldsymbol{D}$ (3.4), and there is a flow equilibrium in the intermediate nodes(3.5).

Constraints (3.6) compute the total flow in each link $(i,j) \in \boldsymbol{R}$. The AVs flow involves an efficiency benefit that is computed through the auxiliary variable $z_{ijod}^{h_i h_f}$. Note that the benefit varies if it is mixed or automated road traffic. The flow of CVs is kept for equilibrium purposes, and the penalty flow means a considerable cost in the objective function (3.1). Constraints (3.6) compute the driving flow of CVs by discounting the pedestrians flow through auxiliary variable w_{ijod}.

Constraints (3.7) to (3.9) define the penalty variables when CVs are inside AVs dedicated roads, forcing the CV detouring around these zones. Constraints (3.7) and (3.8) assure that for a dedicated link ($x_{ij} = 1$) the penalty flow is identical to the CV flow. In the remaining roads, i.e., $x_{ij} = 0$, the range is bounded to be in the interval $\left[0; f_{ijod}^{CV}\right] \forall (i,j) \in \boldsymbol{R}, (o,d) \in \boldsymbol{P}$. Yet the lower limit of that interval is naturally chosen since this is a minimization problem. Constraints (3.9) assure that the penalty flow of link $(i,j) \in \boldsymbol{R}$ is limited to the road link capacity if such road is dedicated $(j,i) \in \boldsymbol{R}$, otherwise the p,enalty is null in regular roads.

Constraints (3.10)-(3.12) compute the auxiliary variables z_{ijod} to differentiate efficiency on dedicated and regular roads, automated and mixed traffic, respectively. In dedicated roads, the variable assumes AV flow through constraints (3.10) and (3.11), whereas in regular roads, this variable is null by constraints (3.12).

Constraints (3.13) assure that a dedicated road for AVs comprises both directions of the road. Constraints (3.14) give a valid inequality so that the variable is only plausible to be considered when there is flow passing by. Constraints (3.15) assure that all road network is dedicated when all the fleet is composed by AVs (100%).

Constraints (3.16) and (3.17) set the domain of the decision variables.

3.4.2. PROGRESSIVE AV SUBNETWORKS: EVOLUTION OF THE RNDP-AVS MODEL:

The decision process of the RNDP-AVs during this transition process can be designed as the AV penetration rate evolves, creating progressive subnetworks. Three urban transport planning approaches are tested:

- Incremental planning: dedicated roads are added incrementally as the penetration rate evolves. It starts with the computation of the first design stage, and henceforth, the solution from the precedent period is maintained with new constraints to the model. Prior investment is removed from the objective function. This means that the model evaluates at each design stage if the existing subnetwork should be expanded so that the travel time cost savings make up for the road investment needed for that expansion. The road investment required must be available at each design stage.
- Long-term planning: the optimal solution at a long-term horizon and the investment needed for the following period are constraints to create progressive AV subnetworks. It starts by solving the RNDP-AVs for the last design stage (maximum penetration rate) and reversely reduces that subnetwork by limiting the creation of the decision variables at each stage. The investment needed for the following stage is included in the objective function so that the travel time cost-saving balance out the road investment of the subsequent design stage.
- Hybrid planning: a mix planning strategy is combining both the incremental and long-term planning approaches. The model first computes the optimal long-term solution, e.g., 90% AVs. Henceforth, the network works incrementally towards the optimal final configuration, always limiting the creation of decision variables.

The pseudo-code used to run the incremental, long-term and hybrid planning approaches are detailed in the following algorithms 1, 2 and 3, respectively. The following parameters are required for performing dynamic mathematical programming:

$\boldsymbol{S} = (1, \dots, s, \dots, S)$:	design stages, where S is the latest with the maximum AV penetration considered.
ρ^s :	AV penetration rate of stage s. Note that $\rho^s > \rho^{s-1}$.
S_{ij}^s :	optimal solution (x_{ij} vector) of each design stage s.
RI^s :	road investment of design stage s

Algorithm 1 Incremental planning

$s = 1$	➢ Starts calculating from the first design stage with the minimum penetration rate ρ^1
while $\boldsymbol{s} \leq \boldsymbol{S}$ do	
get ρ^s	
create all decision variables $\forall\ (i,j) \in \boldsymbol{R}, (o,d) \in \mathbf{P}$	
if $s > 1$ **then**	
if $S_{ij}^{s-1} = 1$ **then**	➢ New constraints from prior design stage: dedicated roads from stage $s-1$ remain in stage s.
$x_{ij} = 1$	
end-if	
$RI^{s-1} = VOI\ \sum_{(i,j)\in \boldsymbol{R}} S_{ij}^{s-1}\ L_{ij}$	
function OBJECTIVE FUNCTION	➢ Adjustment of the objective function "$Cost$" (3.1) by removing the investment done in prior design stages, $s-1$.
$\min(Cost\text{–}\ RI^{s-1})$	
end-function	
else	
function OBJECTIVE FUNCTION	
$\min(Cost)$	
end-function	
end-if	
$S_{ij}^s \leftarrow x_{ij}$	
$s = s + 1$	➢ Save solution from design stage s.
Clear all decision variables	
end	

Algorithm 2 Long-term planning

$s = S$	➢ Starts calculating the last design stage starts with the maximum penetration rate ρ^S (e.g., 90% of AVs).
while $s > 0$ do	
get ρ^s	
if $s = S$ **then**	
create all decision variables $\forall\ (i,j) \in \boldsymbol{R}, (o,d) \in \mathbf{P}$	
$RI^s = VOI\ \sum_{(i,j)\in \boldsymbol{R}} x_{ij}\ L_{ij}$	
function OBJECTIVE FUNCTION	➢ Adjustment of the objective function "$Cost$" (3.1): no investment considered in the last stage
$\min(Cost - RI^s)$	
end-function	
else	➢ Calculation of the solutions in reverse
create $x_{ij}\ \forall\ (i,j) \in R\ \cap\ S_{ij}^{s+1} = 1$	
create remaining decision variables, $\forall\ (i,j) \in$ $\boldsymbol{R}, (o,d) \in \mathbf{P}$	Limits the solution space by evaluating only the dedicated roads that belong to the following design stage.
$RI^s = VOI\ \sum_{(i,j)\in \boldsymbol{R}} x_i\ L_{ij}$	
function OBJECTIVE FUNCTION	
$\min(Cost + (RI^{s+1} - RI^s))$	
end-function	➢ Adjustment the objective function "$Cost$" (3.1), only including the investment required to upgrade for the following design stage, i.e., the differential from stage s to $s + 1$..
end-if	
$S_{ij}^s \leftarrow x_{ij}$	
Clear all decision variables	
$s = s - 1$	
end	

Algorithm 3 Hybrid planning

Algorithm	Comments
$s = S$	➢ Starts calculating the last design stage starts with the maximum penetration rate ρ^S (e.g., 90% of AVs).
create all decision variables $\forall\ (i,j) \in \boldsymbol{R}, (o,d) \in \mathbf{P}$	
function OBJECTIVE FUNCTION	
$\min\left(Cost - VOI\ \sum_{(i,j)\in \boldsymbol{R}} x_{ij}\ L_{ij}\right)$	
end-function	
$S_{ij}^{S} \leftarrow x_{ij}$	
Clear all decision variables	➢ Starts calculating from the first design stage with the minimum penetration rate ρ^1.
$s = 1$	
while $\boldsymbol{s < S}$ **do**	
get ρ^s	
create all decision variables $\forall\ (i,j) \in \boldsymbol{R}, (o,d) \in \mathbf{P}$	➢ Limits the solution space by evaluating only the dedicated roads that belong to the last design stage.
if $s > 1$ **then**	
if $S_{ij}^{s-1} = 1$ **then**	
$x_{ij} = 1$	➢ New constraints from prior design stage: dedicated roads from stage $s-1$ remain in the stage s.
end-if	
$RI^{s-1} = VOI\ \sum_{(i,j)\in \boldsymbol{R}} S_{ij}^{s-1}\ L_{ij}$	
function OBJECTIVE FUNCTION	➢ Adjustment of the objective function "*Cost*" (3.1) by removing the investment done in prior design stages, $s-1$.
$\min(Cost - RI^{s-1})$	
end-function	
else	
function OBJECTIVE FUNCTION	
$\min(Cost)$	
end-function	
end-if	
$S_{ij}^{s} \leftarrow x_{ij}$	➢ Save solution from design stage s.
$s = s + 1$	
Clear all decision variables	
end	

3.5. SETTING UP THE CASE STUDY OF THE CITY OF DELFT, THE NETHERLANDS

The application of the RNDP-AVs model is exemplified in a quasi-real case study: the city of Delft, in the Netherlands, located in the province of South Holland. Figure 3.3 shows all nodes (46) and links (61) in the simplified network of Delft in a map of the region. The city center is represented by node 3 and has the highest demand. TU Delft campus is node 31, and major residential areas are located in node 6 and 45. Two types of roads exist, one or two lanes per road direction, with a lane-capacity of 1441 vehicles per hour, and the free flow speed is 50 and 70 km/h, respectively. These data comes from a simplified traffic model of the city (Correia and van Arem, 2016). The application is for demonstration purposes and it intends to exemplify what type of results could be obtained for planning such networks.

The original travel database (MON 2007/2008) was provided by the Dutch government and is available for transport research. The application is called a quasi-real case-study because the data is not completely real. Only the trips of families who travel inside the city during the course of a whole working day in the year 2008 were obtained, ignoring external trips. The filtered dataset contains a collection of 152 trips from 29 households sampled. Sampling expansion factors for each family were given for a typical working day, usually varying from 200 to 1300. With this correction factor, the original dataset with 152 trips corresponds to 68640 trips by 14,640 households, yielding an average sample rate of 0.2% -see Figure 3.2. Therefore, 60300 trips were considered through 58 O-D pairs distributed between 12 centroids (see grey circles in Figure 3.3, proportional to their demand) (Correia and van Arem, 2016).

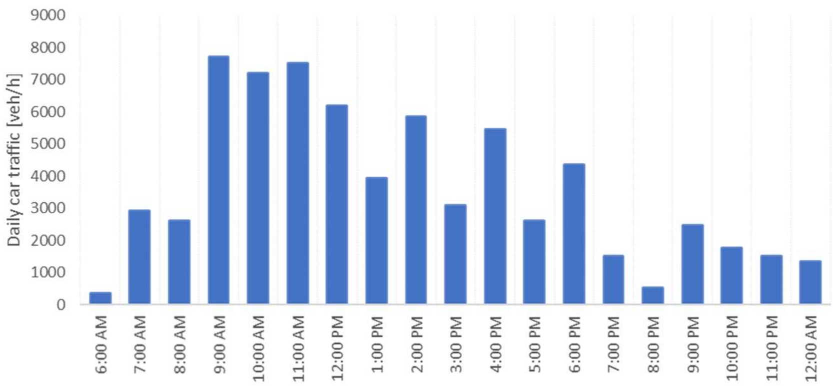


Figure 3.2 – Travel data of the case study.

The long-term is envisioned for 90% of AVs, which will likely happen somewhere between 2060 and 2080 (Nieuwenhuijsen et al., 2018). This means that this experiment focuses on a transition period for the next 40-60 years when still 10% of CVs will be present in the network. According to Nieuwenhuijsen et al. (2018), the full deployment will only occur after 2100. Some may argue that there will never be a 100% fleet of AVs since there will still be CVs circulating such as historical cars.

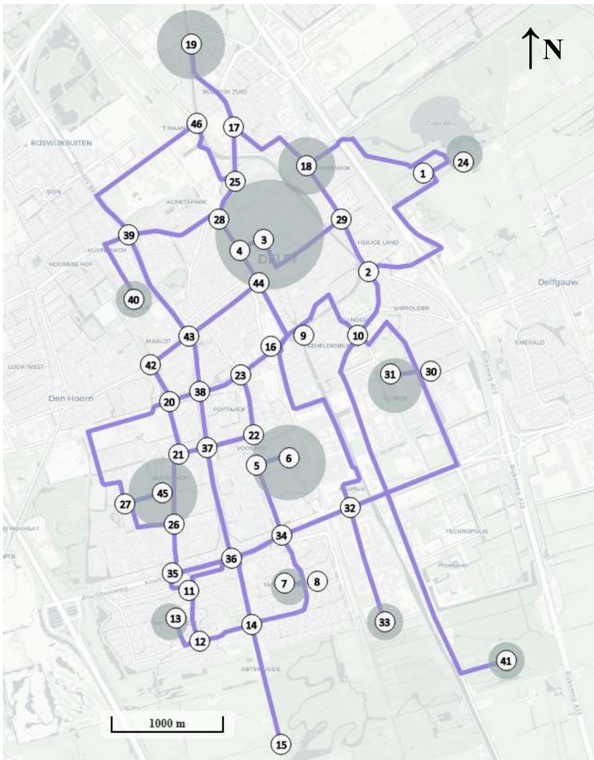


Figure 3.3 – Map of the case study with network and centroids representation (extracted and adapted from OpenLayers maps).

Traffic simulations that tested AVs with cooperative adaptive cruise control systems found road capacity gains in mixed traffic conditions (Calvert et al., 2011). A second-degree parabolic curve ($Adujsted\ Capacity = 1 + 0.1636\,\rho + 0.5087\,\rho^2;\ R^2 = 0.9981$) was adapted from their primary results: for a 10% penetration rate of AVs, there's a benefit of 3%; when 50% of the vehicle fleet is automated, road capacity increases 22%; for 75% of AVs, a 39% increase is considered; and with 100%, a maximum benefit of 68% is used – see Figure 3.4. This 68% increased capacity goes along with the main findings already introduced in the previous chapter 2.3.1, stating that the capacity benefit in urban roads can range between 40% to 80% depending on whether V2I is present.

The AVs flow is discounted through a coefficient (PCU) that has an inverse relationship with the adjusted capacity: in mixed traffic (regular roads), $\alpha_{mixed} = \frac{1}{Adjusted\ Capacity}$; whereas in dedicated roads, each AV corresponds to 0.60 CV, $\alpha_{automated} = {}^{1}/_{1.68} \approx 0.60$.

The link performance function is a BPR function, as defined before (3.2), with the reference values ($\alpha = 0.15, \beta = 4$). The minimum travel time (t_{ij}^{min}) is computed from the free-flow speed of each link $(i,j) \in \boldsymbol{R}$.

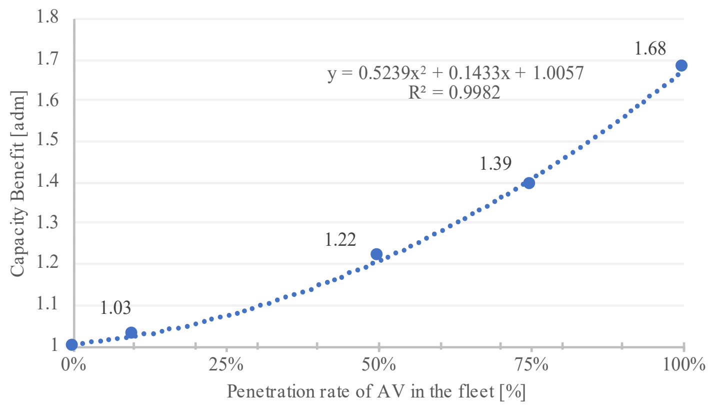


Figure 3.4 – Capacity gains in mixed traffic conditions, adapted from Calvert et al. (2011).

The reference value of travel time spent inside CVs (VOT^{car}) in the Netherlands is considered to be 10 € per hour (Yap et al., 2016). Since the total flow is a single variable and the cost function depends on the weights given to the variables, the AVs value of travel time proportionally is reduced in mixed and dedicated roads. Having in mind the inevitable mathematical incoherence mentioned in Section 2, we make use of this incoherence as the AV value of travel time decreases in an inversely proportional way to the road capacity gain that is given by the AVs. The AVs estimated values of travel time in the existent literature could drop as far as 5.50€ in the Netherlands for commuter trips(Correia et al., 2019; Yap et al., 2016). In our experiment, CV passengers always have a higher value of travel time (10€/h), whereas AV passengers have a reduced travel time cost. In dedicated roads, all traffic is automated, so the value of AVs travel time is 5.95€ per hour ($VOT^{car} * \alpha_{automated}$). In regular roads, traffic is mixed and the value of AVs travel time ($VOT^{car} * \alpha_{mixed}$) varies accordingly to Figure 3.5.

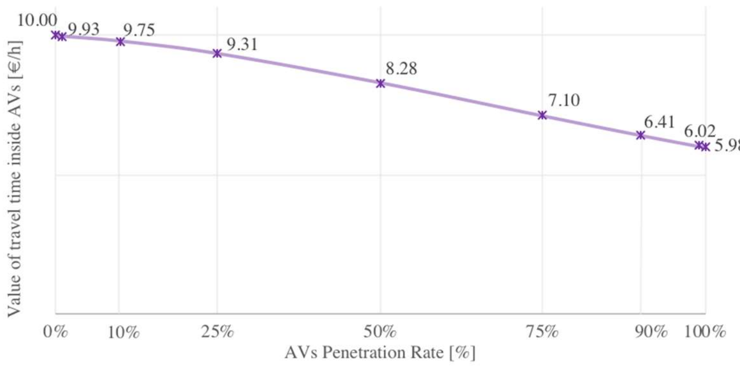


Figure 3.5 – Reduction of the value of travel time as the AV penetration rate evolves

The reference value of road investment (VOI) is 10 euros per kilometer. V2I connectivity was considered as a road upgrade investment. Each dedicated short-range communication site usually costs, on average $51,650 over a 5-kilometer range (Wise, 2015). In this experiment, the interval between design stages must be at least three years (260 weekdays each) so that the road investment is paid for itself.

The RNDP-AVs model is applied for the Delft case study in three scenarios:

- Scenario O is created without AVs' dedicated road links to further compare with the following scenarios.
- Scenario I comprises only the travelers' perspective by minimizing the overall generalized travel costs – balancing AVs travel costs savings and CVs extra travel time costs.
- Scenario II holds both travelers and municipality perspectives because it includes road investment for every dedicated road link – balancing the road investment and road traffic benefits.

The experiments are executed throughout the planning design period in four analyses. The optimality analysis indicates the optimal solutions at each individual design stage (penetration rate) without considering dedicated roads that were found optimal in previous stages. As mentioned before, the incremental planning, the long-term planning, and the hybrid planning are forecasted for an AV penetration rate of 90%, when 10% of CVs still remain in the network.

The RNDP-AVs model has been implemented in the Mosel language and solved by Xpress 8.1 (FICO, 2017) in a computer with a processor of 4.2 GHz Intel Core i7-7700K and 16GB RAM. The NLP problem is solved by the FICO Xpress-NLP SLP solver designed for large scale nonconvex problems that use a mixed-integer successive linear programming approach, combining branch and bound (BB) and successive linear programming (SLP). The reader may consult more information about the Xpress Solver (Fair Isaac Corporation, 2019) and existent solvers (Kronqvist et al., 2019). Since the RNDP-AVs problem is convex, global optimality is guaranteed.

In the next two subsections, the experiments from the application of the RNDP-AVs NLP model to this case-study, the city of Delft in the Netherlands, will be introduced. The first subsection will analyze the RNDP-AVs designed for the peak-hour in order to forecast the upmost benefits as well to depict the "best" design and find out which the strategy planning mitigates most congestion. The following subsection will apply the RNDP-AVs for the whole day that embeds hourly assignments in the formulation, which will be very useful to extract the conclusions on which is the best design strategy for the whole day.

3.6. THE RNDP-AVS DESIGNED FOR THE MOST CONGESTED PEAK-HOUR

According to the Delft dataset, the most congested hour is between 9 to 10 am ($h_i = 9 \cap h_f = 10$), holding 15% of the daily trips. The following analysis considered the peak- hour since AV subnetworks are a permanent strategy intended to solve congestion, which usually happens in this period. The initial dataset included the time window where passengers would perform their trips. The travel data considered for the peak-hour study included the maximum number of trips possible to occur in that hour, i.e., in the time window $[h_i h_f]$.

In this analysis, only the transition period will be analyzed and composed by the design stages considered several AV penetration rates: 1%, 10%, 25%, 50%, 75%, 90%, and 99%. The long-term is envisioned for 90% of AVs which will likely happen somewhere between 2060 and 2080 (Nieuwenhuijsen et al., 2018). This means that this experiment focuses on a transition period for the next 40-60 years when still 10% of CVs will be present in the network. According to Nieuwenhuijsen et al. (2018), full deployment (100% of AVs) will only occur after 2100.

3.6.1. NO AV SUBNETWORKS

In scenario O, vehicles (CVs and AVs) circulate everywhere in mixed traffic conditions, reflecting the impact of AVs deployment in the Delft network without any road traffic segregation. Constraints (3.18) are added to the prior RNDP-AVs formulation to replicate scenario O.

$$x_{ij} = 0 \; \forall \; (i, j) \in \boldsymbol{R} \tag{3.18}$$

Table 3.2 details the results of the experiments for scenario O. Each design stage is calculated in three seconds. Throughout this transition process, costs will reduce proportionally as the value of travel time spent inside AVs decreases (Figure 3.5). Total travel time is somewhat reduced from 1163 to 1057 hours vehicles, 9% difference. Such AVs cooperative adaptive cruise control system will help reduce the average congestion from 47.3% to 29.0%, dramatically reducing total delay from 123 to 16 hours. Roadways above practical capacity are the ones with a degree of saturation above 75%, meaning that flow is close to capacity, drop from 15.15 to 2.75 kilometers. Congested roadways (saturation above 100%) start to be mitigated when AVs reach 50% of the vehicle fleet. The total distance is quite steady throughout the process.

3.6.2. AV SUBNETWORKS

This section presents the results obtained from Scenario I, showing how the optimal road network design varies throughout the process in every planning approach. As aforementioned, scenario I does not includes road infrastructure investment and, therefore, only minimizes the travel time costs of both AVs and CVs. The results for Scenario I are detailed in Table 3.3. Network solutions are depicted in Figure 3.6, Figure 3.7 and Figure 3.8. The optimal solutions were obtained within adequate computation time. The incremental planning analysis took about half an hour to execute the whole process, composed of seven design stages (penetration rates). The long-term planning took less than fourteen minutes. The hybrid planning took about ten minutes.

In incremental planning, dedicated roads are found optimal since the early stages of AVs deployment (1%). Figure 3.6 shows that AV dedicated roads start in four zones and evolve progressively from 13.43 to 29.67 kilometers (more details in Table 3.3). Dedicated roads start appearing in the Delft South region, where most of the households are located, and progressively connecting to the historical center (node 44). Notice that the external demand to the city was not part of the dataset used in this experiment.

Figure 3.7 illustrates the evolution of dedicated roads in long-term planning. AV dedicated roads evolve from 0.00 to 22.23 kilometers. In this approach, AV subnetworks should only start when AVs are 10%, expanding around the city center towards the optimal solution of the design stage concerning 90% of AVs.

The hybrid planning revealed a network configuration, as illustrated in Figure 3.8. AV dedicated roads evolve from 1.87 to 22.23 kilometres. Dedicated roads for AVs start when 1% of AVs are present in the network, though such evolution is more conservative than the incremental planning strategy and starts earlier than the long-term. The optimal long-term network design is obtained when 75% of vehicles are AVs

Table 3.2 – Peak-hour experiments results of current scenario O without AV subnetworks

Scenario O (Currently) RNDP-AVs without AV subnetworks		Generalized Costs				Network		Travel Times				Congestion [1]			Delay [2]			Travel Distances			Computational time	
	AV Penetration Rate	Objective Function	Driving travel times	Penalty	Road Investment	Dedicated Roads		Driving AV trips	Driving CV trips	Penalty CV trips	Total Travel Time	Average Degree of Saturation	Roadways above practical capacity	Congested roadways	AV trips	CV trips	Total Delay	AV trips	CV trips	Total Distance	Each Stage	The whole scenario
		[€]	[%]	[%]	[%]	[no.]	[km]	[h veh]	[h veh]	[h veh]	[h veh]	[%]	[km]	[km]	[h veh]	[h veh]	[h veh]	[%]	[%]	[km veh]	[h:m:s]	[h:m:s]
Optimality	0%	10,655.20 €	100.0%	-	-	-	-	-	1163	-	1163	47.3%	15.15	4.82	0	123	123	0.0%	100.0%	68605	00:00:03	00:00:23
	1%	10,655.00 €	100.0%	-	-	-	-	12	1152	-	1164	47.3%	15.15	4.82	1	122	123	1.0%	99.0%	68591	00:00:03	
	10%	10,630.70 €	100.0%	-	-	-	-	116	1047	-	1163	47.2%	13.98	4.82	12	110	123	10.0%	90.0%	68545	00:00:03	
	25%	10,458.50 €	100.0%	-	-	-	-	289	868	-	1157	47.7%	15.15	4.82	29	87	116	25.0%	75.0%	68564	00:00:03	
	50%	9,665.43 €	100.0%	-	-	-	-	564	564	-	1127	44.4%	11.19	2.75	43	43	87	50.0%	50.0%	68589	00:00:03	
	75%	8,214.52 €	100.0%	-	-	-	-	815	272	-	1087	38.0%	6.06	2.75	35	12	47	75.0%	25.0%	68543	00:00:02	
	90%	7,082.65 €	100.0%	-	-	-	-	960	107	-	1067	32.9%	2.75	2.75	24	3	26	90.0%	10.0%	68552	00:00:02	
	99%	6,329.35 €	100.0%	-	-	-	-	1047	11	-	1057	29.4%	2.75	0.00	17	0	17	99.0%	1.0%	68554	00:00:03	
	100%	6,241.97 €	100.0%	-	-	-	-	1057	-	-	1057	29.0%	2.75	0.00	16	0	16	100.0%	0.0%	68555	00:00:01	

[1] Congestion is calculated as the ratio of flow to capacity on each road link, i.e., the degree of saturation.

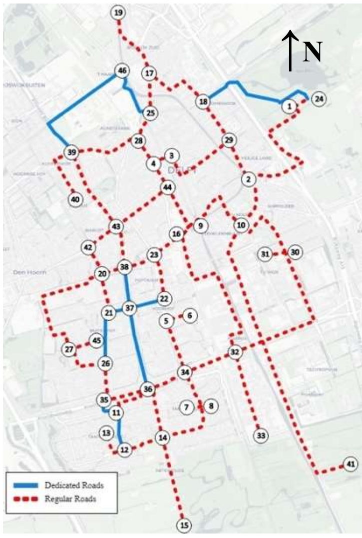
[2] Delay is calculated as the difference between the driven travel time and the minimum travel time on each roadway in free-flow speed conditions, where it is assumed that each vehicle only carries one passenger

Table 3.3 – Peak-hour experiments results of scenario I with AV subnetworks.

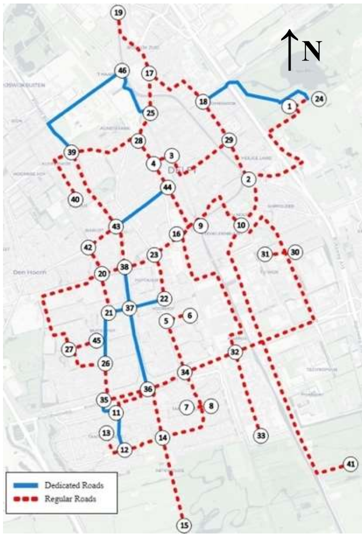
Scenario I (with AV subnetworks) RNDP-AVs without road investment		Generalized Costs				Solution		Travel Times				Congestion [1]			Delay [2]			Travel Distances			Computational time	
	AV Penetration Rate	Objective Function [€]	Driving travel times [%]	Penalty [%]	Road Investment [%]	Dedicated Roads [no.]	AVs subnetworks [km]	Driving AV trips [h veh]	Driving CV trips [h veh]	Penalty CV trips [h veh]	Total Travel Time [h veh]	Average Degree of Saturation [%]	Roadways above practical capacity [km]	Congested roadways [km]	AV trips [h veh]	CV trips [h veh]	Total Delay [h veh]	AV trips [%]	CV trips [%]	Total Distance [km veh]	Each Stage [h:m:s]	The whole scenario [h:m:s]
Optimality	1%	10,650.10 €	100.0%	0.0%	-	10	13.63	13	1153	0	1165	41%	15.15	4.82	1	123	124	1.1%	98.9%	68711	00:03:06	13:38:52
	10%	10,580.60 €	100.0%	0.0%	-	11	15.26	121	1042	0	1164	41%	13.98	4.82	10	106	116	10.9%	89.1%	69027	00:22:06	
	25%	10,329.40 €	100.0%	0.0%	-	13	16.15	299	868	0	1167	40%	13.94	6.58	24	88	112	25.5%	74.5%	71462	00:17:11	
	50%	9,440.45 €	100.0%	0.0%	-	12	12.90	582	576	0	1157	39%	11.19	6.06	49	55	104	48.9%	51.1%	69446	00:47:50	
	75%	7,979.94 €	100.0%	0.0%	-	22	23.03	829	298	0	1127	32%	11.89	4.82	49	23	72	70.8%	29.2%	71445	00:25:13	
	90%	6,955.31 €	100.0%	0.0%	-	21	22.23	963	114	0	1077	29%	6.06	2.75	27	4	31	87.9%	12.1%	69017	00:08:44	
	99%	6,318.18 €	100.0%	0.0%	-	20	23.28	1048	11	0	1059	29%	2.75	0.00	18	0	18	98.8%	1.2%	68471	11:32:13	
Incremental Planning	1%	10,650.10 €	100.0%	0.0%	-	10	13.63	13	1153	0	1165	41%	15.15	4.82	1	123	124	1.1%	98.9%	68711	00:02:29	00:31:17
	10%	10,580.60 €	100.0%	0.0%	-	11	15.26	121	1042	0	1164	41%	13.98	4.82	10	106	116	10.9%	89.1%	69028	00:07:12	
	25%	10,361.30 €	100.0%	0.0%	-	11	15.26	294	859	0	1153	40%	12.92	4.82	24	79	102	26.4%	73.6%	69650	00:10:22	
	50%	9,655.36 €	100.0%	0.0%	-	15	22.31	570	599	0	1169	40%	14.45	6.13	40	44	84	51.0%	49.0%	69764	00:04:52	
	75%	8,492.16 €	100.0%	0.0%	-	23	29.67	826	341	0	1167	35%	14.16	2.75	45	22	67	68.6%	31.4%	73619	00:05:02	
	90%	7,162.51 €	100.0%	0.0%	-	23	29.67	963	131	0	1094	31%	4.00	2.75	26	4	30	86.9%	13.1%	70554	00:00:22	
	99%	6,337.53 €	100.0%	0.0%	-	23	29.67	1047	13	0	1060	25%	2.75	0.00	17	0	17	98.6%	1.4%	67847	00:00:38	
Long-Term Planning	1%	10,655.00 €	100.0%	0.0%	-	0	0.00	12	1151	0	1163	47%	13.98	4.82	1	120	121	1.1%	98.9%	68692	00:00:20	00:13:28
	10%	10,755.50 €	100.0%	0.0%	-	3	3.92	120	1112	0	1232	47%	17.49	7.83	16	173	189	9.6%	90.4%	71439	00:00:16	
	25%	10,393.00 €	100.0%	0.0%	-	8	8.20	297	912	0	1208	45%	15.58	7.83	37	131	167	23.8%	76.2%	70919	00:00:20	
	50%	9,469.99 €	100.0%	0.0%	-	8	8.20	571	578	0	1149	43%	11.19	7.83	51	57	108	48.4%	51.6%	69666	00:02:26	
	75%	7,988.05 €	100.0%	0.0%	-	21	22.23	829	298	0	1127	32%	11.89	4.82	49	23	72	70.8%	29.2%	71445	00:00:39	
	90%	6,955.31 €	100.0%	0.0%	-	21	22.23	964	114	0	1078	29%	6.06	2.75	27	4	31	87.9%	12.1%	69017	00:09:27	
Hybrid Planning	1%	10,654.20 €	100.0%	0.0%	-	2	1.87	12	1151	0	1163	46%	13.98	4.82	1	120	121	1.0%	99.0%	68683	00:00:55	00:10:10
	10%	10,607.00 €	100.0%	0.0%	-	4	4.24	116	1046	0	1162	40%	13.98	4.82	12	109	120	10.1%	89.9%	68377	00:00:20	
	25%	10,405.30 €	100.0%	0.0%	-	4	4.24	289	868	0	1157	39%	13.98	4.82	29	87	116	25.0%	75.0%	68245	00:00:24	
	50%	9,495.20 €	100.0%	0.0%	-	10	10.51	571	585	0	1155	39%	11.19	7.83	51	58	108	47.7%	52.3%	70615	00:00:07	
	75%	7,988.05 €	100.0%	0.0%	-	21	22.23	829	298	0	1127	32%	11.89	4.82	49	23	72	70.8%	29.2%	71445	00:00:02	
	90%	6,955.31 €	100.0%	0.0%	-	21	22.23	964	114	0	1078	29%	6.06	2.75	27	4	31	87.9%	12.1%	69017	00:08:22	

[1] Congestion is calculated as the ratio of flow to capacity on each road link, i.e., the degree of saturation.

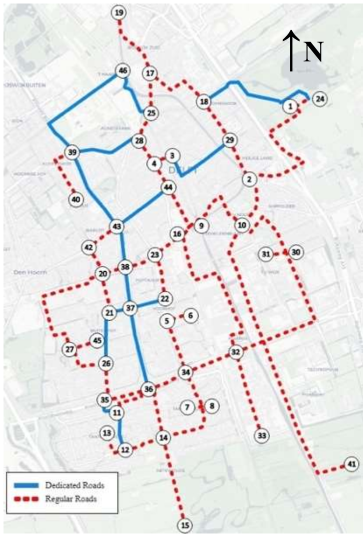
[2] Delay is calculated as the difference between the driven travel time and the minimum travel time on each roadway in free-flow speed conditions, where it is assumed that each vehicle only carries one passenger.



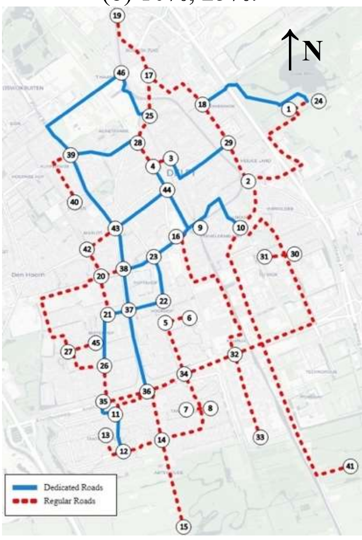
(a) 1%.



(b) 10%, 25%.

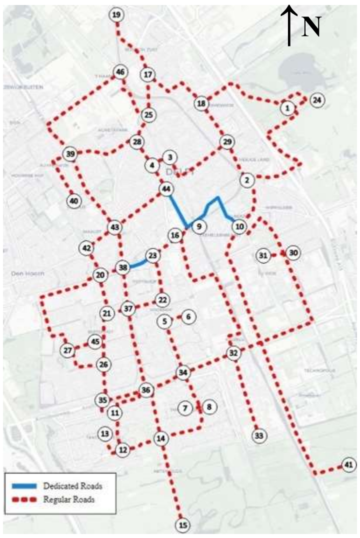


(c) 50%.

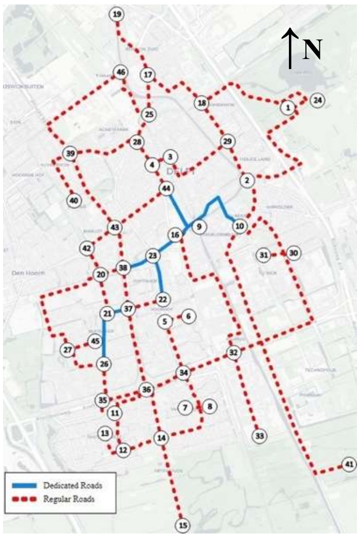


(d) 75%, 90%, 99%.

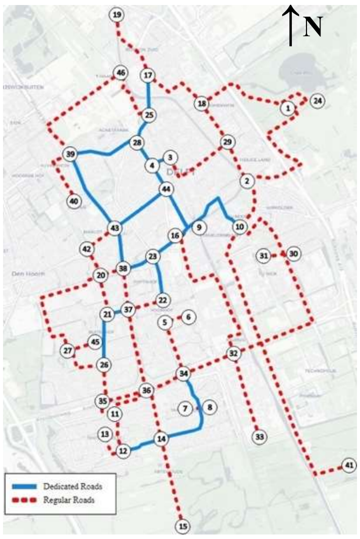
Figure 3.6 – RNDP-AVs peak-hour design: AV subnetworks of Scenario I under Incremental Planning (a), (b), (c), and (d) (% of AV penetration rate).



(a) 10%.

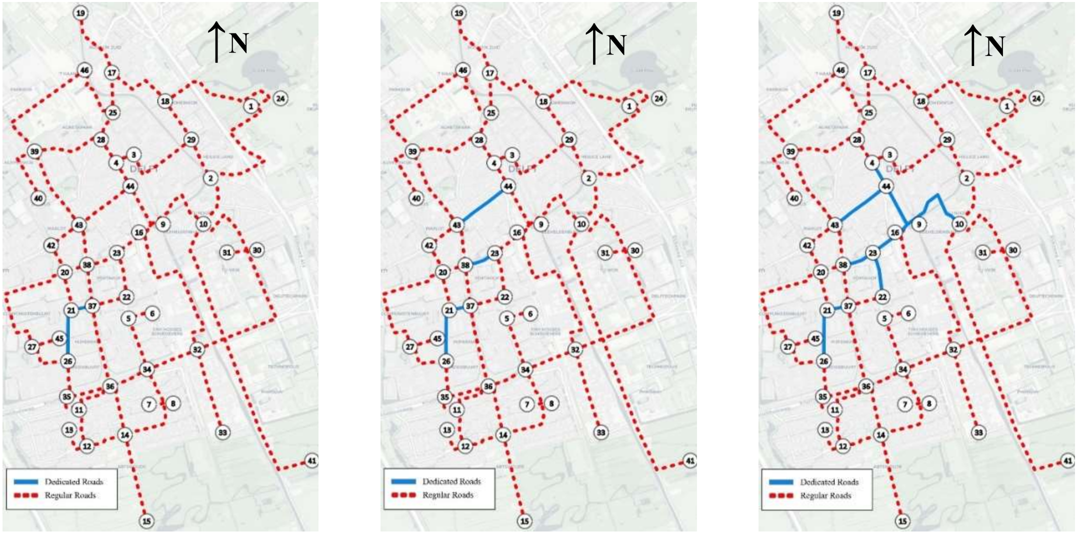


(b) 25%, 50%.

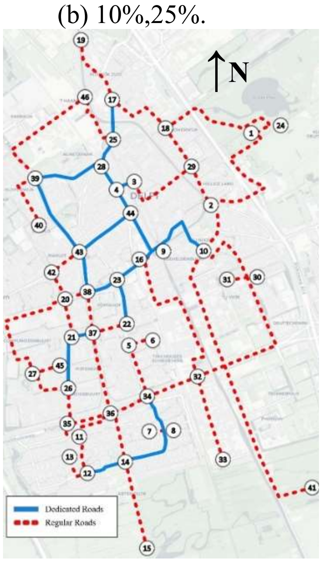


(c) 75%, 90%.

Figure 3.7 – RNDP-AVs peak-hour design: AV subnetworks of Scenario I under Long-Term Planning (a), (b) and (c) (% of AV penetration rate).



(a) 1%. (b) 10%,25%. (c) 50%.



(d) 75%, 90%.

Figure 3.8 – RNDP-AVs peak-hour design: AV subnetworks of Scenario I under Hybrid planning (a), (b), (c), and (d) (% of AV penetration rate).

Figure 3.9 shows the evolution of the network dedicated for AVs in every planning approach. In the incremental planning approach, dedicated roads are already evident since early stages (1%) – closer to optimal solutions of each individual design stage (optimality analysis) at the beginning of AVs deployment (low penetration rates, until 25% of AVs), and distances itself from optimality throughout the process as more AVs are present. Furthermore, the long-term planning strategy only gets closer to individual-stage optimality at the end of the process, with a AVs penetration rate of 75% or more.

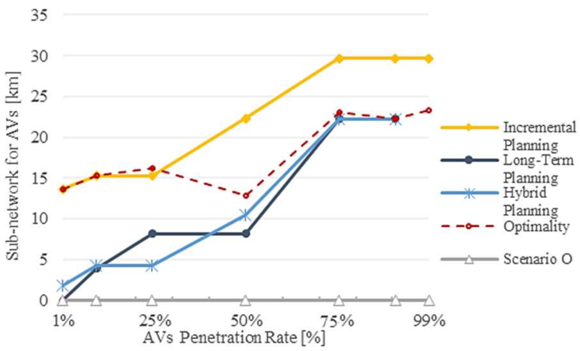


Figure 3.9 – RNDP-AVs peak-hour design: subnetwork evolution in Scenario I.

Generalized costs decrease as the ratio of AVs to CVs increases – see Figure 3.10. During this process, traffic equilibrium is changed as more AVs enter the vehicle fleet, balancing between the possibility of having extra travel time costs of CV detours and the lower AV speed from reduced AV costs. In each planning strategy, the progression of the AV subnetworks constrains the objective function, guaranteeing the formerly dedicated roads. Such dedicated road evolution constraint might not be beneficial in the following deployment stages as CVs detouring increase travel costs. Figure 3.11 illustrates the differential of the total cost of every planning strategy applied to scenario I with scenario O (that does not have dedicated roads).

In incremental planning, dedicated road links are only beneficial in the early stages, with cost savings up to 1%, only happening when CVs are still the majority. However, when AVs penetration is over 75%, the generalized costs surpass up to 3.5% the ones obtained in a scenario O. When CVs are the leading share of vehicles, the model is focused on reducing the CV extra travel times associated to detouring until a point, where AVs are over 50% of the fleet, in which the model tries to obtain more AV travel time cost savings while maintaining the same dedicated roads previously selected. This explains why the former solutions in incremental planning are not optimal for penetrations rates over 50%, and when AVs reach 75%, the model tries to reduce costs by increasing the subnetwork but still got higher costs than scenario O.

The long-term planning seems so far, the best strategy in terms of costs. Dedicated roads are crucial to drop travel costs during most of the transition process. Although the generalized costs might slightly exceed (1%) the ones obtained in scenario O in the early stages, once AV penetration rate reaches 25% dedicated roads proportionate cost savings (up to 3%).

The hybrid planning seems so far the best strategy in terms of costs, dropping those in the first-half of AV's deployment and showing similarity with the long-term planning at the end of the deployment – see Figure 3.11. AV subnetworks start to be valuable since the beginning of the transition process and eventually culminating (up to 3%) when AV penetration rate is 75%.

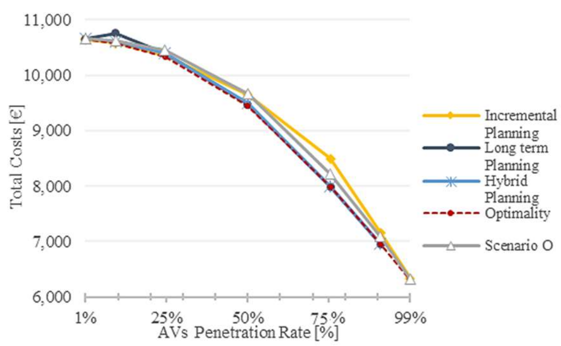


Figure 3.10 – RNDP-AVs peak-hour design: Generalized costs in Scenario I.

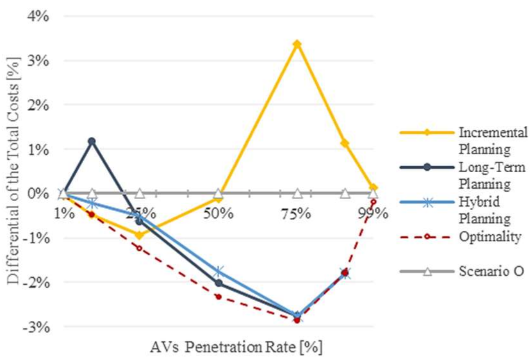


Figure 3.11 – RNDP-AVs peak-hour design: Differential on the generalized costs in Scenario I.

Figure 3.12 gives a broader overview of the congestion effect, showing that congestion is indeed reduced in every analysis and below scenario O – meaning that dedicated roads reduce the overall congestion. The congestion in the incremental planning is always close to optimality and even drops in the end. In long-term planning, the average congestion is progressively approaching the congestion in the individual optimal solutions (optimality). In the first-half of this transition process, the hybrid planning strategy shows similar results to the long-term planning strategy, whilst in the second-half is the best planning strategy for being close to the individual-stage optimality.

From Figure 3.13 to Figure 3.15, congestion is analyzed in detail, focusing on the degree of saturation. Roadways above practical capacity are the ones with a degree of saturation over 75%, meaning that the traffic flow is close to capacity. Congested roadways hold a degree of saturation of 100%, i.e., traffic flow is overcapacity. In the incremental planning (Figure 3.13), both indicators are improved until AVs are 25% of the fleet. However, congestion is intensified henceforth. Congested roadways intensify when the penetration rate is 50% but promptly decrease afterward. In the long-term planning (Figure 3.14), roadways above practical capacity increase analogously, but congested roadways intensify. In hybrid planning (Figure 3.15), the main problem also relies on congested roadways, though only happening in the second-half of this transition process. The main conclusion here is that, although AVs efficiency might indeed reduce the overall congestion indicator, congested roadways might be intensified in some stages.

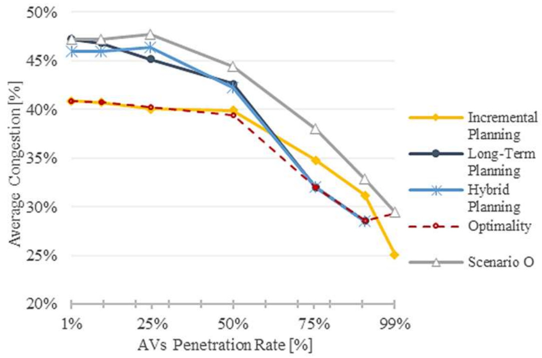


Figure 3.12 – RNDP-AVs peak-hour design: Average degree of saturation in Scenario I.

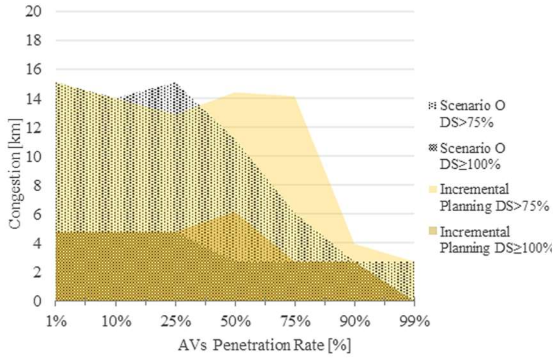


Figure 3.13 – RNDP-AVs peak-hour design: Congestion at incremental planning in Scenario I.

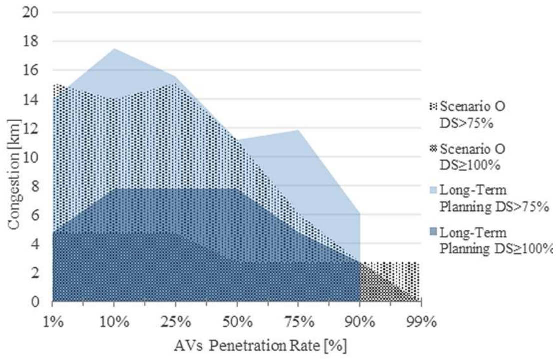


Figure 3.14 – RNDP-AVs peak-hour design: Congestion at long-term planning in Scenario I.

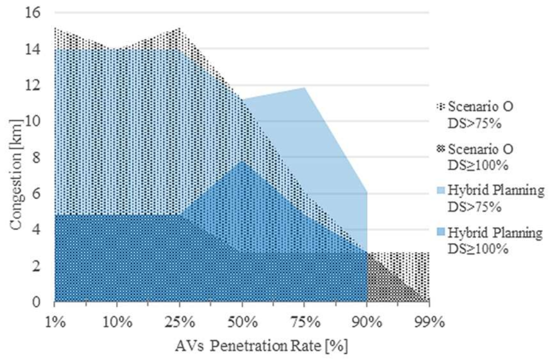


Figure 3.15 – RNDP-AVs peak-hour design: Congestion at hybrid planning in Scenario I.

In order to understand this congestion paradox: the reduction of the overall congestion and the increase of roadways that are above practical capacity, the analysis of the traveled distances in each vehicle is paramount – from Figure 3.16 to Figure 3.18. Longer paths can occur either because of CV detouring by the presence of AV subnetworks or because of the reduced value of travel time spent inside AVs. In dedicated roads, AVs circulate in autopilot mode, and the value of travel time experienced by the passengers is lower than on regular roads.

In the incremental planning (Figure 3.16), the total distance increases mostly in the late stages of the deployment process, i.e., for a penetration rate of 75%. Here, the increase is caused by CV detouring around the AV subnetworks. In the long-term planning (Figure 3.17), the total distance experienced by CV users increases homogeneously along the process. The baseline for AVs is slightly above which indicates that AVs are reducing their travel distances at higher penetration rates due to the presence of dedicated roads. In hybrid planning (Figure 3.18), CV detour is highly intensified throughout every stage in the AVs deployment process.

Total travel time is summarized in Figure 3.19, and the conclusions are similar because travel times are related to traveled distances. The hybrid planning is the strategy with a lower increase in travel time.

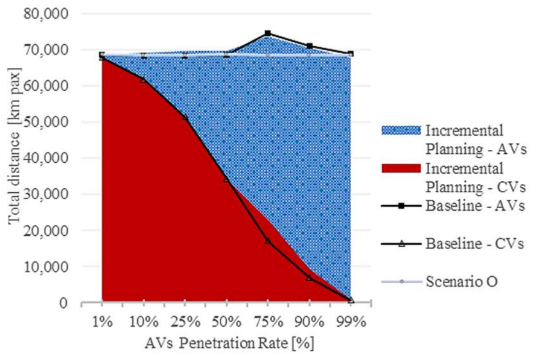


Figure 3.16 – RNDP-AVs peak-hour design: Total distance at incremental planning in Scenario I.

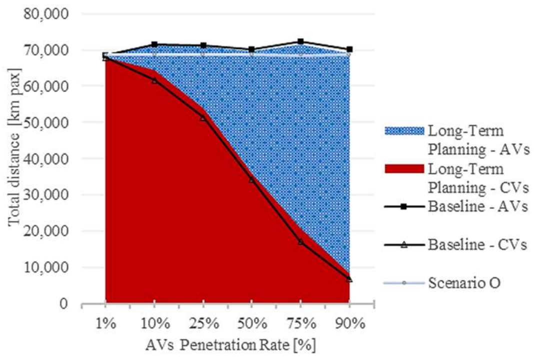


Figure 3.17 – RNDP-AVs peak-hour design: Total distance at long-term planning in Scenario I.

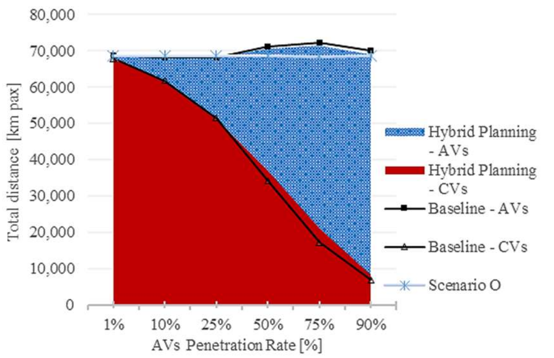


Figure 3.18 – RNDP-AVs peak-hour design: Total distance at hybrid planning in Scenario I.

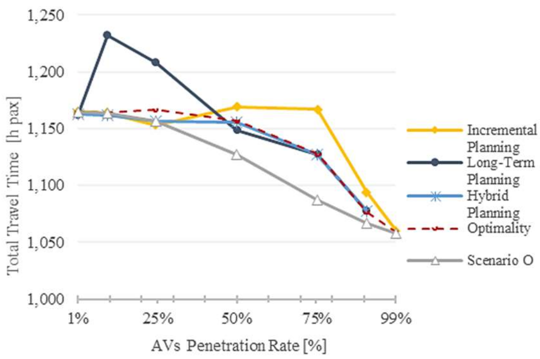


Figure 3.19 – RNDP-AVs peak-hour design: Total travel time in Scenario I.

Figure 3.20 and Figure 3.21 look at the total delay, which is calculated through the difference between the driven and the minimum travel time, having analogous inferences. With regards to CVs, it is perceived that both long-term and hybrid planning imply higher delays than the incremental planning – which only brings delay for CVs when the majority of the vehicles are automated. Regarding AVs, long-term planning brings more delay than any other strategy. In fact, both incremental and hybrid planning approaches reduce total delay until AVs reach the majority share of the vehicle fleet.

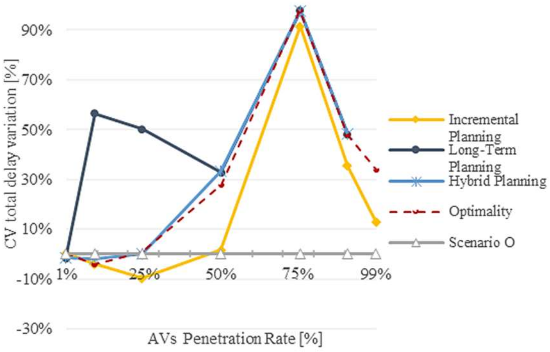


Figure 3.20 – RNDP-AVs peak-hour design: CV total delay variation in Scenario I.

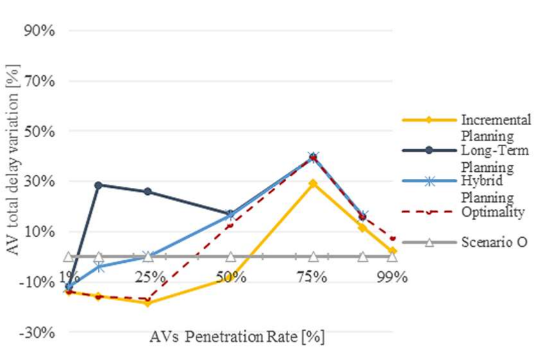


Figure 3.21 – RNDP-AVs peak-hour design: AV total delay variation in Scenario I.

In order to fully understand whether CVs are detouring from the presence of AV subnetworks or AVs are traveling more because of their reduced value of travel time, Figure 3.22 and Figure 3.23

illustrate the total distance variation among CVs and AVs, respectively. In the incremental planning strategy, the main inference relies on CV detour that only starts after AVs reach 50% of the vehicle fleet, with 35% of increased distances. Yet, AVs travel longer towards dedicated links while reducing their total delay and their costs until late stages of deployment (75%). On the contrary, long-term planning produces a network configuration that reduces AVs total distance but concentrates most of AVs traffic flow in dedicated zones, taking advantage of their reduced travel time costs. CV detour occurs up to 5% until AVs reach the majority, and in late stages of deployment, detour increases to 20%. The hybrid planning strategy is the least favorable for both CVs and AVs since early stages, where detour causes more than 15% of increased distances and the reduced AV travel time cost causes up to 7% of increased distances.

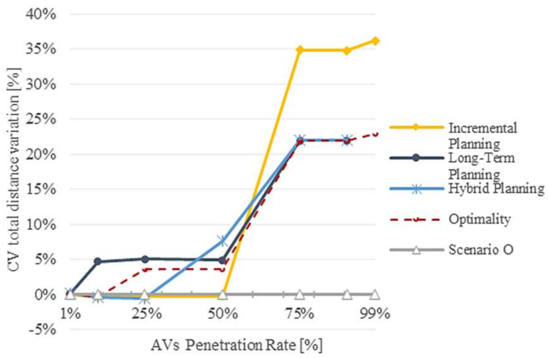


Figure 3.22 – RNDP-AVs peak-hour design: CV total distance variation in Scenario I.

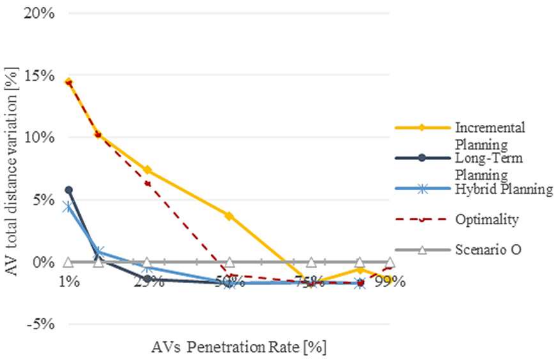


Figure 3.23 – RNDP-AVs peak-hour design: AV total distance variation in Scenario I.

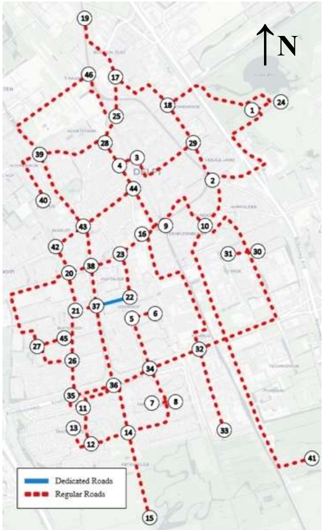
From a transport planning perspective, it is plausible to infer that dedicated roads are advantageous from the early stages of AVs deployment in urban networks. They provide lower travel time costs, with more convenience and comfort, and decrease overall congestion, obtained from AVs efficiency. However, their planning strategy must be carefully selected to avoid longer trips for CVs and congested roadways (fully saturated) in the surroundings of AV subnetworks. In general, AVs' operational efficiency did not reveal much travel time savings, and the decrease of the AVs' value of travel time caused longer trips for AV users in the early stages.

3.6.3. AV SUBNETWORKS THAT REQUIRE ROAD INVESTMENT FOR V2I

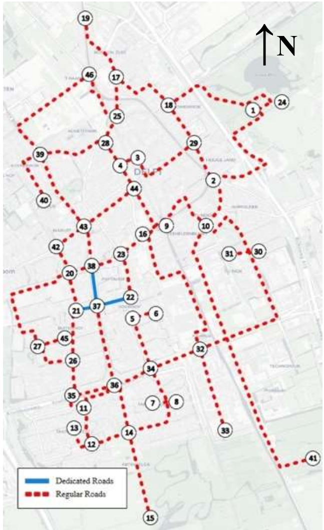
In Scenario II, an investment cost is added to the objective function. Table 3.4 details the Delft experiments where the RNDP-AVs model was applied to scenario II. Network solutions are depicted between Figure 3.24 and Figure 3.26. The decision problem now is more combinatorial; thus, the computational time increased accordingly. The incremental planning took nearly nine hours to execute and calculate all optimal solutions, whereas the long-term planning took seventeen minutes. This difference is explained because, in the long-term planning, the subnetwork is calculated reversely, reducing the solution space in each period over time. The hybrid planning took over five hours.

In incremental planning (Figure 3.24), the investment cost at each dedicated road implies fewer road links chosen at each stage. Accordingly, merely one dedicated road exists for a penetration rate of 10%. Only when automated traffic is over 50%, subnetworks start to grow, and the final configuration is reached when AVs are over 75%. Dedicated roads are mostly located in residential areas.

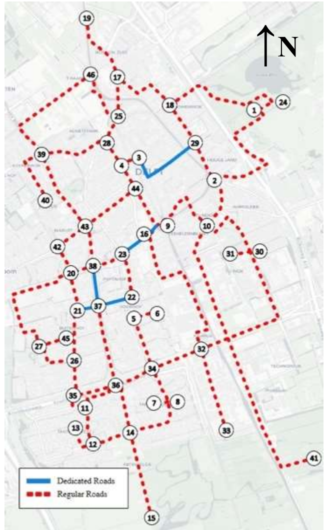
When applied the long-term planning, the optimal network design is calculated for 90% of AVs, and then the network design is reversely calculated – see Figure 3.25. Since investment is guaranteed in the preceding stage , the creation of AV subnetworks starts earlier than the ones obtained in scenario I (Figure 3.7) in order to distribute the total investment since the early stages.



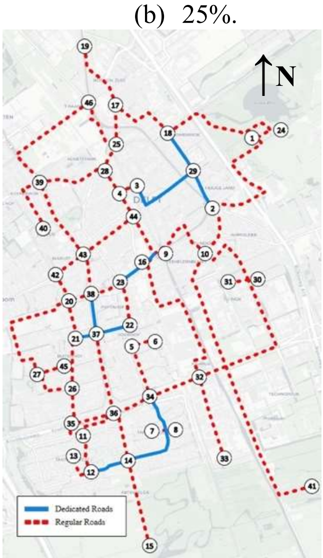
(a) 10%.



(b) 25%.



(c) 50%.



(d) 75%, 90%, 99%.

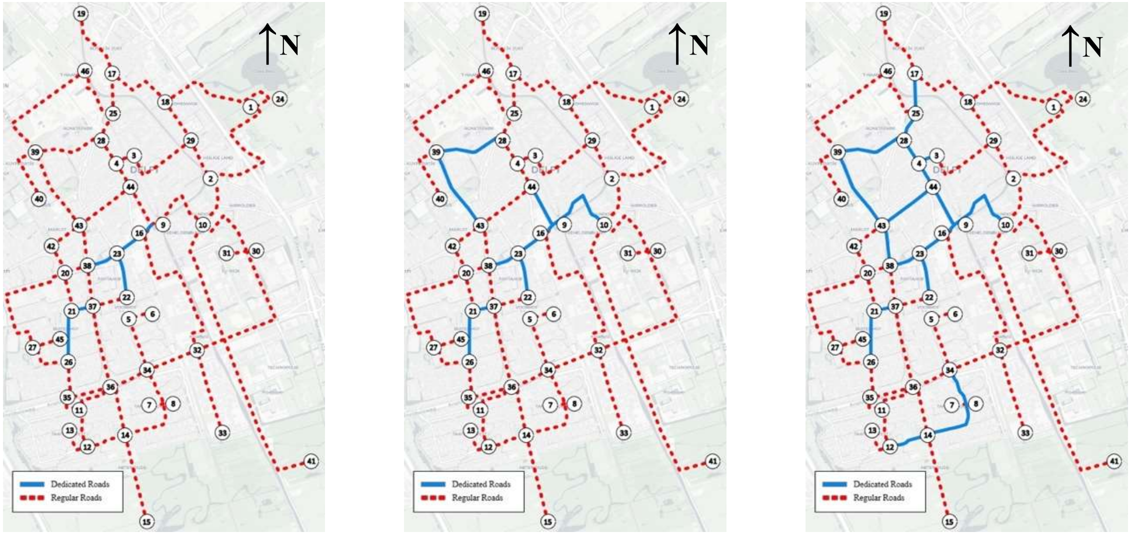
Figure 3.24 – RNDP-AVs peak-hour design: AV subnetworks of Scenario II under Incremental Planning (a), (b), (c), and (d) (% of AV penetration rate).

Table 3.4 – Peak-hour experiments results of scenario II with AV subnetworks that require road investment.

Scenario II (with AV subnetworks) RNDP-AVs with road investment	AV Penetration Rate	Generalized Costs: Objective Function [€]	Generalized Costs: Driving travel times [%]	Generalized Costs: Penalty [%]	Generalized Costs: Road Investment [%]	Solution: Dedicated Roads [no.]	Solution: AVs subnetworks [km]	Travel Times: Driving AV trips [h veh]	Travel Times: Driving CV trips [h veh]	Travel Times: Penalty CV trips [h veh]	Travel Times: Total Travel Time [h veh]	Congestion [1]: Average Degree of Saturation [%]	Congestion [1]: Roadways above practical capacity [km]	Congestion [1]: Congested roadways [km]	Delay [2]: AV trips [h veh]	Delay [2]: CV trips [h veh]	Delay [2]: Total Delay [h veh]	Travel Distances: AV trips [%]	Travel Distances: CV trips [%]	Travel Distances: Total Distance [km veh]	Computational time: Each Stage [h:m:s]	Computational time: The whole scenario [h:m:s]
Optimality	1%	10,655.00 €	100.0%	0.0%	0.0%	0	0.00	12	1151	0	1163	47%	15.15	4.82	1	120	122	1.0%	99.0%	68666	00:01:03	61:25:08
	10%	10,623.40 €	99.9%	0.0%	0.1%	1	0.80	116	1048	0	1164	47%	15.15	4.82	12	111	123	9.9%	90.1%	68529	02:46:04	
	25%	10,414.40 €	99.8%	0.0%	0.2%	3	2.47	289	868	0	1157	46%	13.98	4.82	29	87	116	24.9%	75.1%	68370	14:02:51	
	50%	9,549.98 €	99.3%	0.0%	0.7%	7	6.89	571	578	0	1149	43%	11.19	7.83	51	57	108	48.4%	51.6%	69666	03:19:36	
	75%	8,136.33 €	99.4%	0.0%	0.6%	6	4.81	819	274	0	1093	37%	7.83	2.75	38	14	52	73.8%	26.2%	68531	36:03:34	
	90%	7,070.82 €	99.8%	0.0%	0.2%	3	2.42	962	107	0	1068	34%	2.75	2.75	25	3	28	89.5%	10.5%	67753	05:11:27	
	99%	6,329.35 €	100.0%	0.0%	0.0%	0	0.00	1047	11	0	1057	29%	2.75	0.00	17	0	17	99.0%	1.0%	68554	00:00:33	
Incremental Planning	1%	10,655.00 €	100.0%	0.0%	0.0%	0	0.00	12	1151	0	1163	47%	13.98	4.82	1	120	121	1.1%	98.9%	68699	00:01:52	08:52:13
	10%	10,623.40 €	99.9%	0.0%	0.1%	1	0.80	116	1048	0	1164	47%	15.15	4.82	12	111	123	9.9%	90.1%	68529	00:22:13	
	25%	10,406.30 €	99.8%	0.0%	0.2%	3	2.47	289	868	0	1157	46%	13.98	4.82	29	87	116	24.9%	75.1%	68388	02:55:53	
	50%	9,693.28 €	99.7%	0.0%	0.3%	6	5.70	559	590	0	1149	44%	12.99	7.39	39	45	84	47.9%	52.1%	71229	02:54:31	
	75%	8,181.26 €	99.3%	0.0%	0.7%	11	11.41	814	292	0	1106	33%	9.58	2.86	34	9	43	71.8%	28.2%	71275	02:30:54	
	90%	7,037.58 €	100.0%	0.0%	0.0%	11	11.41	962	115	0	1077	29%	6.06	1.61	25	2	27	88.8%	11.2%	68460	00:06:43	
	99%	6,327.74 €	100.0%	0.0%	0.0%	11	11.41	1048	12	0	1059	28%	2.75	0.00	18	0	18	98.9%	1.1%	68204	00:00:07	
Long-Term Planning	0%	10,705.50 €	99.5%	0.0%	0.5%	0	0.00	-	1164	0	1164	47%	15.15	4.82	0	123	123	0.0%	100.0%	68609	00:00:06	00:16:57
	1%	10,706.70 €	100.0%	0.0%	0.0%	6	5.03	12	1181	0	1193	47%	18.08	6.58	1	151	152	0.9%	99.1%	71895	00:00:10	
	10%	10,694.70 €	99.3%	0.0%	0.7%	6	5.03	117	1067	0	1184	47%	17.01	6.58	13	130	143	9.5%	90.5%	71564	00:00:13	
	25%	10,608.20 €	99.1%	0.0%	0.9%	10	12.11	298	928	0	1225	45%	16.27	7.83	37	133	170	24.1%	75.9%	70182	00:02:26	
	50%	9,518.18 €	100.0%	0.0%	0.0%	21	22.23	589	625	0	1214	39%	18.08	9.58	38	75	114	46.1%	53.9%	77586	00:00:50	
	75%	7,988.05 €	100.0%	0.0%	0.0%	21	22.23	829	298	0	1127	32%	11.89	4.82	49	23	72	70.8%	29.2%	71445	00:00:06	
	90%	6,955.31 €	100.0%	0.0%	0.0%	21	22.23	964	114	0	1078	27%	6.06	2.75	27	4	31	87.9%	12.1%	69017	00:13:06	
Hybrid Planning	1%	10,655.00 €	100.0%	0.0%	0.0%	0	0.00	12	1152	0	1164	47%	15.15	4.82	1	122	123	1.0%	99.0%	68591	00:00:05	05:11:49
	10%	10,630.70 €	100.0%	0.0%	0.0%	0	0.00	116	1047	0	1163	47%	13.98	4.82	12	110	123	10.0%	90.0%	68545	00:00:05	
	25%	10,428.30 €	99.8%	0.0%	0.2%	3	2.42	291	879	0	1170	47%	16.17	6.58	31	99	130	75.9%	24.1%	70761	00:00:08	
	50%	9,562.86 €	100.0%	0.0%	0.0%	3	2.42	565	567	0	1132	43%	11.19	4.52	45	47	92	51.3%	48.7%	69873	00:00:02	
	75%	8,134.37 €	100.0%	0.0%	0.0%	3	2.42	816	272	0	1088	37%	7.83	2.75	36	12	48	26.0%	74.0%	69082	00:00:02	
	90%	7,070.82 €	100.0%	0.0%	0.0%	3	2.42	962	107	0	1068	34%	2.75	2.75	25	3	28	10.5%	89.5%	67753	05:11:27	

[1] Congestion is calculated as the ratio of flow to capacity on each road link, i.e., the degree of saturation.

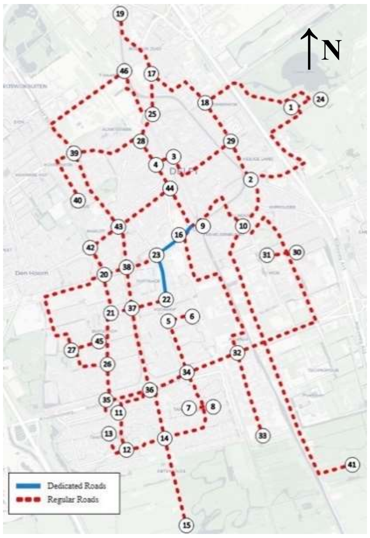
[2] Delay is calculated as the difference between the driven travel time and the minimum travel time on each roadway in free-flow speed conditions, where it is assumed that each vehicle only carries one passenger



(a) 1%, 10%. (b) 25%. (c) 50%, 75%, 90%.

Figure 3.25 – RNDP-AVs peak-hour design: AV subnetworks of Scenario II under Long-Term Planning (a), (b), and (c) (% of AV penetration rate).

The hybrid planning (Figure 3.26) produces a single configuration since the AV penetration rate is 25%. This occurs because the model only gets to choose incrementally the links that are part of the optimal network design in the long-term. After 25% of AVs, it is too costly to invest in more road links, and while the model minimizes the costs at each stage, the travel time savings do not surpass the road investment.



(a) 25%, 50%, 75%, 90%.

Figure 3.26 – RNDP-AVs peak-hour design: AV subnetworks of Scenario II under Hybrid planning (a) (% of AV penetration rate).

Figure 3.27 shows the evolution of AV subnetworks obtained from the experiments done at each strategy in Scenario II. In this case, the optimality shows that dedicated links decrease for penetration rates over 50% because the amount of investment needed shall surpass the travel cost savings obtained by this strategy. Therefore, after 50% of AVs, in incremental planning, the AV network design continues evolving because the amount of investment needed to upgrade at each stage is also lower. For long-term planning, the progressive subnetwork seems to be far from the optimality that considers road investment. The hybrid planning limits the creation of dedicated roads with a small network since 25% of AVs. Nevertheless, it is essential to note that these three planning approaches have completely different algorithms. The investment is different being proportional to the AVs subnetwork dimension: higher in the long-term planning, then slender in the incremental planning and minor in the hybrid planning strategy. In Figure 3.28, both incremental and hybrid planning seem suitable planning approaches because the generalized differential costs do not exceed as much as the ones obtained in the long-term planning. However, the long-term planning strategy holds a higher differential, increasing the costs up to 1.5% for a penetration rate of 25% and then reducing up to 3% when 75% of the vehicles are automated.

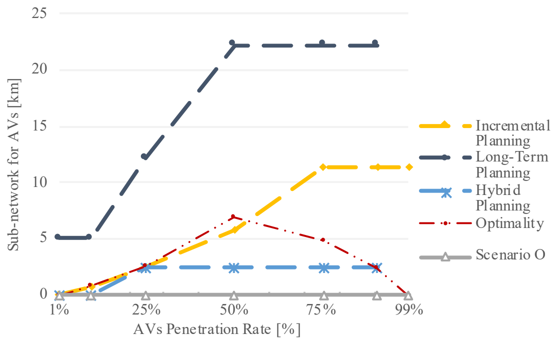


Figure 3.27 – RNDP-AVs peak-hour design: subnetwork evolution in Scenario II.

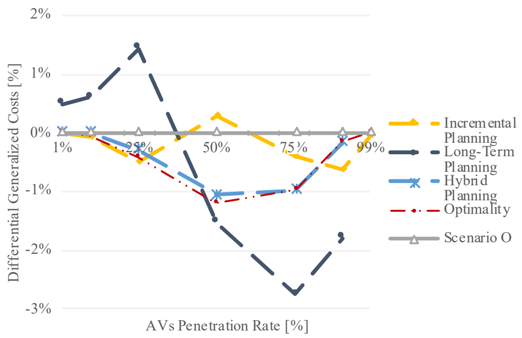


Figure 3.28 – RNDP-AVs peak-hour design: Differential on the generalized costs in Scenario II.

Figure 3.29 illustrates the average congestion throughout the AVs deployment, being the long-term planning the one that most reduces congestion. Similar conclusions were found in the analysis of roadways above practical capacity and congested roadways: the presence of dedicated roads during the deployment process will cause extra congestion from CV detour. The incremental planning revealed less congested roadways than the long-term planning, whereas the hybrid has such a small network that almost does not cause detour. Figure 3.30 illustrates the total travel time amongst the planning approaches. The long-term strategy holds extra travel times, despite reducing the overall congestion. Figure 3.31 and Figure 3.32 depict the total distance traveled and compare it to scenario O, showing that dedicated roads might force CVs to detour up to 25% while reducing AVs distances for most of the process.

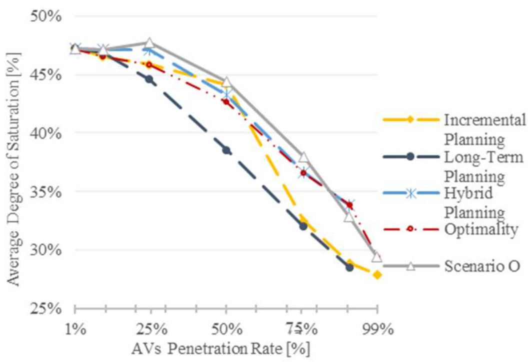


Figure 3.29 – RNDP-AVs peak-hour design: Average degree of saturation in Scenario II.

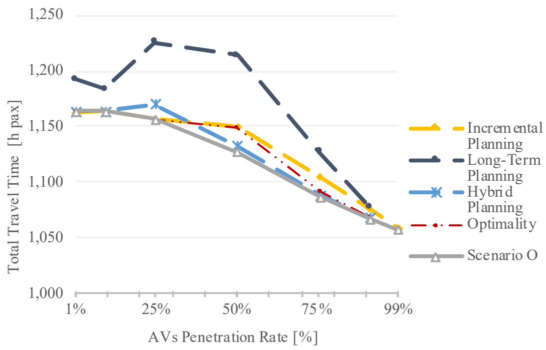


Figure 3.30 – RNDP-AVs peak-hour design: AV Total travel time in Scenario II.

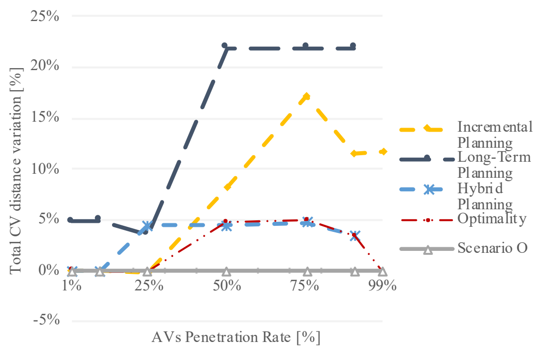


Figure 3.31 – RNDP-AVs peak-hour design: CV total distance variation in Scenario II.

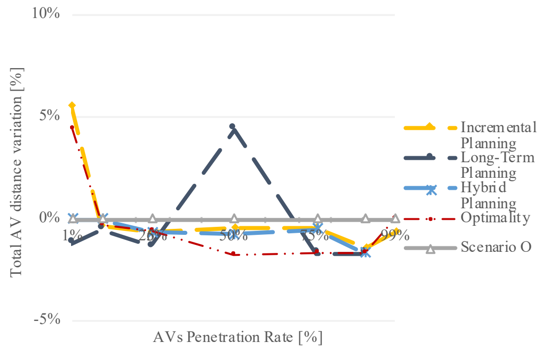


Figure 3.32 – RNDP-AVs peak-hour design: AV total distance variation in Scenario II.

3.6.4. PLANNING STRATEGIES OVERVIEW

The previous analyses were crucial to estimate the impacts of AV subnetworks throughout the whole transition process. Despite the benefits - lower travel time costs and lower congestion - one thing is sure; CV detour will happen at some point of the process. AVs might also travel longer distances, mostly in the early stages of their deployment to take advantage of their reduced value of travel time and higher efficiency.

The strategy considered for the selection of dedicated roads in each scenario is debatable and dependent on the desired results. Two patterns are noticeable: When most of the vehicles are conventional the model aims to reduce CV detour costs by selecting dedicated roads with lower capacity, and therefore lower speed, putting AV traffic away from regular roads. As more AVs are present in the system, the model aims to increase their cost savings by increasing the subnetworks dimension. Amongst the planning strategies, the model balances the CV detour extra costs and AV cost savings, given a penetration rate. This is why the incremental planning strategy starts avoiding CV detour and forces an increase of distances travelled for the AVs in the early stages. On the other hand, the long-term planning starts from the optimal long-term network design, where 90% of the vehicles are automated, and 10% are conventional. In this case, the model creates the network reversely by maximizing the travel time cost savings, which is naturally far from optimality at the early stages, because detour is unavoidable – the reverse design gives preference to AVs savings and worsens CV detour. At last, the hybrid planning revealed surprising results because it proved that, limiting the incremental planning to the optimal solution obtained in the long term, strongly diminish the negative effects of both incremental and long-term planning strategies throughout the transition process. Moreover, in the first half of the transition period, the hybrid planning diminishes the extra travel costs from implementing the long-term planning strategy; whilst, in the second half of the transition process, the hybrid planning diminishes CV detour from implementing the incremental planning.

This subsection aims to help decide the strategy that is best for implementing dedicated roads, either if road investment is part of the problem or not (scenarios I or II). The evolution of the subnetwork in each strategy applied to both scenarios is depicted in Figure 3.33. The generalized differential costs are shown in Figure 3.34. Scenario I (without road investment) is represented at continuous lines, while Scenario II (with road investment) is pictured with dashed lines. At pink shadow is represented the optimal area. The optimal zone is between both optimality analyses, with and without road investment, whereas in the differential costs are optimal when the differential is negative. To summarize the analysis, the planning approaches that fit in this optimal zone are thickened and therefore correspond the best planning strategies: scenario I with hybrid planning; and scenario II with incremental planning.

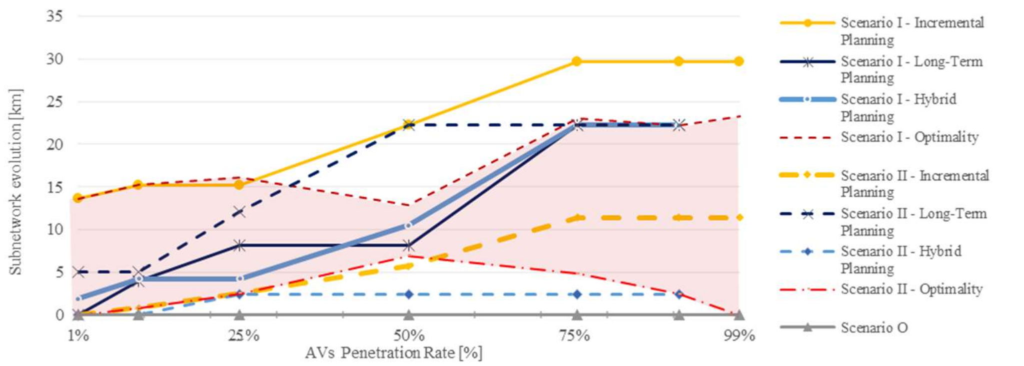


Figure 3.33 – RNDP-AVs peak-hour design: Progressive subnetworks in every planning strategy.

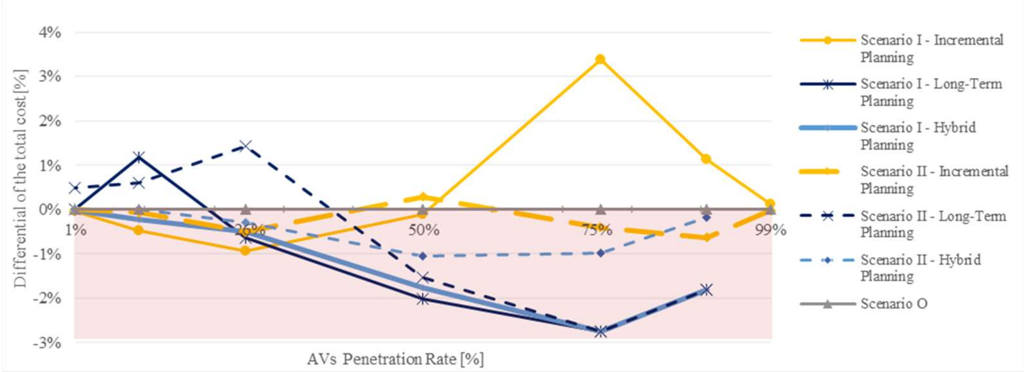


Figure 3.34 – RNDP-AVs peak-hour design: Differential generalized costs in every planning strategy.

As expected, the long-term planning creates a suitable network design at higher penetration rates (second-half of the transition process), whereas the incremental planning is more desirable in the short-term rates (first-half of the transition process). When road investment is ignored (scenario I), the hybrid planning is very satisfactory. The long-term planning is also beneficial in terms of the total cost, except in the early stages (penetration rate of 10%). Therefore, to avoid those early extra costs from CV detour, the long-term planning strategy should be implemented when at least 25% of the vehicles are automated. The incremental planning strategy is inadequate in the second-half of the transition process. In the same way, if road investment is part of the decision problem, the incremental and hybrid planning strategies will demand a significant investment at every design stage. The long-term planning distributes the investment needed for the next upgrade beforehand Furthermore, in this case (scenario II), the best strategy is the incremental planning. The implementation of the long-term planning strategy would increase costs when AVs are 10%, so it should only be implemented afterwards. Hence, the decision to choose amongst the planning strategies might not be trivial.

In this sense, the CV detour problem might be used as tie-breaking criteria. CV detour problem reflects in increased travelled distances, total travel time and consequently congestion. The best strategy to mitigate this problem would be the incremental without investment and the hybrid planning with investment. The long-term planning revealed higher CV travelled distances, i.e., more CV detour.

However, the decision upon the strategy also depends on the evolution of the penetration rate over time, i.e., how the transition process will take place. The time lag from 1% to 50% of AVs might take much longer than the time lag from 50% to 90% of AVs. In this case, the CV detour would be very present, which turns out to be a priority to address. Time plays here an important role, yet forecasts on the diffusion of AVs are still very vulnerable and dependent on policy and technology evolution.

3.6.5. Daily Implications of the RNDP-AVs designed for the peak-hour

Designing for the most congested hour can be quite delicate when considering the remaining part of the day that involves different mobility patterns and different trips demand, with likely different O-D pairs. When such O-D pairs are inside these AV subnetworks, CV owners cannot drive, and therefore a new mode of transport is necessary. The RNDP-AVs formulation model evaluates only the detour problem through a penalty variable. In order to estimate the impacts of the AV subnetworks throughout the day, a different formulation must guarantee that CV trips starting inside AV subnetworks throughout the day aren't ignored – this means giving a new alternative mode of transport, for example, walking.

The main difference from the previous (and general) formulation involves the penalty variables that in this subsection will be called "walking variables." This framework evaluates whether walking is cost-efficient as an alternative to driving when a detour is expensive or even when a detour is not possible (CV owners start their trips inside the AV subnetwork).

An assumption is added: "every road link has sidewalks for pedestrians," but that is natural to occur in urban areas. Two parameters are added to the formulation:

τ: walking speed, expressed in kilometers per hour.

VOT^{walk}: value of travel time while walking in monetary units per hour.

The second component in the objective function previously presented (3.1) was modified to include the cost of the walking (travel time) trips – the square area in (3.19).

$$\text{Min(Cost)} = VOT^{car} \sum_{(i,j)\in \boldsymbol{R}} \int_0^{f_{ij}^{h_i h_f}} t_{ij}^{h_i h_f} df + \boxed{VOT^{walk} \sum_{(i,j)\in \boldsymbol{R}} \sum_{(o,d)\in \boldsymbol{P}} p_{ijod}^{h_i h_f} \frac{L_{ij}}{\tau}} + VOI \sum_{(i,j)\in \boldsymbol{R}} x_{ij} L_{ij} \quad (3.19)$$

Constraints (3.7),(3.8), (3.20)-(3.23) define the walking flows. CV travelers can park and walk until destination when their driving path is blocked by a dedicated road, and if walking is more cost-efficient than detouring. From the previous formulation, constraints (3.7) and (3.8) are maintained (see page 39), while (3.9) is adapted to (3.20). Constraints (3.20) assure that the walking flow of every link $(i,j) \in \boldsymbol{R}$ is limited to the preceding flow of link $(j,i) \in \boldsymbol{R}$ and extra walking flow might be added if that link is dedicated. Constraints (3.21) guarantee the continuity of the walking flow through the network: walking flow departing node $i \in \boldsymbol{I}$ shall be higher than the walking flow arriving to that node, except in the origin and destination of every O-D pair. Constraints (3.22) assure that travelers shall start their trips with CVs if such trip origin is not entirely surrounded by AV subnetworks, yet they must start their trips on walking if the origin is inside an AV subnetwork. Constraints (3.23) absorb the walking flows from the preceding links in the links surrounding the destination node of every trip.

$$p_{ijod}^{h_i h_f} \le p_{ijod}^{h_i h_f} + C_{ij} * x_{ij}, \forall\, i,j \in \boldsymbol{I}, (o,d) \in \boldsymbol{P}, i \ne o,d, D_{od}^{CV\ h_i h_f} > 0 \quad (3.20)$$

$$\sum_{j\in \boldsymbol{I}} p_{jiod}^{h_i h_f} \le \sum_{j\in \boldsymbol{I}} p_{ijod}^{h_i h_f}, \forall\, i \in \boldsymbol{I}, (o,d) \in \boldsymbol{P}, i \ne o,d, D_{od}^{CV\ h_i h_f} > 0 \quad (3.21)$$

$$p_{ojod}^{h_i h_f} \le D_{od}^{CV} * x_{oj}, \forall\, j \in \boldsymbol{I}, (o,d) \in \boldsymbol{P} o \ne d\ , D_{od}^{CV\ h_i h_f} > 0 \quad (3.22)$$

$$p_{idod}^{h_i h_f} \le \sum_{j\in \boldsymbol{I}} p_{jiod}^{h_i h_f} + C_{id} * x_{id}, \forall\, i \in \boldsymbol{I}, (o,d) \in \boldsymbol{P}, i \ne d, D_{od}^{CV\ h_i h_f} > 0 \quad (3.23)$$

The reference value of time while walking (VOT^{walk}) is considered 20% higher than while driving: 12 € per hour. The walking cost is higher than the driving cost, which is believed to represent the best reality nowadays. The walking travel time was computed from the average pedestrian's speed on an empty sidewalk, of 5.0 ft/s equivalent to 5.48 km/h, i.e., a default walking free-flow speed (HCM, 2010).

This section evaluates the scenarios found most appropriate in previous section 3.6.4 amongst the incremental and long-term planning strategies: scenario O, without AV subnetworks (for comparison purposes only); scenario I under the long-term planning strategy, and scenario II under the incremental planning strategy. Each hourly traffic assignment was computed in a few seconds. Here the trips were simulated to start $]h_i h_f]$. Figure 3.36 reminds the progression of AV subnetworks in each scenario. Results are presented from Table 3.5 to Table 3.7 (pages 66 to74).

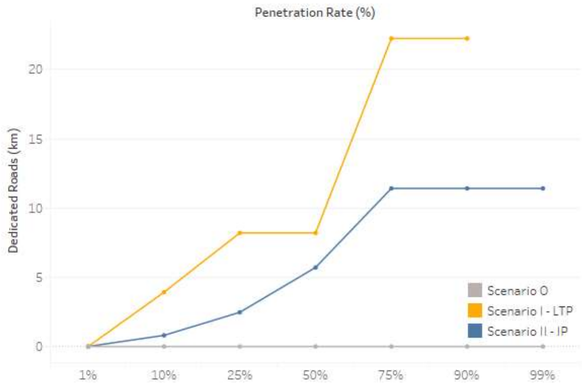


Figure 3.35 – RNDP-AVs peak-hour design: AV subnetworks progression in Scenarios I-LTP and II-IP.

Figure 3.36 summarizes the daily costs obtained for each scenario experimented. Both scenarios with AV subnetworks revealed particularly alarming results, with increased 26.0% and 43.8% travel costs for an AV penetration rate of 75% when compared to scenario O. It seems that walking, as the alternative mode of transport, would only occur for the AV subnetworks designed for those stages.

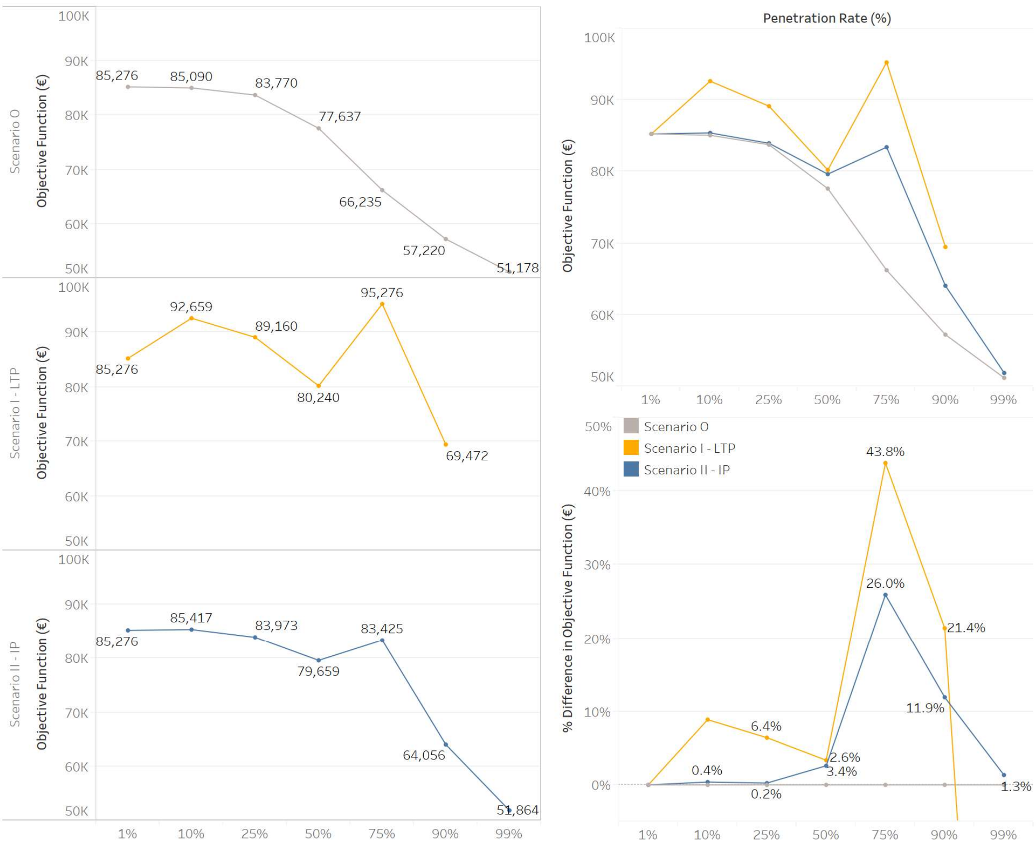
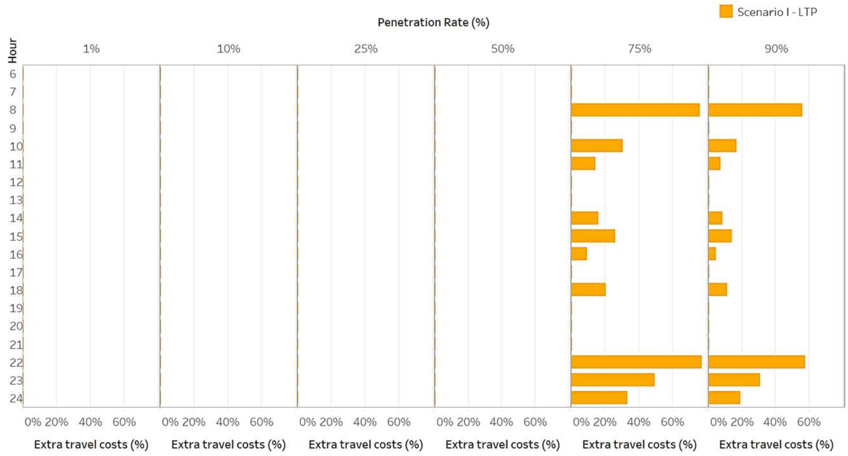
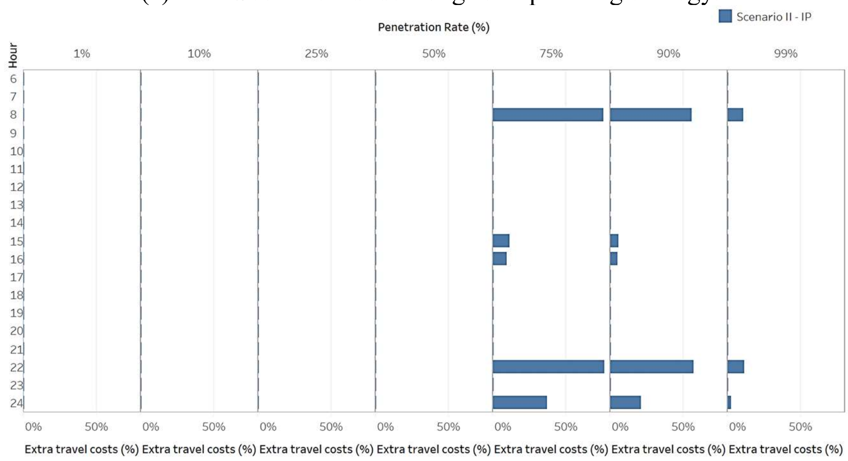


Figure 3.36 – RNDP-AVs peak-hour design with walking as an alternative: Daily costs.

Figure 3.37 confirm that walking occurs when AVs reach a penetration rate of 75%, onwards. The worst-case (higher costs) is scenario I, as it implies more extensive AV subnetworks because no road investment is associated. Walking occurs throughout the day in scenario I, almost every hour. This happens because of the shifting trips demand (O-D matrix) that varies throughout the day. In scenario II – where road investment is assumed in the creation of AV subnetworks – as the AV subnetworks are substantially smaller (see Figure 3.38), less walking occurs throughout the day.



(a) Scenario I under long-term planning strategy.



(b) Scenario II under incremental strategy.

Figure 3.37 – RNDP-AVs peak-hour design with walking as an alternative: Hourly extra travel costs (a) and (b).

Figure 3.38 shows the length (in kilometers) of congested roads throughout the day, i.e., when traffic flow is near practical capacity, above a degree of saturation of 75%. Congested roads are not obvious to predict, given the shifting trips demand throughout the day. The peak depicted in scenario I under long-term planning for a penetration rate of 10% may suggest that AV subnetworks should only start when AVs reach 25% of the vehicle fleet (in case that AVs level 4 do not need any investment to be able to read the roads). Overall, it is conclusive AV subnetworks mitigate the length of congested roads after that penetration rate (25% of AVs).

Figure 3.39 illustrates the average degree of saturation experienced during the day. Scenario I under long-term planning is able to reduce the degree of saturation by 8.8% when AVs are 10% of the fleet, and when AVs reach 90%, the degree of saturation reduces 13.1%. Scenario II – when an investment is necessary – it only reduces 4.0% when AVs are 10% of the fleet and 9.7% at the end of the transition period. In scenario II, the most significant contribution of AV subnetworks is during the transition period from 25% to 90% of AVs, achieving 7.0-13.1% of reduction.

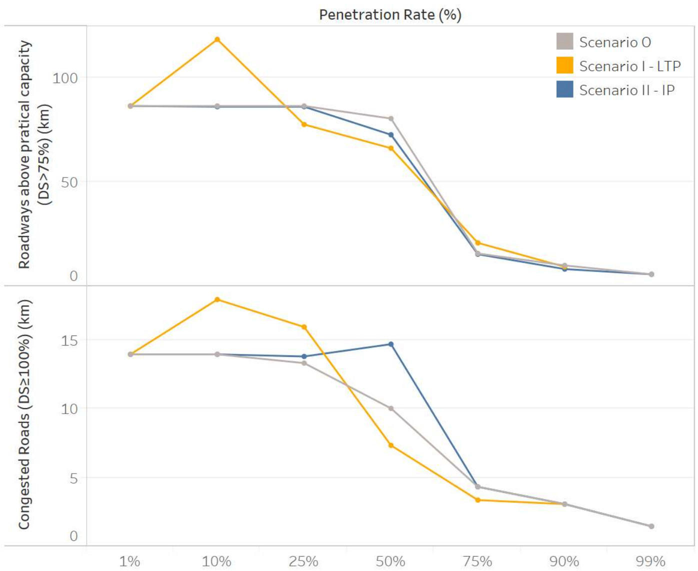


Figure 3.38 – RNDP-AVs peak-hour design with walking as an alternative: Daily congested roads.

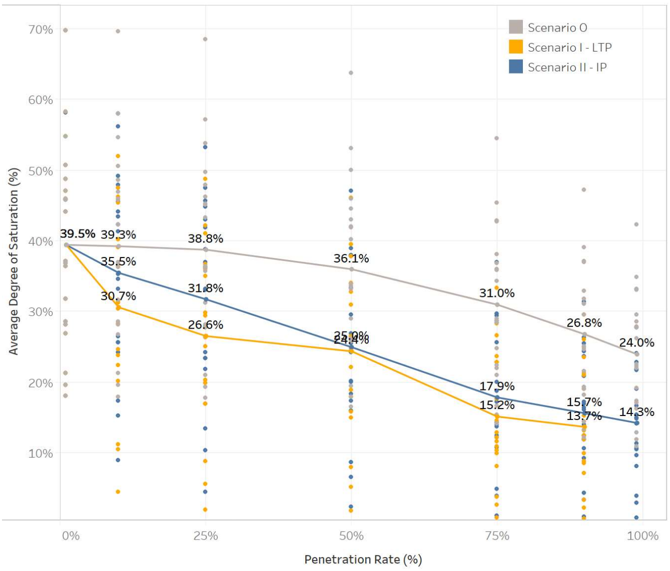


Figure 3.39 – RNDP-AVs peak-hour design with walking as an alternative: Daily average degree of saturation.

Figure 3.40 compares the daily delay among AVs and CVs to scenario O where AV subnetworks do not exist. The results suggest that in scenario I under long-term strategy, CV delay increases in the beginning of the transition period and decreases in the latest stages, starting at 50%. In scenario II under an incremental strategy, CV delay is essentially reduced after 75%. Note for a penetration rate of 75 and 90%, the reduction of the delay is due to the existence of walking trips in this deployment stage. Looking at the AV outcomes, delay is always reduced, no matter which stage of the transition period, except for a penetration rate of 1% where AV delay increases about 2% in both scenarios.

Figure 3.41 illustrate the daily distance results of AVs and CVs in both scenarios It seems that the use of AV subnetworks imply that CVs may have to travel longer in the latest stages of the transition period but note that there are fewer CVs in these stages. In scenario I, AVs also travel longer except when there is 1% of AVs. In terms of distance, scenario II is the one that presents best results. CV distance increase about 5% and up to 7% in the end of the period, while AV distance is close to null throughout the transition period.

Figure 3.40 – RNDP-AVs peak-hour design with walking as an alternative: Daily delay.

Figure 3.41 – RNDP-AVs peak-hour design with walking as an alternative: daily distance.

Table 3.5 – Hourly traffic assignment of scenario O – no AV subnetworks.

Scenario O No AV subnetworks		Generalized Costs			AV Subnetwork		Congestion			Travel Times				Travel Delays			Travel Distances		
		Objective Function	Driving travel times	Walking travel times	Dedicated Roads		Average degree of saturation	Roads above practical capacity (DS>75%)	Congested Roads (DS≥100%)	Driving AV trips	Driving CV trips	Walking CV trips	Total	AV trips	CV trips	Total	AV trips	CV trips	Total Distance
Analysis	Penetration rate (%)	[€]	[%]	[%]	[no.]	[km]	[%]	[km]	[km]	[h veh]	[h veh]	[h veh]	[h veh]	[%]	[%]	[h veh]	[%]	[%]	[km veh]
6h-7h	1%	525.52 €	100.0%	0.0%	0	0.00	19.6%	0.00	0.00	1	52	0	53	0	0	0	1.1%	98.9%	2988
	10%	524.42 €	100.0%	0.0%	0	0.00	19.6%	0.00	0.00	5	47	0	53	0	0	0	10.0%	90.0%	2988
	25%	516.62 €	100.0%	0.0%	0	0.00	19.3%	0.00	0.00	13	39	0	53	0	0	0	25.0%	75.0%	2988
	50%	480.10 €	100.0%	0.0%	0	0.00	17.9%	0.00	0.00	26	26	0	53	0	0	0	50.0%	50.0%	2988
	75%	411.13 €	100.0%	0.0%	0	0.00	15.4%	0.00	0.00	39	13	0	53	0	0	0	75.0%	25.0%	2988
	90%	355.86 €	100.0%	0.0%	0	0.00	13.3%	0.00	0.00	47	5	0	53	0	0	0	90.0%	10.0%	2988
	99%	318.78 €	100.0%	0.0%	0	0.00	11.9%	0.00	0.00	52	1	0	53	0	0	0	98.9%	1.1%	2988
7h-8h	1%	3,387.05 €	100.0%	0.0%	0	0.00	36.8%	0.87	0.87	4	342	0	346	0	9	9	1.0%	99.0%	20347
	10%	3,379.85 €	100.0%	0.0%	0	0.00	36.7%	0.87	0.87	35	311	0	346	1	8	9	10.0%	90.0%	20347
	25%	3,328.61 €	100.0%	0.0%	0	0.00	36.2%	0.87	0.87	86	259	0	345	2	6	8	25.0%	75.0%	20347
	50%	3,089.60 €	100.0%	0.0%	0	0.00	33.6%	0.87	0.29	171	171	0	343	3	3	6	50.0%	50.0%	20347
	75%	2,641.49 €	100.0%	0.0%	0	0.00	28.8%	0.87	0.00	255	85	0	340	2	1	3	75.0%	25.0%	20347
	90%	2,284.50 €	100.0%	0.0%	0	0.00	24.9%	0.29	0.00	305	34	0	339	2	0	2	90.0%	10.0%	20347
	99%	2,044.55 €	100.0%	0.0%	0	0.00	22.3%	0.29	0.00	335	3	0	338	1	0	1	99.0%	1.0%	20347
8h-9h	1%	5,823.06 €	100.0%	0.0%	0	0.00	47.1%	9.12	0.00	6	603	0	609	0	33	33	1.0%	99.0%	32913
	10%	5,810.38 €	100.0%	0.0%	0	0.00	47.0%	9.12	0.00	61	548	0	609	3	30	33	10.0%	90.0%	32913
	25%	5,720.19 €	100.0%	0.0%	0	0.00	46.3%	9.12	0.00	152	455	0	607	8	23	31	25.0%	75.0%	32913
	50%	5,301.44 €	100.0%	0.0%	0	0.00	43.0%	8.77	0.00	299	299	0	599	12	12	23	50.0%	50.0%	32913
	75%	4,523.19 €	100.0%	0.0%	0	0.00	36.8%	0.00	0.00	441	147	0	588	9	3	12	75.0%	25.0%	32913
	90%	3,907.77 €	100.0%	0.0%	0	0.00	31.9%	0.00	0.00	524	58	0	583	6	1	7	90.0%	10.0%	32913
	99%	3,494.07 €	100.0%	0.0%	0	0.00	28.5%	0.00	0.00	575	6	0	580	4	0	4	99.0%	1.0%	32913
9h-10h	1%	9,792.96 €	100.0%	0.0%	0	0.00	58.3%	12.55	2.75	11	1049	0	1059	1	99	100	1.0%	99.0%	50000
	10%	9,770.90 €	100.0%	0.0%	0	0.00	58.1%	12.55	2.75	106	953	0	1059	10	90	99	10.0%	90.0%	49957
	25%	9,614.21 €	100.0%	0.0%	0	0.00	57.2%	12.55	2.75	263	790	0	1053	23	70	94	25.0%	75.0%	49956
	50%	8,891.15 €	100.0%	0.0%	0	0.00	53.2%	12.55	2.75	515	515	0	1029	35	35	70	50.0%	50.0%	49956
	75%	7,563.52 €	100.0%	0.0%	0	0.00	45.4%	2.75	1.61	748	249	0	997	28	9	38	75.0%	25.0%	49899
	90%	6,524.35 €	100.0%	0.0%	0	0.00	39.2%	2.75	1.61	883	98	0	981	19	2	21	90.0%	10.0%	49850
	99%	5,831.57 €	100.0%	0.0%	0	0.00	34.9%	2.75	0.00	963	10	0	973	14	0	14	99.0%	1.0%	49746

Scenario O No AV subnetworks		Generalized Costs			AV Subnetwork		Congestion			Travel Times				Travel Delays			Travel Distances		
		Objective Function	Driving travel times	Walking travel times	Dedicated Roads		Average degree of saturation	Roads above practical capacity (DS>75%)	Congested Roads (DS≥100%)	Driving AV trips	Driving CV trips	Walking CV trips	Total	AV trips	CV trips	Total	AV trips	CV trips	Total Distance
Analysis	Penetration rate (%)	[€]	[%]	[%]	[no.]	[km]	[%]	[km]	[km]	[h veh]	[h veh]	[h veh]	[h veh]	[%]	[%]	[h veh]	[%]	[%]	[km veh]
10h-11h	1%	8,117.75 €	100.0%	0.0%	0	0.00	44.2%	4.93	0.48	8	820	0	828	0	20	20	1.0%	99.0%	42913
	10%	8,100.59 €	100.0%	0.0%	0	0.00	42.3%	4.93	0.48	83	745	0	828	2	18	20	10.0%	90.0%	42885
	25%	7,977.78 €	100.0%	0.0%	0	0.00	43.4%	4.93	0.00	207	620	0	827	5	14	19	25.0%	75.0%	42885
	50%	7,405.05 €	100.0%	0.0%	0	0.00	40.2%	1.73	0.00	411	411	0	822	7	7	14	50.0%	50.0%	42868
	75%	6,331.04 €	100.0%	0.0%	0	0.00	34.3%	1.73	0.00	612	204	0	816	6	2	8	75.0%	25.0%	42814
	90%	5,475.26 €	100.0%	0.0%	0	0.00	29.5%	0.00	0.00	731	81	0	812	4	0	5	90.0%	10.0%	42714
	99%	4,899.16 €	100.0%	0.0%	0	0.00	26.2%	0.00	0.00	803	8	0	811	3	0	3	99.0%	1.0%	42606
11h-12h	1%	10,076.38 €	100.0%	0.0%	0	0.00	46.0%	8.96	2.76	11	1026	0	1036	0	36	36	1.0%	99.0%	53295
	10%	10,054.79 €	100.0%	0.0%	0	0.00	45.9%	8.96	2.76	104	933	0	1036	4	32	36	10.0%	90.0%	53295
	25%	9,901.17 €	100.0%	0.0%	0	0.00	45.2%	8.96	2.76	259	776	0	1034	8	25	34	25.0%	75.0%	53295
	50%	9,185.72 €	100.0%	0.0%	0	0.00	42.1%	6.62	0.48	513	513	0	1026	13	13	25	50.0%	50.0%	53295
	75%	7,848.19 €	100.0%	0.0%	0	0.00	36.0%	2.76	0.48	760	253	0	1014	10	3	13	75.0%	25.0%	53295
	90%	6,785.22 €	100.0%	0.0%	0	0.00	31.2%	0.48	0.00	907	101	0	1008	7	1	8	90.0%	10.0%	53295
	99%	6,071.48 €	100.0%	0.0%	0	0.00	27.9%	0.48	0.00	995	10	0	1005	5	0	5	99.0%	1.0%	53295
12h-13h	1%	8,581.41 €	100.0%	0.0%	0	0.00	45.9%	5.60	0.60	9	865	0	874	0	19	20	1.0%	99.0%	49093
	10%	8,563.21 €	100.0%	0.0%	0	0.00	45.8%	5.60	0.60	87	786	0	874	2	17	19	10.0%	90.0%	49093
	25%	8,433.62 €	100.0%	0.0%	0	0.00	45.1%	5.60	0.44	218	654	0	873	5	14	18	25.0%	75.0%	49093
	50%	7,829.02 €	100.0%	0.0%	0	0.00	41.9%	5.60	0.00	434	434	0	868	7	7	14	50.0%	50.0%	49093
	75%	6,694.62 €	100.0%	0.0%	0	0.00	35.9%	0.60	0.00	646	215	0	862	6	2	7	75.0%	25.0%	49093
	90%	5,790.36 €	100.0%	0.0%	0	0.00	31.1%	0.00	0.00	773	86	0	858	4	0	4	90.0%	10.0%	49093
	99%	5,181.95 €	100.0%	0.0%	0	0.00	27.8%	0.00	0.00	848	9	0	857	3	0	3	99.0%	1.0%	49093
13h-14h	1%	1,719.74 €	100.0%	0.0%	0	0.00	28.6%	0.63	0.00	2	171	0	173	0	1	1	1.0%	99.0%	9888
	10%	1,716.13 €	100.0%	0.0%	0	0.00	28.6%	0.63	0.00	17	156	0	173	0	1	1	10.0%	90.0%	9888
	25%	1,690.44 €	100.0%	0.0%	0	0.00	28.2%	0.63	0.00	43	130	0	173	0	1	1	25.0%	75.0%	9888
	50%	1,570.31 €	100.0%	0.0%	0	0.00	26.2%	0.48	0.00	86	86	0	173	1	1	1	50.0%	50.0%	9888
	75%	1,344.00 €	100.0%	0.0%	0	0.00	22.4%	0.00	0.00	129	43	0	172	0	0	1	75.0%	25.0%	9888
	90%	1,163.01 €	100.0%	0.0%	0	0.00	19.4%	0.00	0.00	155	17	0	172	0	0	0	90.0%	10.0%	9888
	99%	1,040.78 €	100.0%	0.0%	0	0.00	17.4%	0.00	0.00	170	2	0	172	0	0	0	99.0%	1.0%	9888
14h-15h	1%	5,895.88 €	100.0%	0.0%	0	0.00	50.8%	10.97	3.69	7	703	0	711	1	150	151	1.1%	98.9%	29657
	10%	5,881.02 €	100.0%	0.0%	0	0.00	50.5%	10.97	3.69	71	640	0	711	15	137	152	10.0%	90.0%	29608
	25%	5,776.17 €	100.0%	0.0%	0	0.00	49.8%	10.97	3.69	176	527	0	703	36	108	144	25.0%	75.0%	29599
	50%	5,300.55 €	100.0%	0.0%	0	0.00	46.0%	10.97	3.69	334	334	0	669	55	55	111	50.0%	50.0%	29512
	75%	4,456.62 €	100.0%	0.0%	0	0.00	42.8%	3.69	1.94	465	155	0	620	47	16	63	75.0%	25.0%	29405
	90%	3,820.29 €	100.0%	0.0%	0	0.00	37.0%	3.69	1.46	533	59	0	592	32	4	35	90.0%	10.0%	29405
	99%	3,405.06 €	100.0%	0.0%	0	0.00	33.1%	1.94	1.46	574	6	0	580	22	0	23	99.0%	1.0%	29405

Scenario O No AV subnetworks		Generalized Costs			AV Subnetwork		Congestion			Travel Times				Travel Delays			Travel Distances		
		Objective Function	Driving travel times	Walking travel times	Dedicated Roads		Average degree of saturation	Roads above practical capacity (DS>75%)	Congested Roads (DS≥100%)	Driving AV trips	Driving CV trips	Walking CV trips	Total	AV trips	CV trips	Total	AV trips	CV trips	Total Distance
Analysis	Penetration rate (%)	[€]	[%]	[%]	[no.]	[km]	[%]	[km]	[km]	[h veh]	[h veh]	[h veh]	[h veh]	[%]	[%]	[h veh]	[%]	[%]	[km veh]
15h-16h	1%	4,182.07 €	100.0%	0.0%	0	0.00	28.2%	0.00	0.00	4	415	0	419	0	1	1	1.1%	98.9%	22379
	10%	4,173.35 €	100.0%	0.0%	0	0.00	28.2%	0.00	0.00	42	377	0	419	0	1	1	10.0%	90.0%	22379
	25%	4,111.16 €	100.0%	0.0%	0	0.00	27.7%	0.00	0.00	105	314	0	419	0	1	1	25.0%	75.0%	22379
	50%	3,820.11 €	100.0%	0.0%	0	0.00	25.8%	0.00	0.00	209	209	0	419	0	0	1	50.0%	50.0%	22379
	75%	3,270.88 €	100.0%	0.0%	0	0.00	22.1%	0.00	0.00	314	105	0	418	0	0	0	75.0%	25.0%	22379
	90%	2,830.96 €	100.0%	0.0%	0	0.00	19.1%	0.00	0.00	376	42	0	418	0	0	0	90.0%	10.0%	22379
	99%	2,534.89 €	100.0%	0.0%	0	0.00	17.1%	0.00	0.00	414	4	0	418	0	0	0	98.9%	1.1%	22379
16h-17h	1%	9,127.91 €	100.0%	0.0%	0	0.00	54.8%	21.83	2.24	10	962	0	971	1	72	73	1.0%	99.0%	50241
	10%	9,107.69 €	100.0%	0.0%	0	0.00	54.7%	21.83	2.24	97	874	0	971	7	65	72	10.0%	90.0%	50241
	25%	8,963.94 €	100.0%	0.0%	0	0.00	53.9%	21.83	2.24	242	725	0	966	17	51	68	25.0%	75.0%	50241
	50%	8,298.68 €	100.0%	0.0%	0	0.00	50.1%	21.83	2.24	475	475	0	949	25	25	51	50.0%	50.0%	50241
	75%	7,069.89 €	100.0%	0.0%	0	0.00	42.9%	2.81	0.29	694	231	0	926	21	7	27	75.0%	25.0%	50241
	90%	6,103.29 €	100.0%	0.0%	0	0.00	37.1%	2.24	0.00	822	91	0	914	14	2	15	90.0%	10.0%	50241
	99%	5,456.86 €	100.0%	0.0%	0	0.00	33.2%	0.29	0.00	899	9	0	908	10	0	10	99.0%	1.0%	50241
17h-18h	1%	1,847.42 €	100.0%	0.0%	0	0.00	31.8%	0.00	0.00	2	183	0	185	0	1	1	1.0%	99.0%	9694
	10%	1,843.57 €	100.0%	0.0%	0	0.00	31.7%	0.00	0.00	19	167	0	185	0	1	1	10.0%	90.0%	9694
	25%	1,816.07 €	100.0%	0.0%	0	0.00	31.3%	0.00	0.00	46	139	0	185	0	0	1	25.0%	75.0%	9694
	50%	1,687.41 €	100.0%	0.0%	0	0.00	29.0%	0.00	0.00	93	93	0	185	0	0	0	50.0%	50.0%	9694
	75%	1,444.70 €	100.0%	0.0%	0	0.00	24.9%	0.00	0.00	139	46	0	185	0	0	0	75.0%	25.0%	9694
	90%	1,250.35 €	100.0%	0.0%	0	0.00	21.5%	0.00	0.00	166	18	0	185	0	0	0	90.0%	10.0%	9694
	99%	1,119.18 €	100.0%	0.0%	0	0.00	19.3%	0.00	0.00	183	2	0	185	0	0	0	99.0%	1.0%	9694
18h-19h	1%	5,376.20 €	100.0%	0.0%	0	0.00	37.1%	0.57	0.57	5	538	0	544	0	7	7	1.0%	99.0%	31562
	10%	5,364.88 €	100.0%	0.0%	0	0.00	37.0%	0.57	0.57	54	489	0	544	1	7	7	10.0%	90.0%	31562
	25%	5,284.24 €	100.0%	0.0%	0	0.00	36.5%	0.57	0.57	136	407	0	543	2	5	7	25.0%	75.0%	31562
	50%	4,907.52 €	100.0%	0.0%	0	0.00	33.9%	0.57	0.57	271	271	0	541	3	3	5	50.0%	50.0%	31562
	75%	4,198.88 €	100.0%	0.0%	0	0.00	29.0%	0.57	0.00	404	135	0	539	2	1	3	75.0%	25.0%	31562
	90%	3,632.80 €	100.0%	0.0%	0	0.00	25.1%	0.57	0.00	484	54	0	538	1	0	2	90.0%	10.0%	31562
	99%	3,251.40 €	100.0%	0.0%	0	0.00	22.5%	0.00	0.00	532	5	0	537	1	0	1	99.0%	1.0%	31562
19h-20h	1%	1,234.02 €	100.0%	0.0%	0	0.00	21.4%	0.00	0.00	1	122	0	123	0	0	0	0.9%	99.1%	6750
	10%	1,231.45 €	100.0%	0.0%	0	0.00	21.3%	0.00	0.00	12	111	0	123	0	0	0	10.0%	90.0%	6750
	25%	1,213.12 €	100.0%	0.0%	0	0.00	21.0%	0.00	0.00	31	93	0	123	0	0	0	25.0%	75.0%	6750
	50%	1,127.33 €	100.0%	0.0%	0	0.00	19.5%	0.00	0.00	62	62	0	123	0	0	0	50.0%	50.0%	6750
	75%	965.35 €	100.0%	0.0%	0	0.00	16.7%	0.00	0.00	93	31	0	123	0	0	0	75.0%	25.0%	6750
	90%	835.56 €	100.0%	0.0%	0	0.00	14.5%	0.00	0.00	111	12	0	123	0	0	0	90.0%	10.0%	6750
	99%	747.67 €	100.0%	0.0%	0	0.00	12.9%	0.00	0.00	122	1	0	123	0	0	0	99.1%	0.9%	6750

Scenario O No AV subnetworks		Generalized Costs			AV Subnetwork		Congestion			Travel Times				Travel Delays			Travel Distances		
		Objective Function	Driving travel times	Walking travel times	Dedicated Roads		Average degree of saturation	Roads above practical capacity (DS>75%)	Congested Roads (DS≥100%)	Driving AV trips	Driving CV trips	Walking CV trips	Total	AV trips	CV trips	Total	AV trips	CV trips	Total Distance
Analysis	Penetration rate (%)	[€]	[%]	[%]	[no.]	[km]	[%]	[km]	[km]	[h veh]	[h veh]	[h veh]	[h veh]	[%]	[%]	[h veh]	[%]	[%]	[km veh]
20h-21h	1%	166.97 €	100.0%	0.0%	0	0.00	18.0%	0.00	0.00	0	17	0	17	0	0	0	1.2%	98.8%	835
	10%	166.63 €	100.0%	0.0%	0	0.00	18.0%	0.00	0.00	2	15	0	17	0	0	0	10.0%	90.0%	835
	25%	164.15 €	100.0%	0.0%	0	0.00	17.7%	0.00	0.00	4	13	0	17	0	0	0	25.0%	75.0%	835
	50%	152.54 €	100.0%	0.0%	0	0.00	16.5%	0.00	0.00	8	8	0	17	0	0	0	50.0%	50.0%	835
	75%	130.63 €	100.0%	0.0%	0	0.00	14.1%	0.00	0.00	13	4	0	17	0	0	0	75.0%	25.0%	835
	90%	113.07 €	100.0%	0.0%	0	0.00	12.2%	0.00	0.00	15	2	0	17	0	0	0	90.0%	10.0%	835
	99%	101.32 €	100.0%	0.0%	0	0.00	10.9%	0.00	0.00	17	0	0	17	0	0	0	98.8%	1.2%	835
21h-22h	1%	3,036.16 €	100.0%	0.0%	0	0.00	36.4%	4.02	0.00	3	308	0	311	0	9	9	1.0%	99.0%	18483
	10%	3,029.69 €	100.0%	0.0%	0	0.00	36.3%	4.02	0.00	31	280	0	311	1	8	9	10.0%	90.0%	18483
	25%	2,983.60 €	100.0%	0.0%	0	0.00	35.8%	4.02	0.00	78	233	0	310	2	6	8	25.0%	75.0%	18483
	50%	2,768.84 €	100.0%	0.0%	0	0.00	33.3%	4.02	0.00	154	154	0	308	3	3	6	50.0%	50.0%	18483
	75%	2,366.62 €	100.0%	0.0%	0	0.00	28.5%	0.00	0.00	229	76	0	305	3	1	3	75.0%	25.0%	18483
	90%	2,046.51 €	100.0%	0.0%	0	0.00	24.7%	0.00	0.00	273	30	0	304	2	0	2	90.0%	10.0%	18483
	99%	1,831.03 €	100.0%	0.0%	0	0.00	22.1%	0.00	0.00	300	3	0	303	1	0	1	99.0%	1.0%	18483
22h-23h	1%	2,665.08 €	100.0%	0.0%	0	0.00	48.7%	3.31	0.00	3	272	0	275	0	10	11	1.0%	99.0%	15411
	10%	2,659.35 €	100.0%	0.0%	0	0.00	48.6%	3.31	0.00	27	247	0	275	1	9	11	10.0%	90.0%	15411
	25%	2,618.59 €	100.0%	0.0%	0	0.00	47.9%	3.31	0.00	69	206	0	274	2	7	10	25.0%	75.0%	15411
	50%	2,428.91 €	100.0%	0.0%	0	0.00	44.5%	3.31	0.00	136	136	0	272	4	4	7	50.0%	50.0%	15411
	75%	2,074.70 €	100.0%	0.0%	0	0.00	38.1%	0.00	0.00	201	67	0	268	3	1	4	75.0%	25.0%	15411
	90%	1,793.46 €	100.0%	0.0%	0	0.00	33.0%	0.00	0.00	240	27	0	267	2	0	2	90.0%	10.0%	15411
	99%	1,604.08 €	100.0%	0.0%	0	0.00	29.5%	0.00	0.00	263	3	0	266	1	0	1	99.0%	1.0%	15411
23h-24h	1%	2,006.59 €	100.0%	0.0%	0	0.00	26.9%	0.00	0.00	2	199	0	201	0	0	0	1.1%	98.9%	11760
	10%	2,002.41 €	100.0%	0.0%	0	0.00	26.8%	0.00	0.00	20	181	0	201	0	0	0	10.0%	90.0%	11760
	25%	1,972.57 €	100.0%	0.0%	0	0.00	26.4%	0.00	0.00	50	151	0	201	0	0	0	25.0%	75.0%	11760
	50%	1,832.93 €	100.0%	0.0%	0	0.00	24.6%	0.00	0.00	100	100	0	201	0	0	0	50.0%	50.0%	11760
	75%	1,569.40 €	100.0%	0.0%	0	0.00	21.0%	0.00	0.00	151	50	0	201	0	0	0	75.0%	25.0%	11760
	90%	1,358.33 €	100.0%	0.0%	0	0.00	18.2%	0.00	0.00	181	20	0	201	0	0	0	90.0%	10.0%	11760
	99%	1,216.30 €	100.0%	0.0%	0	0.00	16.3%	0.00	0.00	199	2	0	201	0	0	0	98.9%	1.1%	11760
24h-1h	1%	1,713.70 €	100.0%	0.0%	0	0.00	69.7%	3.31	0.00	2	178	0	180	0	10	11	1.0%	99.0%	10074
	10%	1,709.95 €	100.0%	0.0%	0	0.00	69.6%	3.31	0.00	18	162	0	180	1	9	10	10.0%	90.0%	10074
	25%	1,683.33 €	100.0%	0.0%	0	0.00	68.6%	3.31	0.00	45	134	0	179	2	7	10	25.0%	75.0%	10074
	50%	1,559.78 €	100.0%	0.0%	0	0.00	63.7%	3.31	0.00	88	88	0	177	4	4	7	50.0%	50.0%	10074
	75%	1,330.44 €	100.0%	0.0%	0	0.00	54.6%	0.00	0.00	130	43	0	173	3	1	4	75.0%	25.0%	10074
	90%	1,149.26 €	100.0%	0.0%	0	0.00	47.2%	0.00	0.00	154	17	0	171	2	0	2	90.0%	10.0%	10074
	99%	1,027.61 €	100.0%	0.0%	0	0.00	42.3%	0.00	0.00	169	2	0	171	1	0	1	99.0%	1.0%	10074

Table 3.6 – RNDP-AVs peak-hour design with walking as the alternative mode of transport: daily impacts results from scenario I under an long-term planning.

Scenario I + Long-Term planning		Generalized Costs			AV Subnetwork		Congestion			Travel Times				Travel Delays			Travel Distances		
		Objective Function	Driving travel times	Walking travel times	Dedicated Roads		Average Degree of Saturation	Roadways above practical capacity (DS>75%)	Congested Roads (DS≥100%)	Driving AV trips	Driving CV trips	Walking CV trips	Total	AV trips	CV trips	Total	AV trips	CV trips	Total Distance
Analysis	Penetration rate (%)	[€]	[%]	[%]	[no.]	[km]	[%]	[km]	[km]	[h veh]	[h veh]	[h veh]	[h veh]	[%]	[%]	[h veh]	[%]	[%]	[km veh]
6h-7h	1%	525.52 €	100.0%	0.0%	0	0.00	19.6%	0.00	0.00	1	52	0	52.6	0	0	0.0	1.1%	98.9%	2988
	10%	579.86 €	100.0%	0.0%	3	3.92	10.6%	0.00	0.00	5	47	0	52.7	0	0	0.0	10.2%	89.8%	2994
	25%	632.62 €	100.0%	0.0%	8	8.20	5.6%	0.00	0.00	13	39	0	52.8	0	0	0.0	25.3%	74.7%	3000
	50%	596.11 €	100.0%	0.0%	8	8.20	5.2%	0.00	0.00	26	26	0	52.8	0	0	0.0	50.2%	49.8%	3000
	75%	726.28 €	100.0%	0.0%	21	22.23	2.7%	0.00	0.00	40	13	0	53.2	0	0	0.0	75.3%	24.7%	3022
	90%	671.03 €	100.0%	0.0%	21	22.23	2.2%	0.00	0.00	48	5	0	53.2	0	0	0.0	90.1%	9.9%	3022
7h-8h	1%	3,387.05 €	100.0%	0.0%	0	0.00	36.8%	0.87	0.87	4	342	0	345.6	0	9	8.6	1.0%	99.0%	20347
	10%	3,686.02 €	100.0%	0.0%	3	3.92	28.3%	0.87	0.87	35	339	0	374.2	1	8	8.6	10.2%	89.8%	20258
	25%	3,613.16 €	100.0%	0.0%	8	8.20	26.3%	0.87	0.87	89	285	0	373.9	2	6	8.2	25.0%	75.0%	20759
	50%	3,260.64 €	100.0%	0.0%	8	8.20	24.8%	2.63	0.29	177	189	0	366.3	4	3	7.3	49.9%	50.1%	20746
	75%	3,141.15 €	100.0%	0.0%	21	22.23	15.3%	0.87	0.00	263	113	0	375.9	4	1	5.0	71.8%	28.2%	21607
	90%	2,668.59 €	100.0%	0.0%	21	22.23	13.2%	0.29	0.00	305	45	0	350.3	2	0	1.9	88.3%	11.7%	20760
8h-9h	1%	5,823.06 €	100.0%	0.0%	0	0.00	47.1%	9.12	0.00	6	603	0	608.9	0	33	33.3	1.0%	99.0%	32913
	10%	6,174.07 €	100.0%	0.0%	3	3.92	30.4%	10.54	1.76	60	602	0	662.3	3	49	51.7	9.7%	90.3%	34095
	25%	5,932.65 €	100.0%	0.0%	8	8.20	27.8%	10.54	1.76	150	493	0	642.9	6	29	35.2	24.0%	76.0%	34276
	50%	5,350.28 €	100.0%	0.0%	8	8.20	26.4%	8.77	0.00	297	320	0	617.2	9	11	20.2	48.7%	51.3%	33822
	75%	14,605.77 €	23.9%	76.1%	21	22.23	14.6%	0.00	0.00	438	149	51314	51901.3	2	1	3.2	74.4%	25.6%	33035
	90%	7,937.12 €	44.0%	56.0%	21	22.23	14.5%	0.00	0.00	522	60	23363	23944.2	3	0	3.6	89.7%	10.3%	33011
9h-10h	1%	9,792.92 €	100.0%	0.0%	0	0.00	58.3%	12.55	2.75	11	1049	0	1059.4	1	99	100.2	1.0%	99.0%	49989
	10%	11,086.12 €	100.0%	0.0%	3	3.92	52.0%	18.39	5.16	107	1103	0	1210.2	11	114	124.5	9.5%	90.5%	53974
	25%	10,656.16 €	100.0%	0.0%	8	8.20	48.8%	11.27	5.84	267	912	0	1178.8	25	83	108.2	23.6%	76.4%	53821
	50%	9,480.88 €	100.0%	0.0%	8	8.20	46.1%	11.96	2.30	522	592	0	1113.9	38	41	79.2	48.4%	51.6%	52278
	75%	8,397.53 €	100.0%	0.0%	21	22.23	33.3%	5.77	1.61	767	339	0	1106.1	40	9	48.5	69.8%	30.2%	56009
	90%	7,043.96 €	100.0%	0.0%	21	22.23	29.6%	2.10	1.61	885	134	0	1019.3	21	2	23.1	87.1%	12.9%	52546
10h-11h	1%	8,117.76 €	100.0%	0.0%	0	0.00	44.2%	4.93	0.48	8	820	0	828.1	0	20	20.3	1.0%	99.0%	42908
	10%	9,125.62 €	100.0%	0.0%	3	3.92	40.3%	12.49	0.00	84	868	0	951.3	3	39	41.7	9.5%	90.5%	45566
	25%	8,702.68 €	100.0%	0.0%	8	8.20	36.7%	10.08	0.00	208	716	0	924.2	6	25	31.5	24.0%	76.0%	45128
	50%	7,773.53 €	100.0%	0.0%	8	8.20	32.8%	5.54	0.00	412	470	0	882.1	8	10	17.7	48.6%	51.4%	44384
	75%	9,153.60 €	69.6%	30.4%	21	22.23	22.8%	3.48	0.00	622	266	3422	4309.1	11	2	13.3	73.0%	27.0%	46000
	90%	6,600.58 €	83.2%	16.8%	21	22.23	21.0%	2.23	0.00	736	106	1642	2483.0	7	0	7.8	88.9%	11.1%	44917

Scenario I + Long-Term planning		Generalized Costs			AV Subnetwork		Congestion			Travel Times				Travel Delays			Travel Distances		
		Objective Function	Driving travel times	Walking travel times	Dedicated Roads		Average Degree of Saturation	Roadways above practical capacity (DS>75%)	Congested Roads (DS≥100%)	Driving AV trips	Driving CV trips	Walking CV trips	Total	AV trips	CV trips	Total	AV trips	CV trips	Total Distance
Analysis	Penetration rate (%)	[€]	[%]	[%]	[no.]	[km]	[%]	[km]	[km]	[h veh]	[h veh]	[h veh]	[h veh]	[%]	[%]	[h veh]	[%]	[%]	[km veh]
11h-12h	1%	10,076.38 €	100.0%	0.0%	0	0.00	46.0%	8.96	2.76	11	1026	0	1036.4	0	36	36.0	1.0%	99.0%	53295
	10%	10,522.90 €	100.0%	0.0%	3	3.92	39.1%	11.27	2.27	104	984	0	1087.6	3	33	36.2	10.1%	89.9%	53405
	25%	10,224.54 €	100.0%	0.0%	8	8.20	36.2%	9.50	2.27	260	815	0	1075.5	7	23	29.4	25.6%	74.4%	53743
	50%	9,350.82 €	100.0%	0.0%	8	8.20	34.0%	6.62	0.00	518	538	0	1056.3	10	10	20.3	50.8%	49.2%	54163
	75%	9,203.36 €	85.4%	14.6%	21	22.23	23.7%	2.27	0.00	764	289	1047	2100.6	7	2	9.7	74.4%	25.6%	55000
	90%	7,333.29 €	92.7%	7.3%	21	22.23	21.3%	0.48	0.00	908	115	503	1526.3	7	1	7.5	89.6%	10.4%	53984
12h-13h	1%	8,581.41 €	100.0%	0.0%	0	0.00	45.9%	5.60	0.60	9	865	0	873.8	0	19	19.6	1.0%	99.0%	49093
	10%	9,071.23 €	100.0%	0.0%	3	3.92	36.8%	2.87	0.60	89	837	0	925.7	1	14	15.7	9.8%	90.2%	49876
	25%	8,756.74 €	100.0%	0.0%	8	8.20	36.1%	2.87	0.44	223	699	0	921.7	3	11	14.2	24.8%	75.2%	50211
	50%	7,968.43 €	100.0%	0.0%	8	8.20	34.0%	2.87	0.00	445	464	0	908.5	6	5	10.7	49.8%	50.2%	50106
	75%	7,062.55 €	100.0%	0.0%	21	22.23	26.7%	2.36	0.00	662	270	0	932.0	7	2	8.9	72.1%	27.9%	51401
	90%	5,933.11 €	100.0%	0.0%	21	22.23	23.5%	0.00	0.00	773	108	0	880.3	3	0	3.7	88.6%	11.4%	50312
13h-14h	1%	1,719.74 €	100.0%	0.0%	0	0.00	28.6%	0.63	0.00	2	171	0	173.2	0	1	1.5	1.0%	99.0%	9888
	10%	1,961.77 €	100.0%	0.0%	3	3.92	23.9%	0.63	0.00	17	181	0	198.7	0	2	1.8	9.3%	90.7%	10652
	25%	1,862.70 €	100.0%	0.0%	8	8.20	19.9%	0.63	0.00	43	151	0	194.1	0	1	1.4	23.5%	76.5%	10526
	50%	1,658.59 €	100.0%	0.0%	8	8.20	17.9%	0.48	0.00	86	100	0	186.6	0	0	0.9	48.0%	52.0%	10315
	75%	1,648.49 €	100.0%	0.0%	21	22.23	10.3%	0.00	0.00	133	82	0	214.9	0	0	0.1	63.3%	36.7%	11544
	90%	1,285.03 €	100.0%	0.0%	21	22.23	10.0%	0.00	0.00	155	33	0	187.7	0	0	0.1	84.0%	16.0%	10603
14h-15h	1%	5,895.79 €	100.0%	0.0%	0	0.00	50.7%	10.97	3.69	7	704	0	711.2	2	150	152.0	1.0%	99.0%	29642
	10%	6,272.21 €	100.0%	0.0%	3	3.92	46.2%	14.44	3.69	71	689	0	759.4	14	145	158.9	10.0%	90.0%	30721
	25%	6,005.77 €	100.0%	0.0%	8	8.20	41.1%	8.84	1.94	175	559	0	734.0	33	106	138.5	25.1%	74.9%	30745
	50%	5,390.75 €	100.0%	0.0%	8	8.20	37.8%	7.09	1.94	337	352	0	688.5	52	50	101.5	50.1%	49.9%	30781
	75%	5,667.83 €	83.8%	16.2%	21	22.23	22.8%	1.46	1.46	464	214	842	1519.9	37	12	48.2	70.6%	29.4%	32793
	90%	4,324.48 €	91.5%	8.5%	21	22.23	19.1%	1.94	1.46	531	84	403	1018.6	27	3	29.8	87.4%	12.6%	30661
15h-16h	1%	4,182.07 €	100.0%	0.0%	0	0.00	28.2%	0.00	0.00	4	415	0	419.1	0	1	1.1	1.1%	98.9%	22379
	10%	4,330.22 €	100.0%	0.0%	3	3.92	22.4%	0.80	0.00	43	395	0	437.7	0	2	1.8	10.2%	89.8%	22894
	25%	4,245.26 €	100.0%	0.0%	8	8.20	20.3%	0.00	0.00	107	335	0	441.4	0	0	0.6	24.6%	75.4%	23780
	50%	3,868.29 €	100.0%	0.0%	8	8.20	18.9%	0.00	0.00	214	223	0	436.6	0	0	0.4	49.5%	50.5%	23653
	75%	4,354.79 €	74.1%	25.9%	21	22.23	12.9%	0.00	0.00	321	122	599	1042.2	0	0	0.2	73.1%	26.9%	24018
	90%	3,277.03 €	86.2%	13.8%	21	22.23	11.9%	0.00	0.00	377	49	288	713.3	0	0	0.2	88.6%	11.4%	22736

Scenario I + Long-Term planning		Generalized Costs			AV Subnetwork		Congestion			Travel Times				Travel Delays			Travel Distances		
		Objective Function	Driving travel times	Walking travel times	Dedicated Roads		Average Degree of Saturation	Roadways above practical capacity (DS>75%)	Congested Roads (DS≥100%)	Driving AV trips	Driving CV trips	Walking CV trips	Total	AV trips	CV trips	Total	AV trips	CV trips	Total Distance
Analysis	Penetration rate (%)	[€]	[%]	[%]	[no.]	[km]	[%]	[km]	[km]	[h veh]	[h veh]	[h veh]	[h veh]	[%]	[%]	[h veh]	[%]	[%]	[km veh]
16h-17h	1%	9,127.91 €	100.0%	0.0%	0	0.00	54.8%	21.83	2.24	10	962	0	971.2	1	72	73.0	1.0%	99.0%	50241
	10%	9,561.15 €	100.0%	0.0%	3	3.92	47.5%	18.44	2.24	97	923	0	1020.3	6	65	70.1	10.0%	90.0%	51813
	25%	9,225.19 €	100.0%	0.0%	8	8.20	42.2%	14.03	2.24	242	766	0	1008.4	14	45	59.0	24.7%	75.3%	52488
	50%	8,350.75 €	100.0%	0.0%	8	8.20	39.5%	14.03	2.24	480	502	0	981.3	22	21	43.6	49.6%	50.4%	52292
	75%	8,154.88 €	90.5%	9.5%	21	22.23	28.3%	4.09	0.29	704	297	5611	6612.1	18	5	23.6	71.4%	28.6%	54552
	90%	6,547.10 €	95.3%	4.7%	21	22.23	26.0%	1.75	0.00	820	118	2693	3631.7	12	1	13.1	87.9%	12.1%	51472
17h-18h	1%	1,847.42 €	100.0%	0.0%	0	0.00	31.8%	0.00	0.00	2	183	0	185.3	0	1	0.7	1.0%	99.0%	9694
	10%	2,090.67 €	100.0%	0.0%	3	3.92	24.6%	0.00	0.00	19	193	0	211.5	0	1	0.8	10.0%	90.0%	9721
	25%	2,024.83 €	100.0%	0.0%	8	8.20	16.9%	0.00	0.00	46	164	0	210.3	0	0	0.5	23.9%	76.1%	10146
	50%	1,796.74 €	100.0%	0.0%	8	8.20	15.8%	0.00	0.00	92	109	0	201.7	0	0	0.3	48.5%	51.5%	9998
	75%	1,472.79 €	100.0%	0.0%	21	22.23	10.0%	0.00	0.00	139	55	0	193.5	0	0	0.1	73.9%	26.1%	9866
	90%	1,259.36 €	100.0%	0.0%	21	22.23	8.8%	0.00	0.00	167	22	0	188.5	0	0	0.1	89.5%	10.5%	9779
18h-19h	1%	5,376.20 €	100.0%	0.0%	0	0.00	37.1%	0.57	0.57	5	538	0	543.6	0	7	7.4	1.0%	99.0%	31562
	10%	5,688.63 €	100.0%	0.0%	3	3.92	31.4%	6.31	1.35	55	534	0	588.9	1	19	19.6	10.1%	89.9%	31304
	25%	5,468.02 €	100.0%	0.0%	8	8.20	29.5%	2.37	0.57	136	441	0	577.4	2	11	13.8	25.2%	74.8%	31351
	50%	4,950.53 €	100.0%	0.0%	8	8.20	26.5%	1.35	0.57	271	290	0	561.3	3	4	6.8	50.2%	49.8%	31421
	75%	5,633.90 €	79.3%	20.7%	21	22.23	17.6%	0.57	0.00	404	189	2724	3318.1	2	1	2.8	69.6%	30.4%	34040
	90%	4,195.89 €	88.9%	11.1%	21	22.23	15.3%	0.57	0.00	484	76	1308	1867.2	1	0	1.5	87.2%	12.8%	32587
19h-20h	1%	1,234.02 €	100.0%	0.0%	0	0.00	21.4%	0.00	0.00	1	122	0	123.5	0	0	0.1	0.9%	99.1%	6750
	10%	1,457.43 €	100.0%	0.0%	3	3.92	11.3%	0.00	0.00	12	134	0	146.6	0	0	0.1	8.4%	91.6%	8099
	25%	1,383.27 €	100.0%	0.0%	8	8.20	8.8%	0.00	0.00	31	112	0	142.8	0	0	0.1	21.5%	78.5%	7878
	50%	1,225.10 €	100.0%	0.0%	8	8.20	8.1%	0.00	0.00	62	75	0	136.4	0	0	0.1	45.1%	54.9%	7504
	75%	1,008.26 €	100.0%	0.0%	21	22.23	3.8%	0.00	0.00	93	37	0	130.4	0	0	0.0	71.2%	28.8%	7151
	90%	853.10 €	100.0%	0.0%	21	22.23	3.4%	0.00	0.00	112	15	0	126.5	0	0	0.0	88.1%	11.9%	6926
20h-21h	1%	166.97 €	100.0%	0.0%	0	0.00	18.0%	0.00	0.00	0	17	0	16.7	0	0	0.0	1.2%	98.8%	835
	10%	167.25 €	100.0%	0.0%	3	3.92	4.5%	0.00	0.00	2	15	0	16.8	0	0	0.0	10.7%	89.3%	841
	25%	165.49 €	100.0%	0.0%	8	8.20	2.0%	0.00	0.00	4	13	0	16.9	0	0	0.0	26.2%	73.8%	849
	50%	153.88 €	100.0%	0.0%	8	8.20	1.9%	0.00	0.00	9	8	0	16.9	0	0	0.0	50.8%	49.2%	849
	75%	134.76 €	100.0%	0.0%	21	22.23	0.8%	0.00	0.00	13	4	0	17.4	0	0	0.0	76.1%	23.9%	872
	90%	117.20 €	100.0%	0.0%	21	22.23	0.7%	0.00	0.00	16	2	0	17.4	0	0	0.0	90.4%	9.6%	872

Scenario I + Long-Term planning		Generalized Costs			AV Subnetwork		Congestion			Travel Times				Travel Delays			Travel Distances		
		Objective Function	Driving travel times	Walking travel times	Dedicated Roads		Average Degree of Saturation	Roadways above practical capacity (DS>75%)	Congested Roads (DS≥100%)	Driving AV trips	Driving CV trips	Walking CV trips	Total	AV trips	CV trips	Total	AV trips	CV trips	Total Distance
Analysis	Penetration rate (%)	[€]	[%]	[%]	[no.]	[km]	[%]	[km]	[km]	[h veh]	[h veh]	[h veh]	[h veh]	[%]	[%]	[h veh]	[%]	[%]	[km veh]
21h-22h	1%	3,036.16 €	100.0%	0.0%	0	0.00	36.4%	4.02	0.00	3	308	0	310.8	0	9	9.0	1.0%	99.0%	18483
	10%	3,293.43 €	100.0%	0.0%	3	3.92	31.2%	8.06	0.00	30	313	0	343.8	0	14	14.5	10.0%	90.0%	18447
	25%	3,140.00 €	100.0%	0.0%	8	8.20	25.2%	2.32	0.00	76	256	0	331.9	1	7	7.1	25.0%	75.0%	18453
	50%	2,817.56 €	100.0%	0.0%	8	8.20	22.2%	0.57	0.00	152	168	0	319.3	1	1	2.1	50.1%	49.9%	18463
	75%	2,601.58 €	100.0%	0.0%	21	22.23	10.9%	0.00	0.00	229	107	0	336.2	2	1	3.1	69.7%	30.3%	19904
	90%	2,136.50 €	100.0%	0.0%	21	22.23	8.6%	0.00	0.00	274	43	0	316.3	2	0	1.8	87.3%	12.7%	19057
22h-23h	1%	2,665.08 €	100.0%	0.0%	0	0.00	48.7%	3.31	0.00	3	272	0	275.0	0	10	10.6	1.0%	99.0%	15411
	10%	3,304.76 €	100.0%	0.0%	3	3.92	36.5%	6.78	0.00	27	318	0	345.0	1	15	15.5	8.6%	91.4%	18029
	25%	3,076.73 €	100.0%	0.0%	8	8.20	29.8%	2.22	0.00	68	261	0	328.9	2	8	10.1	21.9%	78.1%	17596
	50%	2,670.43 €	100.0%	0.0%	8	8.20	26.5%	2.22	0.00	135	171	0	306.1	3	3	5.5	45.7%	54.3%	16869
	75%	6,976.67 €	22.7%	77.3%	21	22.23	11.7%	0.00	0.00	199	73	44825	45096.5	0	0	0.6	73.3%	26.7%	15803
	90%	3,746.76 €	42.4%	57.6%	21	22.23	12.5%	0.00	0.00	239	29	21521	21789.4	1	0	1.0	89.1%	10.9%	15579
23h-24h	1%	2,006.59 €	100.0%	0.0%	0	0.00	26.9%	0.00	0.00	2	199	0	201.1	0	0	0.5	1.1%	98.9%	11760
	10%	2,157.01 €	100.0%	0.0%	3	3.92	20.3%	0.00	0.00	20	198	0	217.7	0	1	0.6	10.0%	90.0%	11768
	25%	2,072.39 €	100.0%	0.0%	8	8.20	17.0%	0.00	0.00	50	164	0	214.7	0	0	0.3	25.0%	75.0%	11767
	50%	1,872.56 €	100.0%	0.0%	8	8.20	15.0%	0.00	0.00	100	110	0	210.0	0	0	0.1	50.0%	50.0%	11765
	75%	3,014.42 €	50.7%	49.3%	21	22.23	8.1%	0.00	0.00	151	66	1089	1306.0	0	0	0.1	70.3%	29.7%	12560
	90%	1,932.60 €	69.2%	30.8%	21	22.23	7.1%	0.00	0.00	181	27	523	730.0	0	0	0.1	87.6%	12.4%	12084
24h-1h	1%	1,713.70 €	100.0%	0.0%	0	0.00	69.7%	3.31	0.00	2	178	0	179.8	0	10	10.5	1.0%	99.0%	10074
	10%	2,129.05 €	100.0%	0.0%	3	3.92	45.4%	6.78	0.00	18	209	0	226.4	1	14	15.0	8.9%	91.1%	11350
	25%	1,971.62 €	100.0%	0.0%	8	8.20	35.0%	2.22	0.00	44	170	0	214.2	2	8	9.7	22.7%	77.3%	11141
	50%	1,704.22 €	100.0%	0.0%	8	8.20	30.9%	2.22	0.00	87	111	0	198.0	2	3	5.3	46.8%	53.2%	10788
	75%	2,317.06 €	66.5%	33.5%	21	22.23	12.3%	0.00	0.00	128	82	5611	5821.3	0	0	0.4	64.6%	35.4%	11725
	90%	1,538.19 €	79.8%	20.2%	21	22.23	11.9%	0.00	0.00	154	33	2693	2879.9	1	0	0.8	84.6%	15.4%	10748

Table 3.7 – RNDP-AVs peak-hour design with walking as the alternative mode of transport: daily impacts results from scenario II under an incremental planning

Scenario II + Incremental planning AV subnetworks		Generalized Costs			AV Subnetwork		Congestion			Travel Times				Travel Delays			Travel Distances		
		Objective Function	Driving travel times	Walking travel times	Dedicated Roads		Average degree of saturation	Roads above practical capacity (DS>75%)	Congested Roads (DS≥100%)	Driving AV trips	Driving CV trips	Walking CV trips	Total	AV trips	CV trips	Total	AV trips	CV trips	Total Distance
Analysis	Penetration rate (%)	[€]	[%]	[%]	[no.]	[km]	[%]	[km]	[km]	[h veh]	[h veh]	[h veh]	[h veh]	[%]	[%]	[h veh]	[%]	[%]	[km veh]
6h-7h	1%	525.52 €	100.0%	0.0%	0	0.00	19.6%	0.00	0.00	1	52	0	52.6	0	0	0.0	1.1%	98.9%	2988
	10%	524.59 €	100.0%	0.0%	1	0.80	15.2%	0.00	0.00	5	47	0	52.6	0	0	0.0	10.0%	90.0%	2989
	25%	517.12 €	100.0%	0.0%	3	2.47	10.4%	0.00	0.00	13	39	0	52.7	0	0	0.0	25.1%	74.9%	2992
	50%	481.45 €	100.0%	0.0%	6	5.70	6.6%	0.00	0.00	27	26	0	52.8	0	0	0.0	50.2%	49.8%	2997
	75%	413.60 €	100.0%	0.0%	11	11.41	3.9%	0.00	0.00	40	13	0	53.0	0	0	0.0	75.1%	24.9%	3005
	90%	358.33 €	100.0%	0.0%	11	11.41	3.4%	0.00	0.00	48	5	0	53.0	0	0	0.0	90.1%	9.9%	3005
	99%	321.25 €	100.0%	0.0%	11	11.41	3.0%	0.00	0.00	52	1	0	53.0	0	0	0.0	98.9%	1.1%	3005
7h-8h	1%	3,387.05 €	100.0%	0.0%	0	0.00	36.8%	0.87	0.87	4	342	0	345.6	0	9	8.6	1.0%	99.0%	20347
	10%	3,418.82 €	100.0%	0.0%	1	0.80	34.7%	0.87	0.87	35	315	0	350.1	1	8	9.1	9.8%	90.2%	20857
	25%	3,354.68 €	100.0%	0.0%	3	2.47	33.0%	0.87	0.87	86	262	0	348.8	2	6	8.4	24.5%	75.5%	20772
	50%	3,101.47 €	100.0%	0.0%	6	5.70	26.0%	0.87	0.29	172	175	0	346.4	3	3	6.1	49.5%	50.5%	20546
	75%	2,643.77 €	100.0%	0.0%	11	11.41	18.8%	0.87	0.00	255	87	0	342.1	2	1	3.3	74.6%	25.4%	20453
	90%	2,285.34 €	100.0%	0.0%	11	11.41	16.5%	0.29	0.00	305	35	0	339.7	2	0	1.8	89.8%	10.2%	20393
	99%	2,046.01 €	100.0%	0.0%	11	11.41	14.9%	0.29	0.00	335	4	0	338.5	1	0	1.2	99.0%	1.0%	20358
8h-9h	1%	5,823.06 €	100.0%	0.0%	0	0.00	47.1%	9.12	0.00	6	603	0	608.9	0	33	33.3	1.0%	99.0%	32913
	10%	5,843.38 €	100.0%	0.0%	1	0.80	41.4%	8.77	0.00	61	551	0	611.9	3	29	32.7	9.9%	90.1%	33366
	25%	5,741.54 €	100.0%	0.0%	3	2.47	36.3%	8.77	0.00	153	457	0	610.6	7	23	29.9	24.5%	75.5%	33186
	50%	5,462.15 €	100.0%	0.0%	6	5.70	24.2%	8.77	0.00	297	320	0	617.3	9	11	20.2	48.7%	51.3%	33821
	75%	14,696.27 €	24.4%	75.6%	11	11.41	17.3%	0.00	0.00	438	149	25184	25771.5	3	1	3.4	74.4%	25.6%	33030
	90%	7,978.92 €	44.3%	55.7%	11	11.41	16.9%	0.00	0.00	522	60	10810	11391.5	3	0	3.7	89.7%	10.3%	33006
	99%	3,889.29 €	88.9%	11.1%	11	11.41	16.7%	0.00	0.00	574	6	1153	1733.6	4	0	4.2	99.0%	1.0%	32923
9h-10h	1%	9,792.95 €	100.0%	0.0%	0	0.00	58.2%	12.55	2.75	11	1049	0	1059.5	1	99	100.3	1.0%	99.0%	49961
	10%	9,831.30 €	100.0%	0.0%	1	0.80	56.2%	12.55	2.75	106	959	0	1064.8	10	89	99.1	9.8%	90.2%	50787
	25%	9,654.43 €	100.0%	0.0%	3	2.47	53.2%	12.55	2.75	263	795	0	1058.0	23	70	93.3	24.7%	75.3%	50652
	50%	9,216.61 €	100.0%	0.0%	6	5.70	47.1%	12.12	6.94	517	575	0	1092.2	37	49	86.9	47.1%	52.9%	52568
	75%	7,604.71 €	100.0%	0.0%	11	11.41	37.0%	5.87	1.61	748	276	0	1023.9	27	12	38.7	72.4%	27.6%	51218
	90%	6,525.53 €	100.0%	0.0%	11	11.41	31.4%	2.75	1.61	881	108	0	989.2	18	2	20.2	88.8%	11.2%	50217
	99%	5,831.89 €	100.0%	0.0%	11	11.41	27.7%	2.75	0.00	964	11	0	975.0	15	0	15.0	98.8%	1.2%	49593

Scenario II + Incremental planning AV subnetworks		Generalized Costs			AV Subnetwork		Congestion			Travel Times				Travel Delays			Travel Distances		
		Objective Function	Driving travel times	Walking travel times	Dedicated Roads		Average degree of saturation	Roads above practical capacity (DS>75%)	Congested Roads (DS≥100%)	Driving AV trips	Driving CV trips	Walking CV trips	Total	AV trips	CV trips	Total	AV trips	CV trips	Total Distance
Analysis	Penetration rate (%)	[€]	[%]	[%]	[no.]	[km]	[%]	[km]	[km]	[h veh]	[h veh]	[h veh]	[h veh]	[%]	[%]	[h veh]	[%]	[%]	[km veh]
10h-11h	1%	8,117.76 €	100.0%	0.0%	0	0.00	44.2%	4.93	0.48	8	820	0	828.1	0	20	20.3	1.0%	99.0%	42908
	10%	8,100.59 €	100.0%	0.0%	1	0.80	42.4%	4.93	0.48	83	745	0	828.0	2	18	20.2	10.0%	90.0%	42897
	25%	7,974.91 €	100.0%	0.0%	3	2.47	38.8%	4.93	0.48	207	620	0	827.3	5	14	18.9	25.0%	75.0%	42911
	50%	7,534.45 €	100.0%	0.0%	6	5.70	33.4%	3.98	0.48	409	449	0	857.8	4	11	14.3	46.8%	53.2%	44582
	75%	6,256.63 €	100.0%	0.0%	11	11.41	25.6%	0.00	0.00	614	220	0	833.9	5	1	5.5	72.5%	27.5%	43055
	90%	5,437.80 €	100.0%	0.0%	11	11.41	20.9%	0.00	0.00	734	88	0	822.1	8	0	8.2	88.8%	11.2%	42315
	99%	4,896.63 €	100.0%	0.0%	11	11.41	19.0%	0.00	0.00	804	9	0	812.5	4	0	4.5	98.9%	1.1%	42404
11h-12h	1%	10,076.38 €	100.0%	0.0%	0	0.00	46.0%	8.96	2.76	11	1026	0	1036.4	0	36	36.0	1.0%	99.0%	53295
	10%	10,054.85 €	100.0%	0.0%	1	0.80	44.1%	8.96	2.76	104	933	0	1036.2	4	32	35.7	10.0%	90.0%	53294
	25%	9,898.65 €	100.0%	0.0%	3	2.47	41.9%	8.96	2.76	259	776	0	1034.8	8	25	33.6	25.0%	75.0%	53289
	50%	9,173.40 €	100.0%	0.0%	6	5.70	38.1%	6.62	0.48	516	516	0	1032.7	15	16	30.7	49.8%	50.2%	53501
	75%	7,818.26 €	100.0%	0.0%	11	11.41	28.4%	2.76	0.48	761	256	0	1017.4	11	4	14.8	74.6%	25.4%	53623
	90%	6,769.94 €	100.0%	0.0%	11	11.41	24.4%	0.48	0.00	908	102	0	1009.2	7	1	7.8	89.8%	10.2%	53431
	99%	6,070.69 €	100.0%	0.0%	11	11.41	21.7%	0.48	0.00	995	10	0	1005.6	5	0	4.9	99.0%	1.0%	53316
12h-13h	1%	8,581.41 €	100.0%	0.0%	0	0.00	45.9%	5.60	0.60	9	865	0	873.8	0	19	19.6	1.0%	99.0%	49093
	10%	8,587.66 €	100.0%	0.0%	1	0.80	45.5%	5.60	0.60	87	789	0	876.8	2	18	20.1	9.9%	90.1%	49405
	25%	8,450.19 €	100.0%	0.0%	3	2.47	43.1%	5.60	0.44	218	657	0	875.1	5	14	18.8	24.9%	75.1%	49355
	50%	7,899.84 €	100.0%	0.0%	6	5.70	37.9%	4.52	0.00	434	446	0	879.7	7	7	13.8	49.2%	50.8%	49939
	75%	6,709.96 €	100.0%	0.0%	11	11.41	29.5%	0.60	0.00	647	221	0	868.6	5	2	7.2	74.3%	25.7%	49479
	90%	5,795.67 €	100.0%	0.0%	11	11.41	25.5%	0.00	0.00	773	88	0	860.7	4	0	4.0	89.7%	10.3%	49265
	99%	5,182.79 €	100.0%	0.0%	11	11.41	22.8%	0.00	0.00	848	9	0	857.2	3	0	2.6	99.0%	1.0%	49113
13h-14h	1%	1,719.74 €	100.0%	0.0%	0	0.00	28.6%	0.63	0.00	2	171	0	173.2	0	1	1.5	1.0%	99.0%	9888
	10%	1,716.29 €	100.0%	0.0%	1	0.80	26.5%	0.63	0.00	17	156	0	173.2	0	1	1.5	10.0%	90.0%	9890
	25%	1,690.82 €	100.0%	0.0%	3	2.47	23.5%	0.63	0.00	43	130	0	173.1	0	1	1.4	25.0%	75.0%	9892
	50%	1,656.70 €	100.0%	0.0%	6	5.70	18.4%	0.48	0.00	86	96	0	182.8	0	0	0.9	47.8%	52.2%	10351
	75%	1,373.86 €	100.0%	0.0%	11	11.41	12.5%	0.00	0.00	133	48	0	181.2	0	0	0.5	73.0%	27.0%	10009
	90%	1,179.27 €	100.0%	0.0%	11	11.41	11.8%	0.00	0.00	155	19	0	174.2	0	0	0.3	89.2%	10.8%	9988
	99%	1,043.63 €	100.0%	0.0%	11	11.41	10.6%	0.00	0.00	170	2	0	172.3	0	0	0.2	98.9%	1.1%	9906
14h-15h	1%	5,895.79 €	100.0%	0.0%	0	0.00	50.7%	10.97	3.69	7	704	0	711.2	2	150	152.0	1.0%	99.0%	29642
	10%	5,881.00 €	100.0%	0.0%	1	0.80	47.9%	10.97	3.69	71	639	0	710.3	15	136	151.2	10.0%	90.0%	29630
	25%	5,773.44 €	100.0%	0.0%	3	2.47	44.9%	10.97	3.69	176	527	0	702.8	36	107	143.2	25.0%	75.0%	29608
	50%	5,432.22 €	100.0%	0.0%	6	5.70	38.0%	9.88	3.69	335	350	0	684.6	54	55	109.0	48.8%	51.2%	30227
	75%	4,487.63 €	100.0%	0.0%	11	11.41	28.7%	1.94	1.94	459	164	0	622.4	41	13	54.0	73.2%	26.8%	30135
	90%	3,830.02 €	100.0%	0.0%	11	11.41	23.6%	1.94	1.46	531	63	0	593.7	29	3	31.9	89.1%	10.9%	29703
	99%	3,407.42 €	100.0%	0.0%	11	11.41	21.9%	1.94	1.46	574	6	0	580.1	22	0	22.3	98.9%	1.1%	29445

Scenario II + Incremental planning AV subnetworks		Generalized Costs			AV Subnetwork		Congestion			Travel Times				Travel Delays			Travel Distances		
		Objective Function	Driving travel times	Walking travel times	Dedicated Roads		Average degree of saturation	Roads above practical capacity (DS>75%)	Congested Roads (DS≥100%)	Driving AV trips	Driving CV trips	Walking CV trips	Total	AV trips	CV trips	Total	AV trips	CV trips	Total Distance
Analysis	Penetration rate (%)	[€]	[%]	[%]	[no.]	[km]	[%]	[km]	[km]	[h veh]	[h veh]	[h veh]	[h veh]	[%]	[%]	[h veh]	[%]	[%]	[km veh]
15h-16h	1%	4,182.07 €	100.0%	0.0%	0	0.00	28.2%	0.00	0.00	4	415	0	419.1	0	1	1.1	1.1%	98.9%	22379
	10%	4,244.50 €	100.0%	0.0%	1	0.80	25.6%	0.00	0.00	42	385	0	426.4	0	1	0.9	9.6%	90.4%	23342
	25%	4,155.49 €	100.0%	0.0%	3	2.47	24.3%	0.00	0.00	105	320	0	425.8	0	1	0.8	24.1%	75.9%	23175
	50%	3,889.33 €	100.0%	0.0%	6	5.70	20.1%	0.00	0.00	211	219	0	430.1	0	0	0.5	48.3%	51.7%	23167
	75%	3,685.38 €	88.2%	11.8%	11	11.41	14.3%	0.00	0.00	314	112	320	745.7	0	0	0.2	72.9%	27.1%	23040
	90%	2,993.52 €	94.2%	5.8%	11	11.41	12.5%	0.00	0.00	377	45	154	574.9	0	0	0.2	89.0%	11.0%	22648
	99%	2,551.26 €	99.4%	0.6%	11	11.41	11.3%	0.00	0.00	414	5	16	434.5	0	0	0.1	98.8%	1.2%	22414
16h-17h	1%	9,127.91 €	100.0%	0.0%	0	0.00	54.8%	21.83	2.24	10	962	0	971.2	1	72	73.0	1.0%	99.0%	50241
	10%	9,167.09 €	100.0%	0.0%	1	0.80	49.3%	21.83	2.24	97	880	0	977.1	7	65	72.7	9.8%	90.2%	51034
	25%	9,003.54 €	100.0%	0.0%	3	2.47	47.5%	21.83	2.24	242	730	0	971.8	17	51	68.4	24.7%	75.3%	50901
	50%	8,497.29 €	100.0%	0.0%	6	5.70	38.9%	19.23	2.24	472	499	0	971.0	22	23	45.1	48.8%	51.2%	51500
	75%	7,817.74 €	90.1%	9.9%	11	11.41	29.7%	2.81	0.29	689	246	5611	6546.8	16	5	20.6	73.6%	26.4%	51195
	90%	6,396.51 €	95.1%	4.9%	11	11.41	26.4%	2.24	0.00	820	98	2693	3611.3	12	1	12.8	89.3%	10.7%	50627
	99%	5,486.24 €	99.5%	0.5%	11	11.41	24.2%	0.29	0.00	899	10	288	1196.2	10	0	9.6	98.9%	1.1%	50286
17h-18h	1%	1,847.42 €	100.0%	0.0%	0	0.00	31.8%	0.00	0.00	2	183	0	185.3	0	1	0.7	1.0%	99.0%	9694
	10%	1,881.43 €	100.0%	0.0%	1	0.80	25.7%	0.00	0.00	19	171	0	189.3	0	1	0.7	9.5%	90.5%	10204
	25%	1,841.47 €	100.0%	0.0%	3	2.47	23.5%	0.00	0.00	46	142	0	188.6	0	0	0.6	24.0%	76.0%	10121
	50%	1,699.09 €	100.0%	0.0%	6	5.70	17.4%	0.00	0.00	93	95	0	187.4	0	0	0.5	48.6%	51.4%	9981
	75%	1,449.21 €	100.0%	0.0%	11	11.41	12.2%	0.00	0.00	139	47	0	186.3	0	0	0.2	74.0%	26.0%	9847
	90%	1,252.65 €	100.0%	0.0%	11	11.41	10.7%	0.00	0.00	167	19	0	185.5	0	0	0.1	89.5%	10.5%	9762
	99%	1,120.98 €	100.0%	0.0%	11	11.41	9.6%	0.00	0.00	183	2	0	185.0	0	0	0.1	98.9%	1.1%	9712
18h-19h	1%	5,376.20 €	100.0%	0.0%	0	0.00	37.1%	0.57	0.57	5	538	0	543.6	0	7	7.4	1.0%	99.0%	31562
	10%	5,364.94 €	100.0%	0.0%	1	0.80	35.3%	0.57	0.57	54	489	0	543.5	1	7	7.4	10.0%	90.0%	31562
	25%	5,281.70 €	100.0%	0.0%	3	2.47	33.3%	0.57	0.57	136	407	0	543.8	2	5	6.9	25.0%	75.0%	31557
	50%	5,038.02 €	100.0%	0.0%	6	5.70	26.9%	1.35	0.57	272	289	0	561.4	3	4	6.9	50.2%	49.8%	31422
	75%	4,207.33 €	100.0%	0.0%	11	11.41	20.0%	0.57	0.00	404	143	0	547.7	2	1	2.9	75.2%	24.8%	31504
	90%	3,631.76 €	100.0%	0.0%	11	11.41	17.2%	0.57	0.00	484	57	0	541.3	1	0	1.5	90.1%	9.9%	31543
	99%	3,252.23 €	100.0%	0.0%	11	11.41	15.4%	0.00	0.00	532	6	0	537.7	1	0	1.0	99.0%	1.0%	31566
19h-20h	1%	1,234.02 €	100.0%	0.0%	0	0.00	21.4%	0.00	0.00	1	122	0	123.5	0	0	0.1	0.9%	99.1%	6750
	10%	1,231.61 €	100.0%	0.0%	1	0.80	17.4%	0.00	0.00	12	111	0	123.5	0	0	0.1	10.0%	90.0%	6751
	25%	1,213.50 €	100.0%	0.0%	3	2.47	13.5%	0.00	0.00	31	93	0	123.6	0	0	0.1	25.0%	75.0%	6753
	50%	1,248.38 €	100.0%	0.0%	6	5.70	8.6%	0.00	0.00	62	75	0	136.4	0	0	0.1	45.1%	54.9%	7504
	75%	1,025.71 €	100.0%	0.0%	11	11.41	5.0%	0.00	0.00	93	37	0	130.2	0	0	0.0	71.1%	28.9%	7140
	90%	860.67 €	100.0%	0.0%	11	11.41	4.3%	0.00	0.00	111	15	0	126.3	0	0	0.0	88.1%	11.9%	6916
	99%	752.06 €	100.0%	0.0%	11	11.41	3.9%	0.00	0.00	123	1	0	124.0	0	0	0.0	98.9%	1.1%	6780

Scenario II + Incremental planning AV subnetworks		Generalized Costs			AV Subnetwork		Congestion			Travel Times				Travel Delays			Travel Distances		
		Objective Function	Driving travel times	Walking travel times	Dedicated Roads		Average degree of saturation	Roads above practical capacity (DS>75%)	Congested Roads (DS≥100%)	Driving AV trips	Driving CV trips	Walking CV trips	Total	AV trips	CV trips	Total	AV trips	CV trips	Total Distance
Analysis	Penetration rate (%)	[€]	[%]	[%]	[no.]	[km]	[%]	[km]	[km]	[h veh]	[h veh]	[h veh]	[h veh]	[%]	[%]	[h veh]	[%]	[%]	[km veh]
20h-21h	1%	166.97 €	100.0%	0.0%	0	0.00	18.0%	0.00	0.00	0	17	0	16.7	0	0	0.0	1.2%	98.8%	835
	10%	166.79 €	100.0%	0.0%	1	0.80	9.0%	0.00	0.00	2	15	0	16.7	0	0	0.0	10.1%	89.9%	836
	25%	164.64 €	100.0%	0.0%	3	2.47	4.5%	0.00	0.00	4	13	0	16.8	0	0	0.0	25.4%	74.6%	839
	50%	153.89 €	100.0%	0.0%	6	5.70	2.4%	0.00	0.00	9	8	0	16.9	0	0	0.0	50.6%	49.4%	844
	75%	133.39 €	100.0%	0.0%	11	11.41	1.1%	0.00	0.00	13	4	0	17.2	0	0	0.0	75.6%	24.4%	856
	90%	115.81 €	100.0%	0.0%	11	11.41	1.0%	0.00	0.00	15	2	0	17.2	0	0	0.0	90.2%	9.8%	856
	99%	104.04 €	100.0%	0.0%	11	11.41	0.9%	0.00	0.00	17	0	0	17.2	0	0	0.0	98.9%	1.1%	856
21h-22h	1%	3,036.16 €	100.0%	0.0%	0	0.00	36.4%	4.02	0.00	3	308	0	310.8	0	9	9.0	1.0%	99.0%	18483
	10%	3,029.85 €	100.0%	0.0%	1	0.80	33.2%	4.02	0.00	31	280	0	310.7	1	8	8.9	10.0%	90.0%	18484
	25%	2,983.89 €	100.0%	0.0%	3	2.47	27.9%	4.02	0.00	78	233	0	310.3	2	6	8.4	25.0%	75.0%	18484
	50%	2,885.81 €	100.0%	0.0%	6	5.70	20.2%	0.57	0.00	152	168	0	319.4	1	1	2.1	50.1%	49.9%	18464
	75%	2,373.53 €	100.0%	0.0%	11	11.41	14.0%	0.00	0.00	227	83	0	310.7	1	0	0.9	75.1%	24.9%	18480
	90%	2,045.97 €	100.0%	0.0%	11	11.41	11.9%	0.00	0.00	273	33	0	306.1	1	0	1.0	90.0%	10.0%	18486
	99%	1,831.97 €	100.0%	0.0%	11	11.41	10.6%	0.00	0.00	300	3	0	303.5	1	0	1.1	99.0%	1.0%	18489
22h-23h	1%	2,665.08 €	100.0%	0.0%	0	0.00	48.7%	3.31	0.00	3	272	0	275.0	0	10	10.6	1.0%	99.0%	15411
	10%	2,659.51 €	100.0%	0.0%	1	0.80	43.5%	3.31	0.00	28	247	0	274.9	1	9	10.5	10.0%	90.0%	15412
	25%	2,618.97 €	100.0%	0.0%	3	2.47	37.0%	3.31	0.00	69	206	0	274.4	2	7	9.9	25.0%	75.0%	15414
	50%	2,689.88 €	100.0%	0.0%	6	5.70	25.6%	2.22	0.00	135	165	0	299.7	3	3	5.5	45.6%	54.4%	16930
	75%	7,071.50 €	23.7%	76.3%	11	11.41	13.7%	0.00	0.00	199	73	16834	17105.8	1	0	0.9	73.2%	26.8%	15800
	90%	3,790.90 €	43.1%	56.9%	11	11.41	14.1%	0.00	0.00	239	29	8080	8348.7	1	0	1.2	89.1%	10.9%	15575
	99%	1,799.50 €	88.4%	11.6%	11	11.41	14.2%	0.00	0.00	264	3	863	1128.9	1	0	1.3	98.9%	1.1%	15440
23h-24h	1%	2,006.59 €	100.0%	0.0%	0	0.00	26.9%	0.00	0.00	2	199	0	201.1	0	0	0.5	1.1%	98.9%	11760
	10%	2,002.46 €	100.0%	0.0%	1	0.80	24.3%	0.00	0.00	20	181	0	201.1	0	0	0.5	10.0%	90.0%	11760
	25%	1,970.04 €	100.0%	0.0%	3	2.47	21.9%	0.00	0.00	51	151	0	201.7	0	0	0.5	25.0%	75.0%	11755
	50%	1,897.71 €	100.0%	0.0%	6	5.70	16.0%	0.00	0.00	102	108	0	210.0	0	0	0.1	49.9%	50.1%	11764
	75%	1,576.05 €	100.0%	0.0%	11	11.41	10.8%	0.00	0.00	151	54	0	204.8	0	0	0.1	75.0%	25.0%	11774
	90%	1,359.58 €	100.0%	0.0%	11	11.41	9.2%	0.00	0.00	181	22	0	202.4	0	0	0.1	90.0%	10.0%	11770
	99%	1,217.57 €	100.0%	0.0%	11	11.41	8.2%	0.00	0.00	199	2	0	201.0	0	0	0.1	98.9%	1.1%	11767
24h-1h	1%	1,713.70 €	100.0%	0.0%	0	0.00	69.7%	3.31	0.00	2	178	0	179.8	0	10	10.5	1.0%	99.0%	10074
	10%	1,710.11 €	100.0%	0.0%	1	0.80	58.0%	3.31	0.00	18	162	0	179.7	1	9	10.4	10.0%	90.0%	10075
	25%	1,683.71 €	100.0%	0.0%	3	2.47	45.7%	3.31	0.00	45	134	0	179.2	2	7	9.8	25.0%	75.0%	10077
	50%	1,700.88 €	100.0%	0.0%	6	5.70	29.5%	2.22	0.00	87	104	0	191.6	3	3	5.2	46.5%	53.5%	10849
	75%	2,080.13 €	62.7%	37.3%	11	11.41	17.7%	0.00	0.00	129	51	5611	5791.1	1	0	1.8	72.3%	27.7%	10473
	90%	1,448.14 €	78.6%	21.4%	11	11.41	16.1%	0.00	0.00	154	20	2693	2867.8	1	0	1.4	88.7%	11.3%	10244
	99%	1,058.38 €	97.2%	2.8%	11	11.41	15.0%	0.00	0.00	169	2	288	458.8	1	0	1.3	98.9%	1.1%	10106

3.7. THE RNDP-AVS DESIGNED FOR THE WHOLE DAY

This subsection applies the RNDP-AVs model for the whole day, according to the general formulation presented in section 3.4. The detour problem is evaluated (and avoided) every hour of the day – CVs and AVs always complete their trips. The experiments were performed in the same case study of the city of Delft in the Netherlands.

In this analysis, the transition period will be analyzed and composed by the design stages considered several AV penetration rates: 10%, 25%, 50%, 75%, and 90%. The AV penetration rate of 0% and 100% are included for comparison purposes. In this analysis, the long-term is envisioned for 100% of AVs which will probably happen somewhere in 2100 (Nieuwenhuijsen et al., 2018).

3.7.1. NO AV SUBNETWORKS

In scenario O, vehicles circulate everywhere in mixed traffic conditions. The previously introduced constraints (3.18) (page 46) are added to replicate scenario O. Table 3.8 details the results of the daily experiments for scenario O. Each design stage is calculated in 1 minute (previously, in the peak-hour, it had been 3 seconds). Throughout this transition process, costs reduce proportionally as the value of travel time spent inside AVs decreases (check again Figure 3.5). Total travel time is reduced from 8915 to 8494 hours vehicles, 4.7% of reduction. The network congestion decreases from 11% to 7%, while the average degree of saturation reduces from 43% to 26%. The total delay is dramatically reduced from 484 to 66 hours. Roadways above practical capacity (degree of saturation above 75%) drop from 86.67 to 5.47 kilometers. Similarly to what happened in the peak-hour design, congested roadways (saturation above 100%) only start to be mitigated when AVs are 50% of the fleet. The total distance is stable throughout the process (0.18% of reduction).

3.7.2. AV SUBNETWORKS

This section evaluates the planning strategies applied to create progressive AV subnetworks (no road investment is included in this analysis). The results of this experiment are presented in Table 3.9. The optimal solutions were obtained within tolerable computation time, less than 24 hours.

Figure 3.42 illustrates the progression of AV subnetworks in each planning strategy: incremental planning (IP), long-term planning (LTP), and hybrid planning.

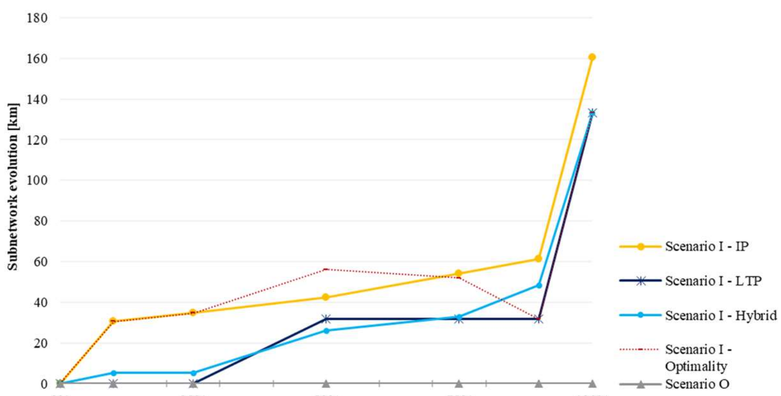


Figure 3.42 – RNDP-AVs daily design: subnetwork evolution in Scenario I.

Table 3.8 – Daily experiments results of current scenario O without AV subnetworks.

Scenario O RNDP without AV subnetworks		Objective Function			Network		Congestion [1]						Travel Times			Delay [2]			Travel Distances			Computational time	
	AV Penetration Rate	Generalized Costs [€]	Travel time [%]	Road Investment [%]	Dedicated Roads [no.]	[km]	Network Congestion [%]	Average degree of saturation [%]	Roadways above practical capacity [km]	Congested roadways [km]	Peak-hour Network Congestion [%]	Peak-hour average degree of saturation [%]	AV trips [h veh]	CV trips [h veh]	Total Travel Times [h veh]	AV trips [h veh]	CV trips [h veh]	Total Delay [h veh]	AV trips [%]	CV trips [%]	Total Distance [km veh]	Each Stage [h:m:s]	The whole scenario [h:m:s]
Optimality at each stage	0%	85277.35	100.0%	-	-	-	11%	43%	86.67	13.95	25%	58%	0	8915	8915	0	484	484	0.0%	100.0%	468258	00:00:44	00:06:43
	10%	85090.08	100.0%	-	-	-	11%	43%	86.67	13.95	25%	58%	891	8021	8912	48	433	481	10.0%	90.0%	468248	00:01:13	
	25%	83769.55	100.0%	-	-	-	11%	42%	86.67	13.32	25%	57%	2221	6663	8884	113	340	453	25.0%	75.0%	468192	00:01:25	
	50%	77637.04	100.0%	-	-	-	10%	39%	80.63	10.03	23%	53%	4386	4386	8772	171	171	342	50.0%	50.0%	468112	00:00:48	
	75%	66235.24	100.0%	-	-	-	9%	33%	15.77	4.33	20%	45%	6462	2154	8616	141	47	188	75.0%	25.0%	467848	00:01:03	
	90%	57220.23	100.0%	-	-	-	7%	29%	10.03	3.07	17%	39%	7681	853	8534	95	11	106	90.0%	10.0%	467735	00:00:53	
	100%	50568.89	100.0%	0.0%	0	0.00	7%	25%	4.99	1.46	15%	34%	8511	0	8511	68	0	68	100.0%	0.0%	465944	00:00:37	

[1] Congestion is calculated as the ratio of flow to capacity on each road link, i.e., the degree of saturation.

[2] Delay is calculated as the difference between the driven travel time and the minimum travel time on each roadway in free-flow speed conditions, where it is assumed that each vehicle only carries one passenger

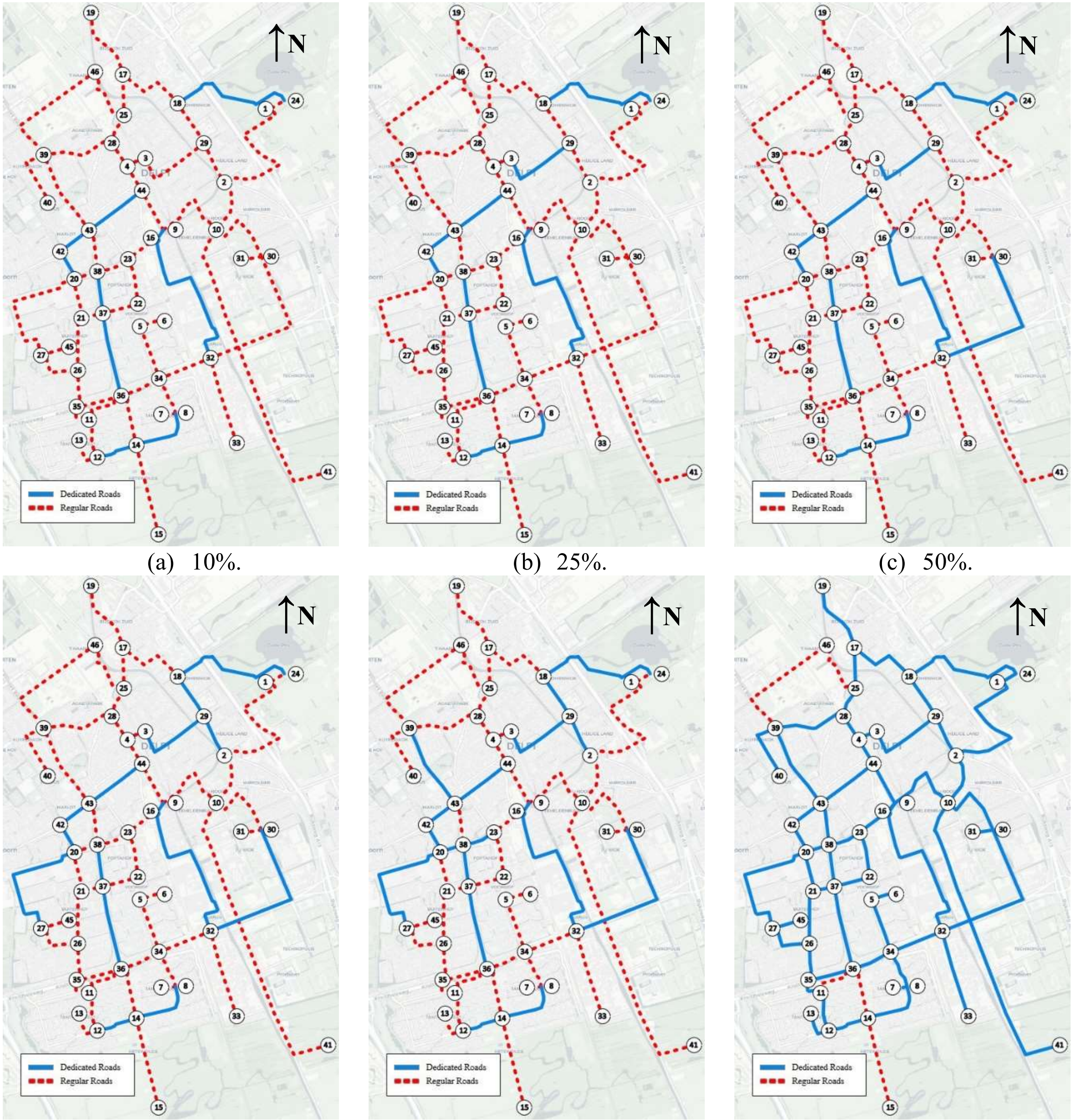
Table 3.9 – Daily experiments results of scenario I with AV subnetworks.

Scenario I RNDP with AV subnetworks		Objective Function			Network		Congestion [1]						Travel Times			Delay [2]			Travel Distances			Computational time	
		Generalized Costs	Travel time	Road Investment		Dedicated Roads	Network Congestion	Average degree of saturation	Roadways above practical capacity	Congested roadways	Peak-hour Network Congestion	Peak-hour average degree of saturation	AV trips	CV trips	Total Travel Times	AV trips	CV trips	Total Delay	AV trips	CV trips	Total Distance	Each Stage	The whole scenario
	AV Penetration Rate	[€]	[%]	[%]	[no.]	[km]	[%]	[%]	[km]	[km]	[%]	[%]	[h veh]	[h veh]	[h veh]	[h veh]	[h veh]	[h veh]	[%]	[%]	[km veh]	[h:m:s]	[h:m:s]
Optimality at each stage	0%	85277.28	100.0%	-	0	0.00	11%	43%	86.67	13.95	25%	58%	0	8915	8915	0	484	484	0.0%	100.0%	468271	00:00:59	
	10%	84974.76	100.0%	-	9	30.54	11%	38%	87.80	13.95	25%	55%	903	8017	8920	47	430	477	10.0%	90.0%	468166	00:25:45	
	25%	83484.38	100.0%	-	10	34.68	11%	38%	83.82	21.46	25%	56%	2281	6748	9029	116	423	539	24.7%	75.3%	470325	04:06:50	
	50%	77056.81	100.0%	-	17	56.09	10%	33%	74.95	11.80	23%	50%	4427	4580	9007	170	230	400	48.7%	51.3%	475806	16:07:06	23:31:52
	75%	65484.03	100.0%	-	15	51.89	9%	28%	19.35	4.33	19%	42%	6479	2223	8702	130	48	178	74.0%	26.0%	470098	09:17:31	
	90%	56860.36	100.0%	-	9	31.71	7%	26%	8.28	3.07	17%	38%	7679	880	8559	94	10	104	89.6%	10.4%	468554	17:32:50	
	100%	50568.89	100.0%	-	49	133.11	7%	25%	4.99	1.46	15%	34%	8511	0	8511	68	0	68	100.0%	0.0%	465944	00:00:51	
Incremental Planning	0%	85277.25	100.0%	-	0	0.00	11%	43%	86.67	13.95	25%	58%	0	8915	8915	0	485	485	0.0%	100.0%	468227	00:00:59	
	10%	84974.78	100.0%	-	9	30.54	11%	38%	86.05	13.95	25%	55%	903	8016	8919	47	429	475	10.0%	90.0%	468136	03:27:06	
	25%	83484.38	100.0%	-	10	34.68	11%	38%	83.82	21.46	25%	56%	2281	6748	9029	116	423	539	24.7%	75.3%	470325	02:23:13	
	50%	77088.29	100.0%	-	11	42.52	10%	36%	84.81	12.26	23%	51%	4409	4431	8840	172	191	363	49.4%	50.6%	469374	01:40:39	07:56:45
	75%	65765.61	100.0%	-	14	54.08	9%	29%	19.35	4.33	20%	44%	6492	2232	8724	132	48	180	74.4%	25.6%	468746	00:17:51	
	90%	57023.08	100.0%	-	17	61.15	7%	25%	8.28	3.07	17%	39%	7680	895	8576	95	10	105	89.6%	10.4%	468411	00:06:05	
	100%	50569.17	100.0%	-	57	160.40	7%	24%	4.99	1.46	15%	34%	8511	0	8511	68	0	68	100.0%	0.0%	465945	00:00:52	
Long-Term Reversal Planning	0%	85277.52	100.0%	-	0	0.00	11%	43%	86.67	14.44	25%	58%	0	8915	8915	0	484	484	0.0%	100.0%	468283	00:00:47	
	10%	85090.08	100.0%	-	0	0.00	11%	43%	86.67	13.95	25%	58%	891	8021	8912	48	433	481	10.0%	90.0%	468248	00:00:59	
	25%	83769.48	100.0%	-	0	0.00	11%	42%	86.67	13.32	25%	57%	2221	6663	8885	114	341	454	25.0%	75.0%	468178	00:07:42	
	50%	77303.68	100.0%	-	9	31.71	10%	36%	76.03	11.80	23%	53%	4418	4578	8996	169	228	397	48.9%	51.1%	477399	00:04:00	03:26:30
	75%	65561.16	100.0%	-	9	31.71	9%	30%	20.52	4.33	19%	45%	6452	2223	8676	132	48	180	74.1%	25.9%	471808	00:01:36	
	90%	56860.36	100.0%	-	9	31.71	7%	26%	8.28	3.07	17%	38%	7679	880	8559	94	10	104	89.6%	10.4%	468554	03:10:35	
	100%	50568.89	100.0%	-	49	133.11	7%	25%	4.99	1.46	15%	34%	8511	0	8511	68	0	68	100.0%	0.0%	465944	00:00:51	
Hybrid Planning	0%	85277.28	100.0%	-	0	0.00	11%	43%	86.67	13.95	25%	58%	0	8915	8915	0	484	484	0.0%	100.0%	468271	00:00:59	
	10%	85069.34	100.0%	-	2	5.25	11%	41%	88.42	13.95	25%	58%	892	8020	8912	48	432	480	10.0%	90.0%	468115	02:12:51	
	25%	83726.86	100.0%	-	2	5.25	11%	41%	86.33	13.80	25%	57%	2223	6661	8884	112	338	450	25.0%	75.0%	467993	02:11:05	
	50%	77498.24	100.0%	-	7	25.93	10%	36%	82.11	10.03	23%	52%	4396	4442	8838	171	177	349	49.5%	50.5%	471494	06:11:52	12:29:02
	75%	65780.86	100.0%	-	10	32.82	9%	29%	19.35	4.33	19%	45%	6459	2223	8682	132	48	180	74.1%	25.9%	471241	01:32:54	
	90%	56900.20	100.0%	-	17	48.34	7%	23%	8.28	3.07	17%	35%	7679	909	8588	94	10	104	89.1%	10.9%	470949	00:18:29	
	100%	50568.89	100.0%	-	49	133.11	7%	25%	4.99	1.46	15%	34%	8511	0	8511	68	0	68	100.0%	0.0%	465944	00:00:52	

1 Congestion is calculated as the ratio of flow to capacity on each road link, i.e., the degree of saturation.

[2] Delay is calculated as the difference between the driven travel time and the minimum travel time on each roadway in free-flow speed conditions, where it is assumed that each vehicle only carries one passenger

In the incremental planning, AV subnetworks align with the optimality of each design stage in the first half of the transition period (see Figure 3.42). The IP analysis took about 8 hours to execute the whole process, composed of seven design stages (penetration rates). Figure 3.43 shows the network representation of AV subnetworks creation under incremental planning throughout the transition period. For 10% of AVs, subnetworks are already 17.1% of the total network (30.54 km). For 90% of AVs, subnetworks are 34.3%. For a penetration rate of 100%, all the roads with traffic flow circulation cover 89.9% of the network (160.40 km out of 178.51 km). External demand to the city was not part of the dataset used in this experiment.



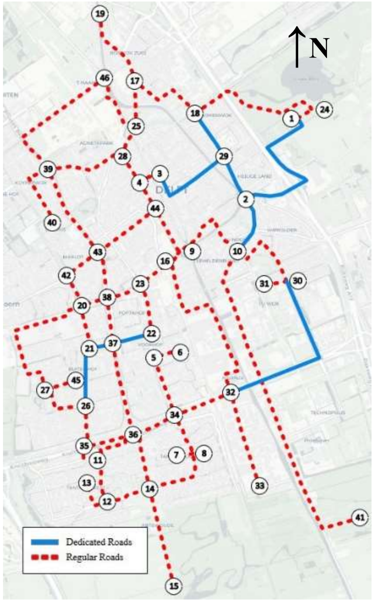
(a) 10%. (b) 25%. (c) 50%.

(d) 75%. (e) 90%. (f) 100%.

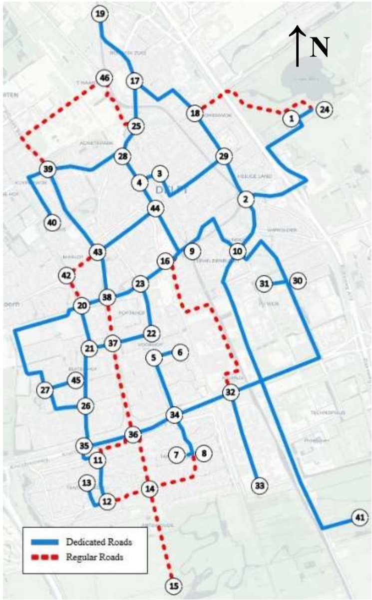
Figure 3.43 – RNDP-AVs daily design: AV subnetworks of Scenario I under Incremental Planning (a), (b), (c), (d), (e) and (f) (% of AV penetration rate).

In the long-term planning, AV subnetworks are only necessary when AVs are 50% of the vehicle fleet and are only close to optimality in the latest design stage of the transition period (90% onwards). The LTP analysis took about 3 and a half hours to compute all solutions composed of seven design stages (penetration rates). This dramatic reduction of the computational time is since the model computes the transition period in a reverse way, so it is less combinatorial.

Figure 3.44 shows the network representation of AV subnetworks creation under an LTP throughout the transition period. The network representation of AV subnetworks prevails from 50% until the end of the transition process (100% of AVs), in three single zones representing 17.8% of the network (31.71 km out of 178.51 km). Also, for 100% of AVs, the whole network needed for traffic is 74.6% of the original (133.11 km out of 178.51 km).



(a) 50%, 75%, 90%.



(b) 100%.

Figure 3.44 – RNDP-AVs daily design: AV subnetworks of Scenario I under Long-Term Planning (a) and (b) (% of AV penetration rate).

In the hybrid planning, AV subnetworks are added incrementally by the combinatorial problem and are limited to the optimal solution at the end of the transition process (100%). This means that, if in the end of the transition process (100% of AVs), only 74.6% (133.11 km out of 178.51 km) is needed, the creation of AVs subnetworks shall only evaluate the roads that will actually be needed in the "end". Figure 3.45 shows the network representation of the AV subnetworks progression. In the first half of the transition period, only two roads are dedicated for AVs – 2.9% of the network (5.25 km out of 178.51 km). AV subnetworks only get relevance in the second half of the transition period, increasing from 14.5% (25.93 km out of 178.51 km) to 74.6%.

The hybrid analysis took about half a day to compute all solutions – seven design stages (penetration rates). This computational time is explained because the at the middle of the transition period (50% of AVs), the model explores more combinations than in the IP analysis, and at this point it is trying to balance the detour problem and the AV travel time savings in a fair way.

(a) 10%, 25%. (b) 50%. (c) 75%.

(d) 90%. (e) 100%.

Figure 3.45 – RNDP-AVs daily design: AV subnetworks of Scenario I under Hybrid planning (a), (b), (c), (d) and (e) (% of AV penetration rate).

The following Figure 3.46 shows the differential of the (generalized) costs of every planning strategy applied to scenario I – which saves up to 1.2% in comparison with scenario O. The IP is closer to the optimality analysis in the first half of the transition period, even until AVs are 50% of the fleet. Similarly, the LTP planning analysis is closer to optimality in the latest stages of the transition period – when AVs are 90% onwards. The hybrid planning performs worse than the others but still brings cost savings up to 0.8%.

Figure 3.47 depicts the total travel time in every planning strategy. Note that the optimal solutions with AV subnetworks implies higher total travel times, which can be explained by analyzing total distance and total delay in the subsequent figures.

As aforementioned, the model always minimizes generalized costs that in scenario I are only founded on the total travel time that considers an AVs value of travel time reduction. It may occur the following situations:

▪ An increase of CVs total travel time (Figure 3.48) can occur if:

- CVs experience congestion especially in the surroundings of AV subnetworks AND is depicted by an increase in total CVs delay (see Figure 3.52). For instance, at the penetration rate of 90%.
- or CVs experience detour away from AV subnetworks to reach destination ND is depicted by an increase in CVs distance (see Figure 3.50). For instance, at the penetration rate of 75%.

▪ An increase of AVs total travel time (Figure 3.49) can occur if:

- AVs longer trips when AVs value of travel time decreases and is depicted by an increase of distance (see Figure 3.51).
- AV face congestion that is depicted by an increase in AVs delay (see Figure 3.53). For instance, at the penetration rate of 25%.
- AVs change their routes to lower speed routes, i.e., when both AV delay and AV distance decrease. For instance, at the penetration rate of 10% at the IP and hybrid planning, and at the penetration rate of 50% in the LTP.

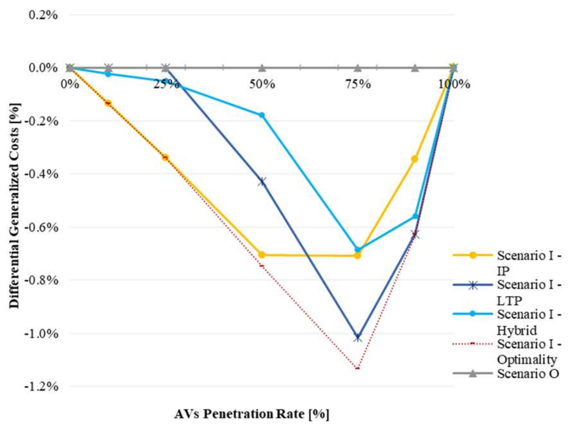


Figure 3.46 – RNDP-AVs daily design: Differential on the generalized costs in Scenario I.

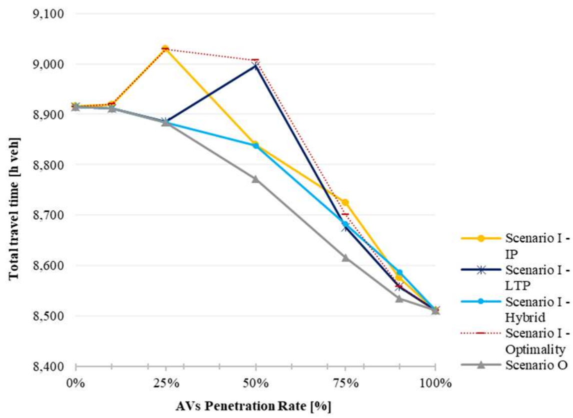


Figure 3.47 – RNDP-AVs daily design: Total travel time in Scenario I.

Figure 3.48 shows that total travel time will increase up to 6.5% for CVs and 3% for AVs. CVs will likely experience longer trips (higher travel times) in the end of the transition process caused by detour (AV penetration rates equal and higher than 50%).

According to Figure 3.49, AVs will only experience shorter trips (lower travel times) for the LTP and hybrid planning when AV penetration rate is higher than 75%. The presence of AV subnetworks does not decrease total travel time for AV passengers as they perceive time differently (lower value of travel time). From this perspective, it seems that AV subnetworks should only start when AVs are the majority of the vehicle fleet. Otherwise, in the beginning of the transition period, AVs may experience longer trips (higher travel times).

Due to the fact that AVs value of travel time, AV trips will be likely conducted in shorter routes (lower distances) – which means that AV subnetworks will surely start to appear in roads that have lower capacity/speeds (check the optimality analysis in Figure 3.51).

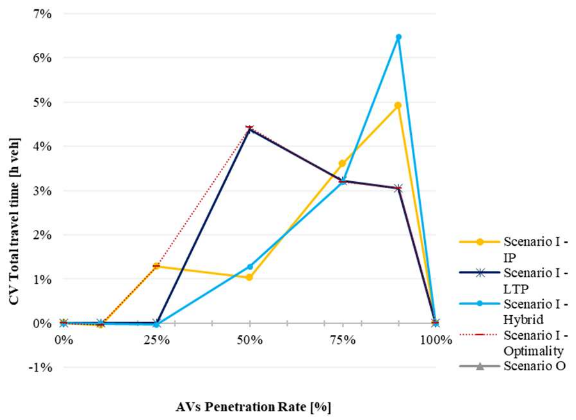


Figure 3.48 – RNDP-AVs daily design: CV Total travel time in Scenario I.

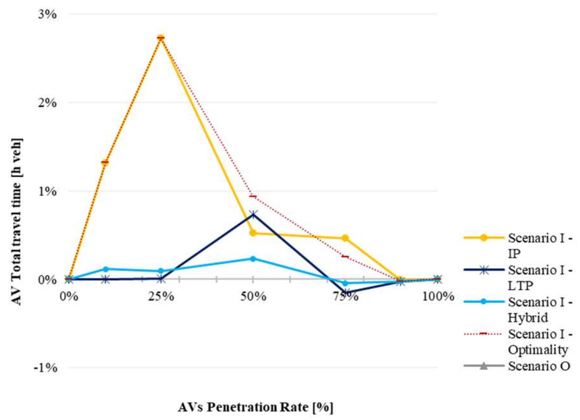


Figure 3.49 – RNDP-AVs daily design: AV Total travel time in Scenario I.

CV detour will likely start when AVs are 50%, or even sooner if the IP is chosen. Figure 3.50 shows that detour is unavoidable in the latest stages of the period, although CV routes will be up to 10% longer. For the detour problem, the "best" strategy would be the incremental if that strategy is designed at least for a design stage that contains 25% of AVs. Otherwise, if the incremental strategy starts for 50% of AVs, the outcome would be different and would coincide with the optimality analysis in the beginning of the decision process. Also, in Figure 3.51, the IP strategy would be the one that mostly searches for shorter routes that allied with an increase of travel times which means that the IP looks forward to select lower capacity roads. Similar reasonings can be drawn for the other strategies.

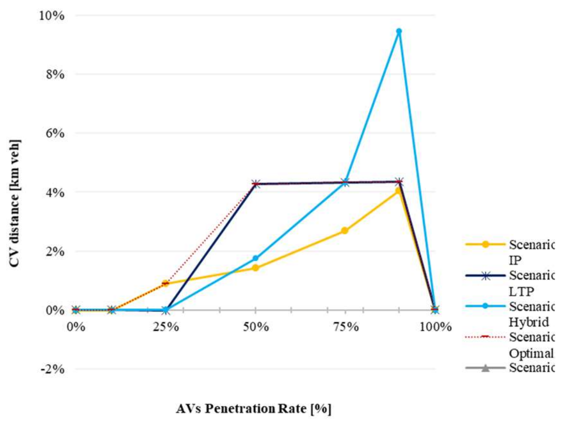


Figure 3.50 – RNDP-AVs daily design: CV total distance variation in Scenario I.

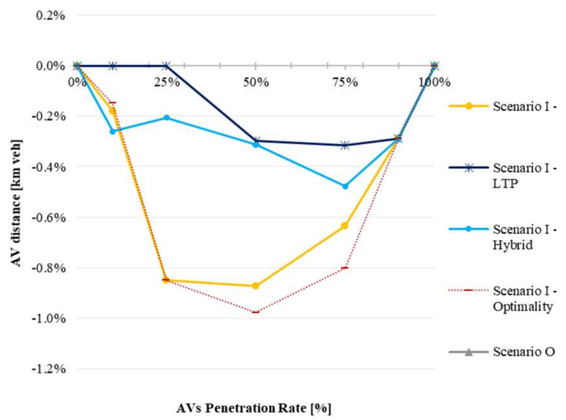


Figure 3.51 – RNDP-AVs daily design: AV total distance variation in Scenario I.

According to Figure 3.52, the IP strategy creates a subnetwork that may cause an increase of 25% of delay to CVs in the first quarter of the transition process. The LTP rises that increasing to 35%. The hybrid planning is the strategy that creates less delay and found optimal in this traffic indicator. Similar conclusions can de drawn from Figure 3.53 for AVs: the hybrid and the LTP strategies reduce delay up to 8%. Meaning that AV subnetworks are important for AVs.

Figure 3.54 to Figure 3.57 analyze congestion during the transition period. Figure 3.54 illustrates the average degree of saturation which indicates that speed is increasing in the majority of the road links of the network. The incremental planning is the one that has lower degree of saturation but, in Figure 3.55, for a penetration rate of 25%, the length of congested roads (DS≥1) is higher than scenario O – meaning that having AV subnetworks is not suitable for this design stage. Both LTP (Figure 3.56) and hybrid planning (Figure 3.57) have similar performance. Overall, it seems that implementing AV subnetworks does not improve/mitigate significantly. In fact, it is the higher efficiency of AVs that will have a significant role in congestion (congestion in scenario O is likewise reduced).

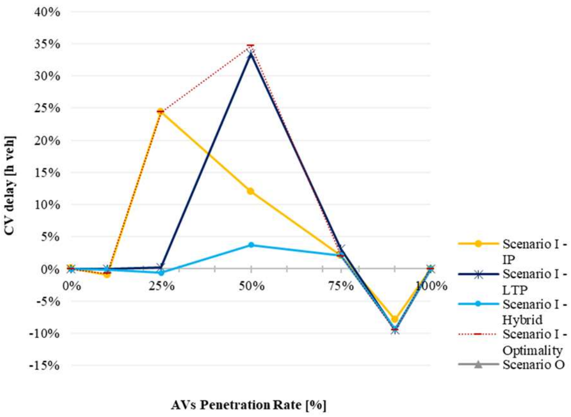


Figure 3.52 – RNDP-AVs daily design: CV total delay in Scenario I.

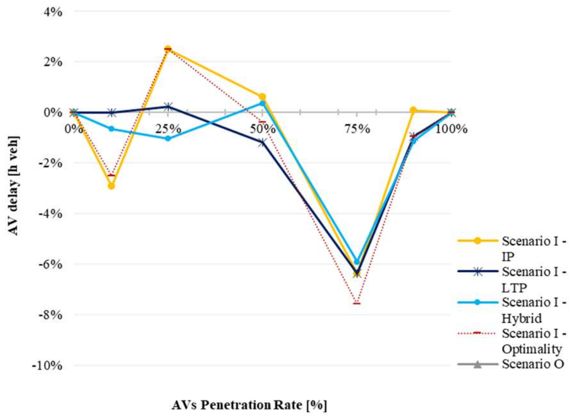


Figure 3.53 – RNDP-AVs daily design: AV total delay in Scenario I.

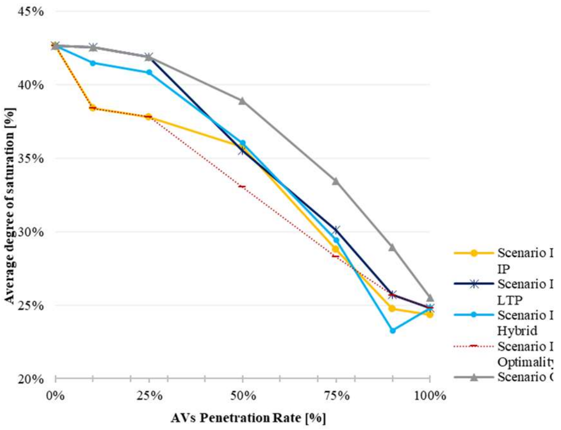


Figure 3.54 – RNDP-AVs daily design: Average degree of saturation in Scenario I.

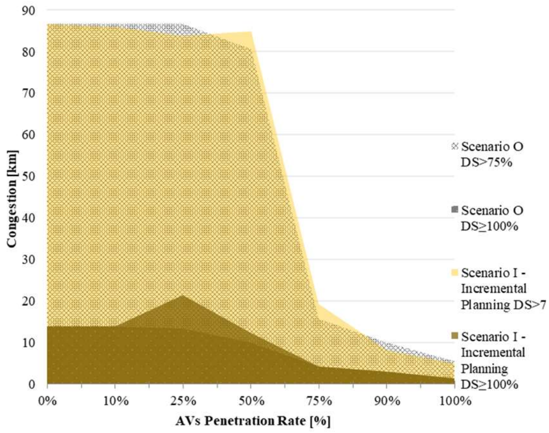


Figure 3.55 – RNDP-AVs daily design: Congestion at incremental planning in Scenario I.

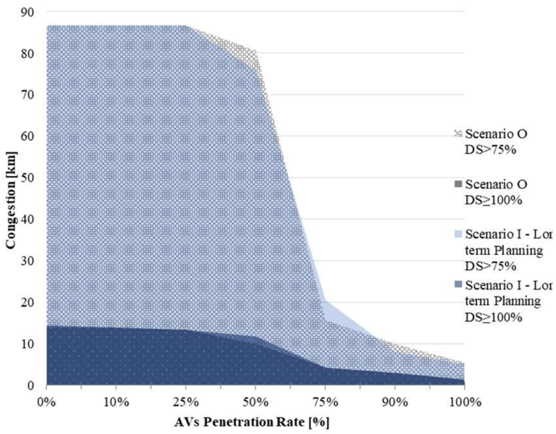


Figure 3.56 – RNDP-AVs daily design: Congestion at long-term planning in Scenario I.

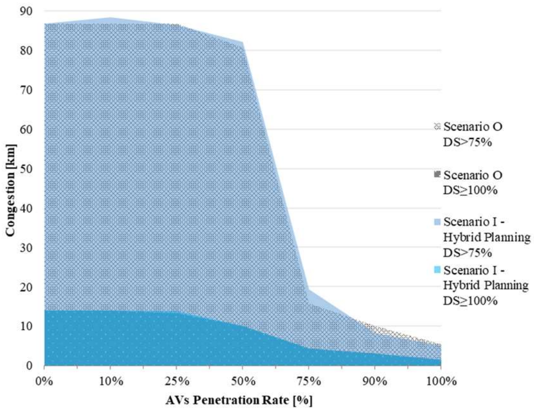


Figure 3.57 – RNDP-AVs daily design: Congestion at hybrid planning in Scenario I.

From a practical perspective, AV subnetworks do have an important role on segregating AVs from mixed traffic and the design of AV subnetworks will induce them shorter routes (lower distances) that will experience lower speed (higher travel times) which might be significant for road safety in urban areas. The role of the need for road investment will be analyzed in the following section.

Nevertheless, when road investment is not a constraint for designing AV subnetworks, the analysis of the three planning strategies revealed that:

- The incremental planning should be used only in cases where the initial design stages are until AV penetration rates of 25%. The IP starts AV subnetworks in lower capacity roads (lower speeds) and leads to a higher network in the end of the transition period. This dispersion of dedicated roads for AVs throughout the network produces less CV detour.
- The long-term planning is the "best" strategy in the second half of the transition period, i.e., when the initial design stages occur when AVs are already a majority. For an equal share between AVs and CVs (50%), CVs will experience high detour and delay, but that effect will be highly mitigated until the end of the period.
- The hybrid planning revealed satisfactory results throughout the entire transition period, and it can be used to help design AV subnetworks since the beginning. The only disadvantage of this strategy is the CV detour (longer trips, longer distances) when AVs are over 90% of the vehicle fleet.

3.7.3. AV SUBNETWORKS THAT REQUIRE ROAD INVESTMENT FOR V2I

This section evaluates the planning strategies applied to create progressive AV subnetworks when road investment is needed, and the aim is to balance somehow with the social travel costs reduction as more AVs penetrate the vehicle fleet. The results from this experiment are presented in Table 3.10. The optimal solutions were obtained within tolerable computation time, less than 20 hours.

Figure 3.58 illustrates the progression of AV subnetworks in each planning strategy: incremental planning (IP), long-term planning (LTP) and hybrid planning. In this example, the LTP creates wider AV subnetworks when AVs are over 50% of the vehicle fleet. In this scenario, the evolution of the subnetwork seems to follow the pattern of the optimality at every design stage except the last one. Note that when AVs are 90%, the "need" from improving traffic efficiency and reducing costs is less prominent.

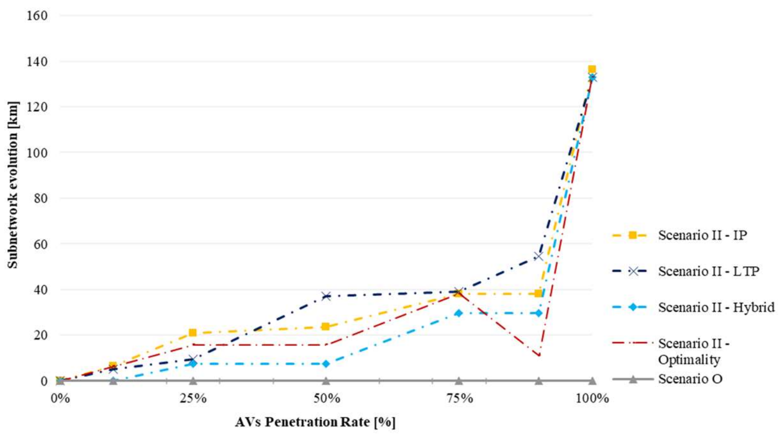


Figure 3.58 – RNDP-AVs daily design: subnetwork evolution in Scenario II.

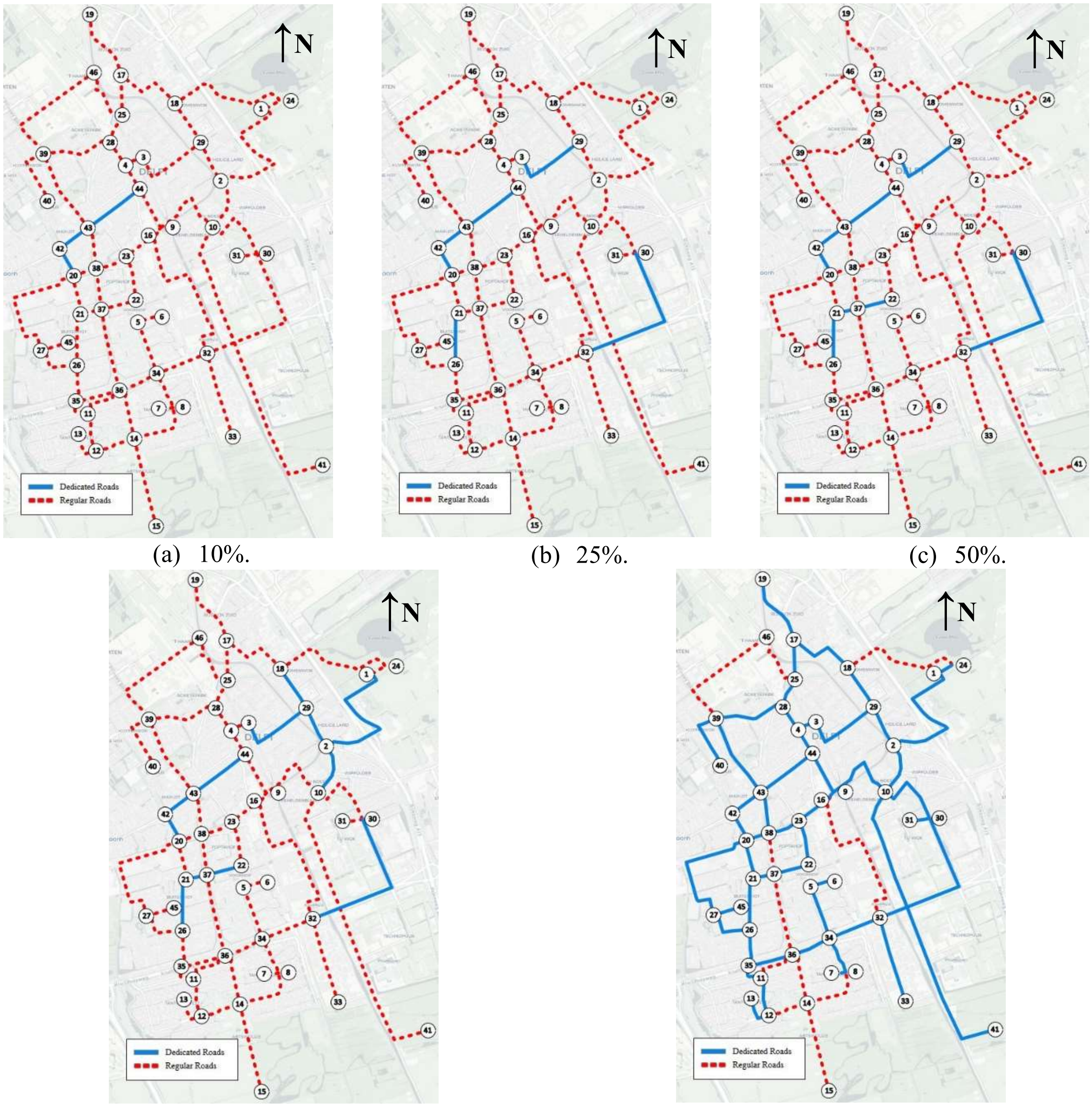
Table 3.10 – Daily experiments results of scenario II with AV subnetworks that require road investment.

Scenario II — RNDP with AV subnetworks that require road investment	AV Penetration Rate	Objective Function: Generalized Costs [€]	Objective Function: Travel time [%]	Objective Function: Road Investment [%]	Network: Dedicated Roads [no.]	Network: Dedicated Roads [km]	Congestion [1]: Network Congestion [%]	Congestion [1]: Average degree of saturation [%]	Congestion [1]: Roadways above practical capacity [km]	Congestion [1]: Congested roadways [km]	Congestion [1]: Peak-hour Network Congestion [%]	Congestion [1]: Peak-hour average degree of saturation [%]	Travel Times: AV trips [h veh]	Travel Times: CV trips [h veh]	Travel Times: Total Travel Times [h veh]	Delay [2]: AV trips [h veh]	Delay [2]: CV trips [h veh]	Delay [2]: Total Delay [h veh]	Travel Distances: AV trips [%]	Travel Distances: CV trips [%]	Travel Distances: Total Distance [km veh]	Computational time: Each Stage [h:m:s]	Computational time: The whole scenario [h:m:s]
Optimality at each stage	0%	85277.25	100.0%	0.0%	0	0.00	11%	43%	88.42	13.95	25%	58%	0	8916	8916	0	485	485	0.0%	100.0%	468257	00:01:00	07:20:36
	10%	85083.08	99.9%	0.1%	3	6.41	11%	41%	86.67	13.95	25%	58%	895	8018	8913	47	430	477	10.0%	90.0%	468110	10:24:48	
	25%	83662.58	99.9%	0.1%	6	15.76	11%	39%	85.92	22.35	25%	56%	2268	6750	9019	118	425	543	24.6%	75.4%	470157	19:09:27	
	50%	77290.54	99.9%	0.1%	6	15.76	10%	36%	83.04	13.15	23%	51%	4402	4402	8805	171	185	357	49.6%	50.4%	468704	15:52:33	
	75%	65770.49	99.6%	0.4%	12	38.11	9%	29%	19.35	4.33	19%	45%	6462	2223	8685	130	48	178	74.1%	25.9%	471106	04:12:26	
	90%	57051.55	99.9%	0.1%	4	11.03	7%	27%	8.28	3.07	17%	39%	7679	871	8550	94	10	104	89.7%	10.3%	467828	05:38:33	
	100%	51500.67	98.2%	1.8%	49	133.11	7%	25%	4.99	1.46	15%	34%	8511	0	8511	68	0	68	100.0%	0.0%	465944	00:01:49	
Incremental Planning	0%	85277.25	100.0%	0.0%	0	0.00	11%	43%	88.42	13.95	25%	58%	0	8916	8916	0	485	485	0.0%	100.0%	468257	00:00:59	19:56:16
	10%	85083.12	99.9%	0.1%	3	6.41	11%	41%	88.42	13.95	25%	58%	895	8018	8913	47	431	478	10.0%	90.0%	468147	10:06:32	
	25%	84097.09	99.8%	0.2%	6	21.00	11%	38%	87.00	24.99	25%	58%	2280	6832	9112	117	444	561	24.4%	75.6%	476101	01:23:51	
	50%	77215.37	99.8%	0.2%	8	23.73	10%	36%	84.47	12.26	23%	53%	4403	4451	8854	173	192	365	49.2%	50.8%	472241	04:23:45	
	75%	65604.38	99.6%	0.4%	12	38.11	9%	29%	19.35	4.33	19%	45%	6462	2223	8685	130	48	178	74.1%	25.9%	471106	02:42:56	
	90%	56860.37	99.5%	0.5%	12	38.11	7%	26%	8.28	3.07	17%	38%	7679	880	8559	94	10	104	89.6%	10.4%	468553	01:17:04	
	100%	51255.97	98.1%	1.9%	51	136.27	7%	25%	4.99	1.46	15%	34%	8511	0	8511	68	0	68	100.0%	0.0%	465944	00:01:09	
Long-Term Reversal Planning	0%	85314.00	100.0%	0.0%	0	0.00	11%	43%	88.42	13.95	25%	58%	0	8916	8916	0	485	485	0.0%	100.0%	468262	00:00:45	16:36:31
	10%	85098.43	100.0%	0.0%	2	5.25	11%	41%	86.67	14.44	25%	58%	892	8019	8911	48	431	479	10.0%	90.0%	468149	00:01:11	
	25%	83892.84	99.9%	0.1%	3	9.38	11%	41%	87.89	21.46	25%	60%	2228	6752	8980	118	426	544	24.7%	75.3%	470644	00:06:20	
	50%	77238.25	99.7%	0.3%	11	36.95	10%	35%	74.95	11.80	23%	53%	4407	4580	8987	170	230	400	48.8%	51.2%	476419	00:04:11	
	75%	65666.52	99.6%	0.4%	12	39.00	9%	29%	19.35	4.33	19%	45%	6457	2232	8689	130	48	178	74.0%	26.0%	471736	00:13:13	
	90%	57471.93	99.3%	0.7%	19	54.72	7%	23%	8.28	3.07	17%	35%	7679	917	8596	94	10	104	89.0%	11.0%	471405	16:10:22	
	100%	50568.89	98.2%	1.8%	49	133.11	7%	25%	4.99	1.46	15%	34%	8511	0	8511	68	0	68	100.0%	0.0%	465944	00:00:29	
Hybrid Planning	0%	85277.25	100.0%	0.0%	0	0.00	11%	43%	88.42	13.95	25%	58%	0	8916	8916	0	485	485	0.0%	100.0%	468257	00:00:59	14:29:05
	10%	85090.13	100.0%	0.0%	0	0.00	11%	43%	88.42	13.95	25%	58%	891	8020	8911	48	432	480	10.0%	90.0%	468269	01:53:30	
	25%	83751.74	99.9%	0.1%	2	7.39	11%	42%	88.23	21.46	25%	60%	2228	6752	8980	118	427	545	24.7%	75.3%	470732	17:05:07	
	50%	77312.14	99.9%	0.1%	2	7.39	10%	38%	83.04	12.26	23%	54%	4389	4402	8791	171	186	357	49.7%	50.3%	469013	11:50:27	
	75%	65742.52	99.7%	0.3%	7	29.62	9%	31%	19.35	4.33	19%	46%	6457	2213	8671	130	48	178	74.3%	25.7%	470030	02:48:06	
	90%	56886.57	99.6%	0.4%	7	29.62	7%	26%	8.28	3.07	17%	39%	7679	876	8555	94	10	104	89.7%	10.3%	468069	04:50:25	
	100%	51293.36	98.2%	1.8%	49	133.11	7%	25%	4.99	1.46	15%	34%	8511	0	8511	68	0	68	100.0%	0.0%	465944	00:00:31	

[1] Congestion is calculated as the ratio of flow to capacity on each road link, i.e., the degree of saturation.

[2] Delay is calculated as the difference between the driven travel time and the minimum travel time on each roadway in free-flow speed conditions, where it is assumed that each vehicle only carries one passenger

Figure 3.59 illustrates the network representation of the AV subnetworks evolution under incremental planning throughout the transition period. The calculation time for this strategy was about 20 hours. For 10% of AVs, subnetworks are already 3.6% of the total network (6.41 km out of 178.51 km). Then, for 25% of AVs, AV subnetworks are 11.8% (21.00 km out of 178.51 km). For 90% of AVs, subnetworks are 21.3% (38.11 km out of 178.51 km). When AVs are 100%, traffic flow circulates in 76.3% of the network (136.27 km out of 178.51 km).



(a) 10%. (b) 25%. (c) 50%.

(d) 75%,90%. (e) 100%.

Figure 3.59 – RNDP-AVs daily design: AV subnetworks of Scenario II under Incremental Planning (a), (b), (c), (d), and (e) (% of AV penetration rate).

In the long-term planning, AV subnetworks are created in a reverse way and since there is a road investment, the model tries to balance the investment with the AV travel savings possible at each design stage. Therefore, this progression is more spread out the transition period than the previous scenario I – see Figure 3.60. For 10% of AVs, only two roads are dedicated for AVs, which corresponds to 2.9% of the network (5.25 km out of 178.51 km). Following, that number increases to 5.2% (9.38 km out of 178.51 km) when 25% of the vehicle fleet is AVs. When the vehicle fleet is balanced (50%), 20.7% of the network is AV subnetworks, which means that only in the second half AV subnetworks are relevant/needed to reduce costs. For an AV penetration rate of 90%, 30.6% of the network is dedicated

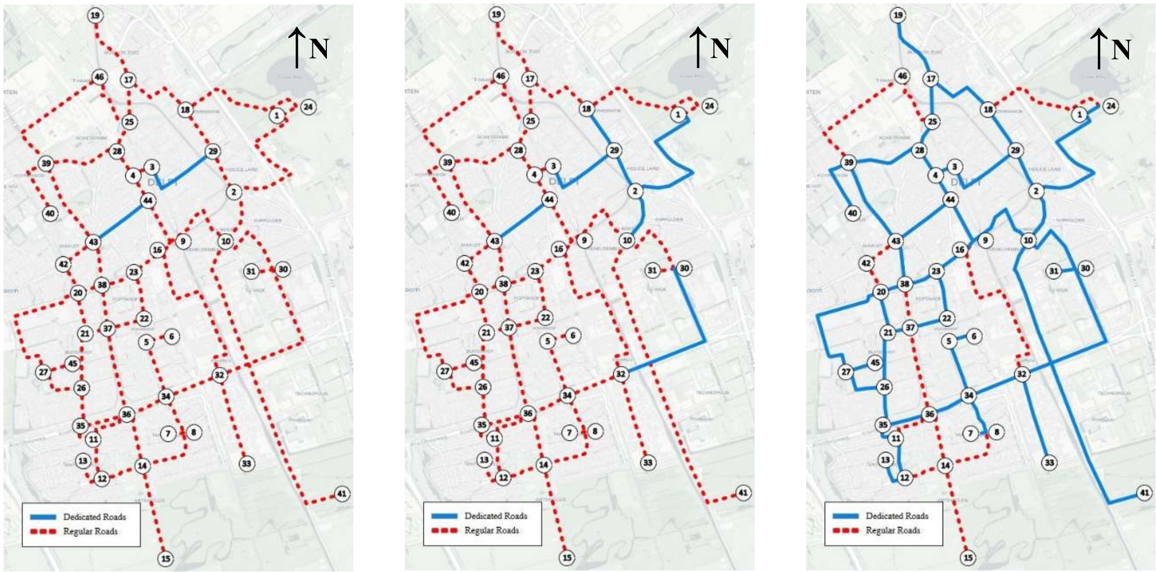
(54.72 km out of 178.51 km). For 100% of AVs, the optimal network needed for traffic circulation is 74.6% of the original one (133.11 km out of 178.51 km). The LTP analysis took about 16 and a half hours to compute all solutions - seven design stages (penetration rates).

(a) 10%. (b) 25%. (c) 50%.

(d) 75%. (e) 90% (f) 100%.

Figure 3.60 – RNDP-AVs daily design: AV subnetworks of Scenario II under Long-Term Planning (a), (b), (c), (d), (e), and (f) (% of AV penetration rate).

Figure 3.61 illustrates the AV subnetwork representation for scenario II under hybrid planning. AV subnetworks are only appropriate when AV penetration rate is over 25%. Moreover, they only get relevance when AVs are over 75% of the fleet. This means that if road investment is present and balanced with the travel time savings given by AVs, that only happens in the latest stages of the transition period. Between AV penetration rates of 25% and 75% of AVs, AV subnetworks are 4.1% (7.39 km out of 178.51 km). Between AV penetration rates of 75% and 100%, it should be 16.6% (29.62 km out of 178.51 km). At the end of the transition period (100% of AVs), the network needed for traffic circulation is 74.6% of the original one (133.11 km out of 178.51 km).



(a) 25%, 50%. (b) 75%, 90%. (c) 100%.

Figure 3.61 – RNDP-AVs daily design: AV subnetworks of Scenario II under Hybrid planning (a), (b), and (c) (% of AV penetration rate).

Figure 3.62 illustrates the differential costs of every planning strategy applied to scenario II – which ranges between -0.9% and +1.8% in comparison with scenario O. In the first half of the transition process, the hybrid planning seems to be the most conservative. However, in both hybrid and IP, significant investment will occur at the last stage (100% of AVs), which is null and spread out in the earlier design stages in the LTP strategy.

Figure 3.63 depicts the total travel time in every planning strategy. Here, the incremental strategy induces higher travel times in the first half of the transition period. The hybrid strategy seems to be the one that least increases travel times.

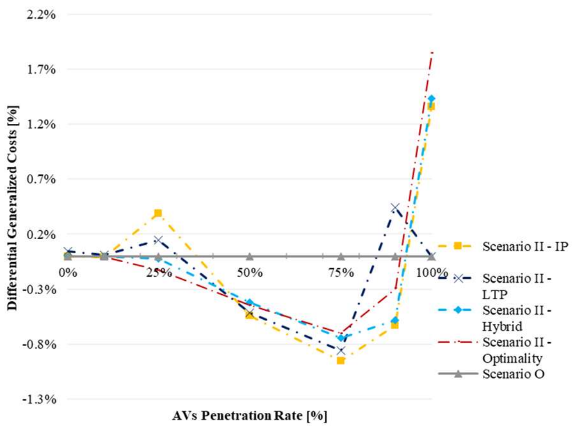


Figure 3.62 – RNDP-AVs daily design: Differential on the generalized costs in Scenario II.

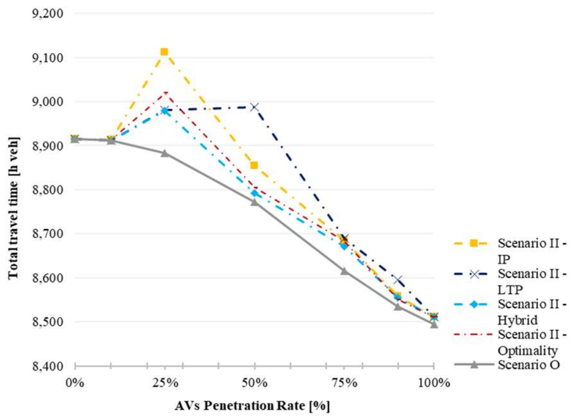


Figure 3.63 – RNDP-AVs daily design: Total travel time in Scenario II.

Once again, according to Figure 3.66, CV detour is unavoidable and the LTP is the strategy that most increases CV detour, although that only happens when AV penetration rate is over 90%. Figure 3.68 shows that CVs will likely experience congestion somewhere between the design stages of AV penetration rates in the second quarter of the transition process, between 25% and 50%.Figure 3.67 shows that AV routes are shortened, which allied with a delay reduction (in Figure 3.69), confirms that AVs are traveling on roads that have lower road capacity and speed. Similarly, to the analysis of scenario I results, Figure 3.69 indicates AVs might experience congestion when they represent 25% of the vehicle fleet.

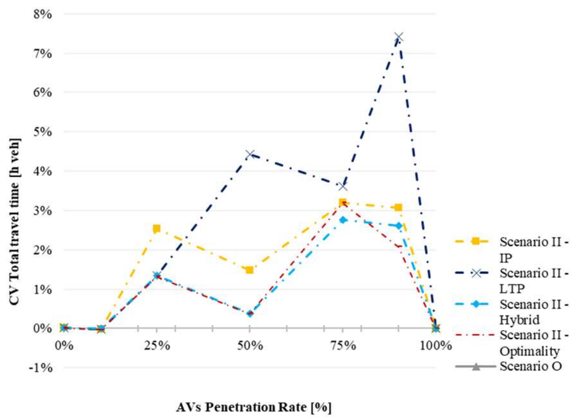


Figure 3.64 – RNDP-AVs daily design: CV Total travel time in Scenario II.

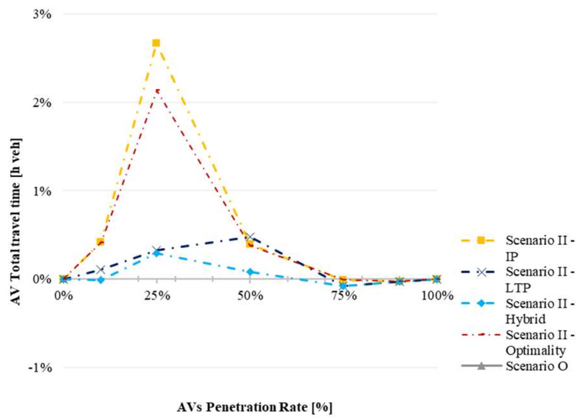


Figure 3.65 – RNDP-AVs daily design: AV Total travel time in Scenario II.

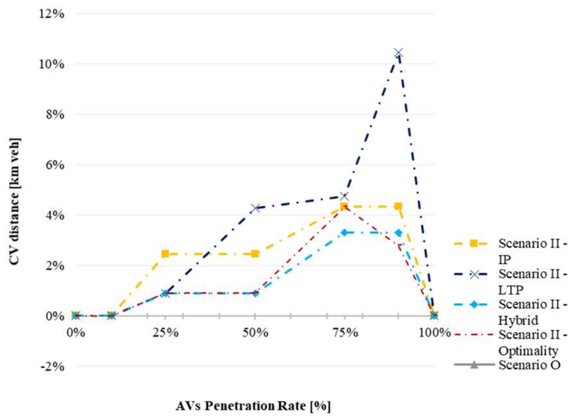


Figure 3.66 – RNDP-AVs daily design: CV total distance variation in Scenario II.

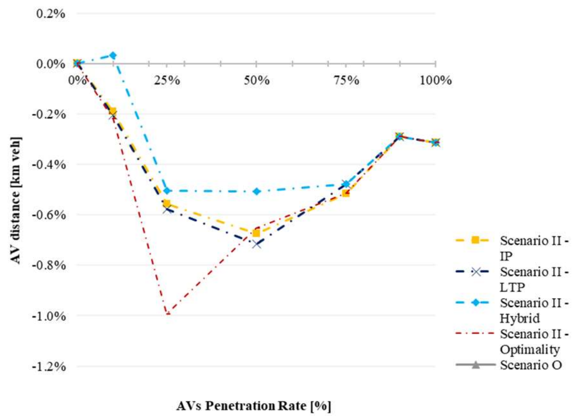


Figure 3.67 – RNDP-AVs daily design: AV total distance variation in Scenario II.

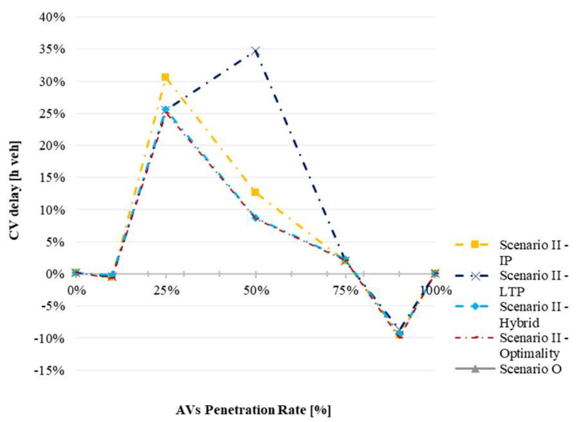


Figure 3.68 – RNDP-AVs daily design: CV total delay in Scenario II.

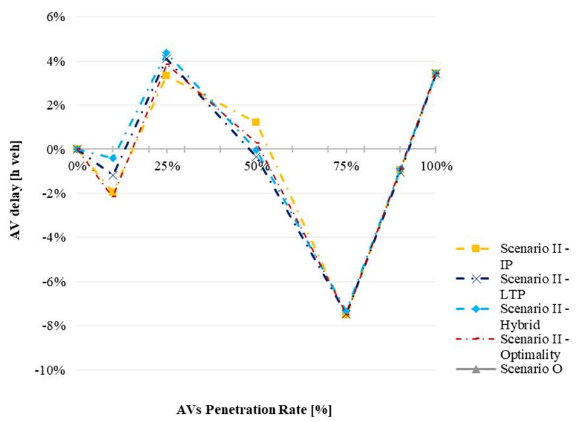


Figure 3.69 – RNDP-AVs daily design: AV total delay in Scenario II.

Between Figure 3.70 and Figure 3.73, the effect of AV subnetworks on congested is evaluated. Figure 3.70 confirms that every planning strategy decreases the average degree of saturation, which indicates that vehicles circulate, on average, at higher speeds. In other words, traffic is more spread out all over the network. Still, the length of roadways above practical capacity (DS≥75%) and the congested roads (DS≥75%) are impacted negatively in every single strategy (Figure 3.71 to Figure 3.73). This might happen, for example, in city centers or zones that absorb a significant share of travel demand, and as AV subnetworks start in roads that have lower capacity/speed and road investment restraints the creation of AV subnetworks, these roads get flow which means more congestion. Therefore, AV subnetworks should only start when AVs are more than 50% of the fleet.

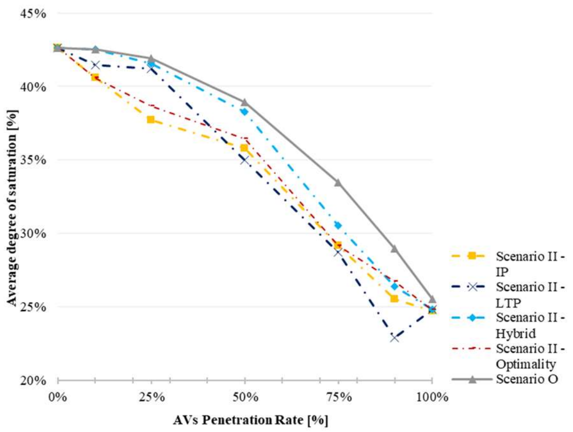


Figure 3.70 – RNDP-AVs daily design: Average degree of saturation in Scenario II.

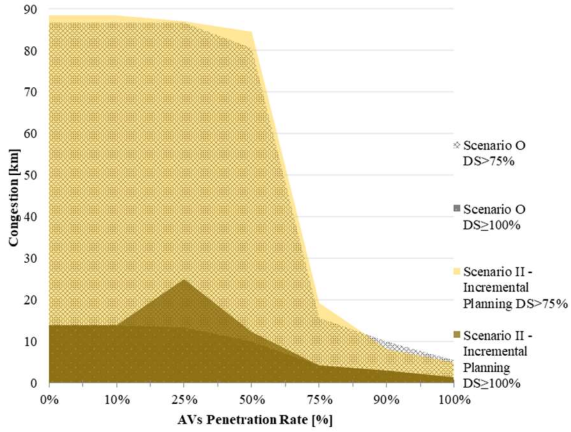


Figure 3.71 – RNDP-AVs daily design: Congestion at incremental planning in Scenario II.

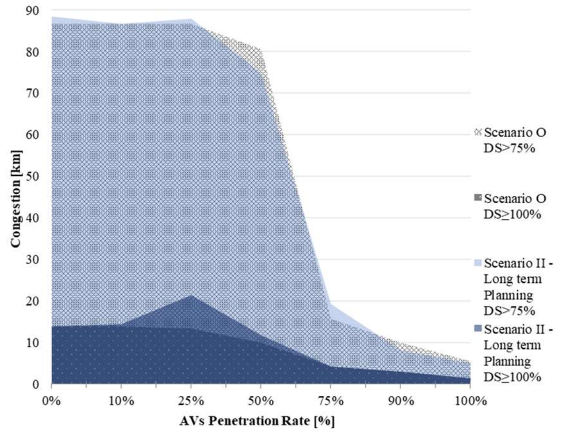


Figure 3.72 – RNDP-AVs daily design: Congestion at long-term planning in Scenario II.

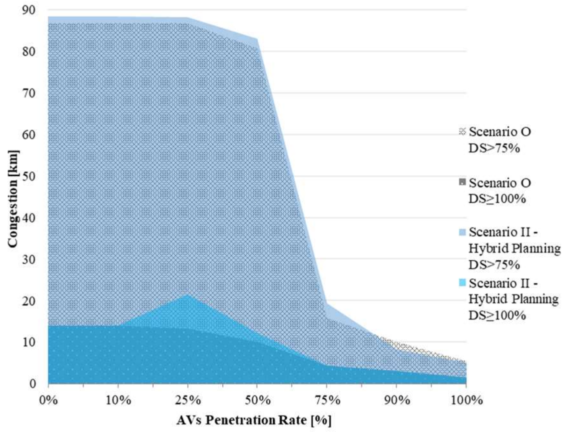


Figure 3.73 – RNDP-AVs daily design: Congestion at hybrid planning in Scenario II.

Nevertheless, when road investment is a constraint for designing AV subnetworks, the analysis of the three planning strategies revealed that:

- The design of AV subnetworks should only be done once AVs level 4 reach 50% of the vehicle fleet, regardless of the strategy.
- The long-term planning should be used in the second half of the transition period, i.e., when the initial design stages occur when AVs are over 50% of the vehicle fleet. It is also the strategy that mostly disperses road investment, and that does not require vast amounts at the end of the period (100% of AVs). Nevertheless, the LTP is the strategy that induces CV congestion in the middle of the period (50% of AVs) and CV detour at the end of the period (AVs over 90%).
- The hybrid planning revealed satisfactory throughout the entire transition period in every indicator, except the amount of road investment needed for the last design stage (100% of AVs). It is the strategy that most mitigates the CV detour problem (in comparison with the other strategies evaluated).

3.7.4. PLANNING STRATEGIES OVERVIEW

The previous analyses were helpful to infer wisely on the AV subnetwork creation. It is somehow consensual that, in order to avoid CV detour, AV subnetworks will likely circulate in shorter routes (lower AV distances) that involve roads with lower capacity/speed since AV passengers experience a lower value of travel time. This evidence has great significance in the remaining results. In the first half of the transition period, CV detour (extra distances) is avoided but congestion will likely happen in the second quarter of the period (between 25% and 50% of AVs) both for CVs and AVs. In the second half, CV detour will likely occur for penetration rates higher than 50%.

Figure 3.74 summarizes the progression of AV subnetworks in both scenarios under every planning strategy. Figure 3.75 depicts the differential generalized costs in comparison with scenario O that did not involve AV subnetworks. At pink shadow is represented the optimal area. The optimal zone is between both optimality analyses, with and without road investment, whereas in the differential costs are optimal when the differential is negative. In both scenarios I and II, without and with road investment, the two best design strategies were the hybrid and the LTP – in fact, lines are quite close to each other in both cases.

When no road investment is associated, the hybrid planning is satisfactory except in the latest stages (90% of AVs) because it worsens CV detour. The LTP planning strategy is beneficial except when CVs have an equal share in the vehicle fleet with AVs (50%) – in this case, CVs will likely experience congestion (higher delays) in the surroundings of AV subnetworks.

When road investment is needed and part of the decision process, the IP and hybrid will demand a significant investment action when all vehicles are AVs. The LTP distributes the investment. However, while the IP and hybrid might start whenever stage (penetration rate), the LTP implies that distribution and should only be applied if the initial design stages are in the first half of the period.

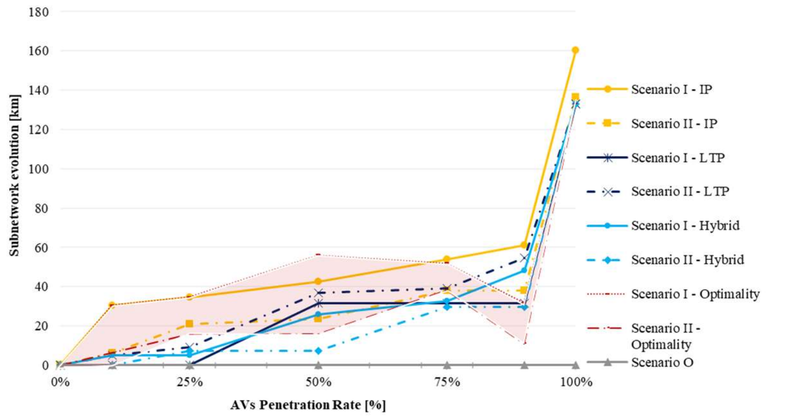


Figure 3.74 – RNDP-AVs daily design: progressive subnetworks in every planning strategy.

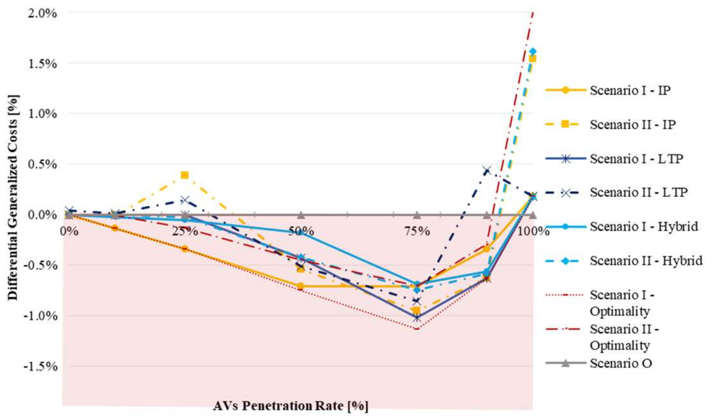


Figure 3.75 – RNDP-AVs daily design: differential generalized costs in every planning strategy.

3.8. SUMMARY

In this chapter, the Road Network Design Problem for the deployment of Automated Vehicles (RNDP-AVs) is proposed to design AV subnetworks in urban areas. The mathematical model is formulated as a binary NLP problem in a single-level formulation, which evaluates most combinations of the initial problem. The main contribution of this research problem is focused on the progressive decision of which planning strategy should be used to design AV subnetworks. The traffic equilibrium varies according to AVs' operational efficiency and the decrease of the occupant's value of travel time. Three progressive planning approaches are proposed and evaluated: the incremental planning, where dedicated roads are added gradually as the AV penetration rate evolves; the long-term planning, where the subnetwork is reversely created from the long-term optimal solution; and the hybrid planning, where the subnetwork is limited from early stages in order to reach the optimal final configuration. The consideration of road investment as part of the decision process and the evaluation of its impact is another contribution. Two types of design are evaluated: first, the most common design in practice is the peak-hour, as it is believed that, by designing that stage, the congestion problem is highly mitigated; the second analyses a travel demand of a typical day that shifts its trips and O-Ds every hour.

The RNDP-AVs model is applied to the urban network of the city of Delft. Three scenarios were performed: one without AV subnetworks, and two scenarios with AV subnetworks, including or not road investment. All scenarios are implemented in several AV market penetration rates. The RNDP-AVs model proved to be an easy tool to guide the creation of AV subnetworks as a function of the penetration rate, either designing for the peak-hour or the whole day. The model is run within acceptable computation time – each transition period under a planning strategy can be obtained in less than a day.

In the peak-hour analysis, AVs subnetwork first appears in zones that are highly demanded (residential areas) and in which there is a compromise between the AV benefits, in terms of travel time cost savings, and CV detours. Through the experiments done at each penetration rate, it was found that for the considered peak-hour, AV subnetworks are a useful strategy to reduce the overall congestion and generalized costs, while degrading congestion in the surroundings of the AV subnetworks.

The following conclusions can be drawn from the experiments on the planning approaches designed for the peak-hour: When road investment for infrastructure improvement is part of the problem, the incremental planning strategy seems to be the best strategy and should be implemented until AVs are 25% of the vehicle fleet. However, the long-term planning strategy is preferred if the road investment should be made beforehand – possibly starting from the early stages of deployment (10%); When the road investment is irrelevant, the hybrid planning strategy is preferred and should be implemented in the first half of the transition period. The long-term planning strategy is equally favourable but should only be initiated when AVs are at least 25% of the vehicle fleet to avoid the extra cost and CV detour in the early stages of AVs deployment. CV detour might be considered the tie-breaking criteria regarding the decision of the best planning strategy - incremental planning is the strategy that mitigates the most this problem.

The implications of the peak-hour design in the remaining hours of the day were tested. Since the travel demand of the peak-hour does not coincide with the remaining demand throughout the day, the design for the peak hour implied that CV owners with other trips routines and would be constrained to get inside or leave AV subnetworks, so an alternative mode of transport is required - walking was evaluated in this sense. Nevertheless, this situation only happened for significant shares of AVs (75% onwards) from the large AV subnetworks at this stage.

Subsequently, designing for the whole day revealed a substantial decrease on the total travel costs for the whole day, as it optimizes the road network configuration for the daily demand. From the experiments on the planning approaches designed for the whole day of the Delft case-study, the following conclusions can be drawn:

- When road investment for infrastructure improvement is part of the problem, the hybrid planning is very satisfactory as it is the strategy that most mitigates the CV detour problem. It should be applied mainly if AV subnetworks only appear after AVs have already a significant share of the vehicle fleet (over AV penetration rates of 25%). Nevertheless, the long-term planning strategy is preferred because it distributes the road investment throughout the period since the early stages of deployment (10%).
- When road investment is not evaluated, the LTP is indicated when AVs subnetworks first start to be designed in the second half of the transition period (50% of AVs onwards). At that stage, i.e., when AVs and CVs are equally balanced (50%), CVs experience more congestion (30% increased delay). The hybrid here revealed a good performance and can be used since the first half of the transition period, but then CV detour occurs when AVs are 90% of the fleet.

Figure 3.76 summarizes the dynamics around the creation of AV subnetworks allied with AVs road capacity increase and AVs value of travel time reduction. The previous experiments showed that the minimization of travel time costs mostly takes advantages of the reduction of the AVs value of travel time to decide whether AV subnetworks should exist. This was depicted by an increase of the total travel time that can be explained either from AVs or CVs perspective. CVs travel time can increase either if CVs detour or if CVs experience congestion in the surroundings of AV subnetworks. Both can be depicted by distance and delay indicators. Similarly, AVs experience higher travel times, also because their value of travel time (cost) is reduced in AV subnetworks. Therefore, travel times can increase either if AVs experience congestion or if AVs detour. AVs detour is explained in one of the following situations: if the total AV distance increases, it means that AVs take longer routes to detour regular roads where CVs circular; or if the total AV distance decreases, it means that AV take shorter routes, but such increase of total travel time can occur regardless the AV delay. If an AV delay increase occurs, it’s congestion that is increasing total travel time. If a AV delay reduction occurs, it means that AVs shorter routes are being performed at lower speed roads that turned into AV dedicated roads. Nevertheless, Figure 3.76 somehow summarizes what happens overall to CVs and AVs in terms of distance and delay.

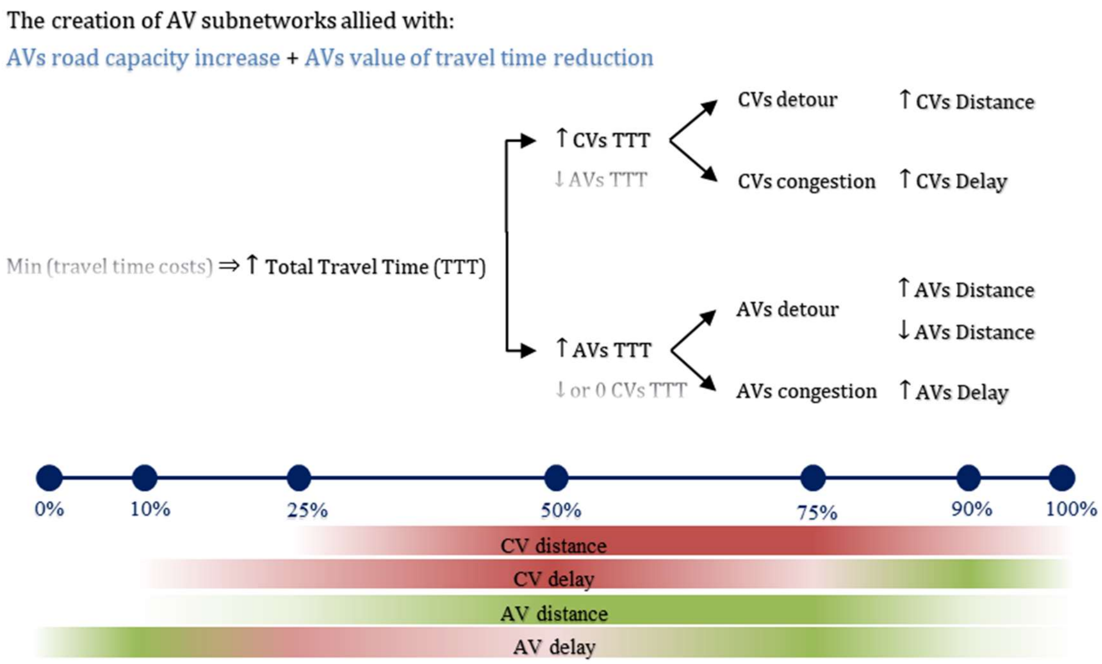


Figure 3.76 – Summary of the RNDP-AVs

AV subnetworks have an essential role in segregating AVs from mixed traffic and the design of AV subnetworks first start in lower capacity roads, deviating AVs to shorter routes (lower distances) on lower speed roads (higher travel times as the AVs value of travel time reduces). The reduction of the

AVs value of travel time might conduct the dispersion of the AVs traffic, leaving highway arterials and driving in smaller urban roads. In this sense, the creation of AV subnetworks in these zones might be welcomed, since it "takes out" AVs from regular roads where CVs are used to drive and lower speeds could be positive at a road safety perspective in urban areas, especially when the first AVs level 4 start to be deployed. Overall, we may conclude that AV subnetworks should be designed once AVs reach 25%, but the performance of the system will only show results when AVs are over 50% of the vehicle fleet.

However, the decision also depends on the AV travel demand and diffusion of AVs over time because it will pressure the road network with more traffic flow and push forward/accelerate the creation of AV subnetworks by influencing the time lag between design stages. For instance, if the time lag from 1% to 50% of AVs is much longer than the time lag from 50% to 90% of AVs, the CV detour would be very present, which turns the incremental the best strategy to be considered regardless the road investment consideration.

The application of the RNDP-AVs model points to the need of designing a subnetwork for AVs. Though the model was formulated with the introduction of some simplifications and assumptions, for example, a constant mixed traffic efficiency coefficient and a constant road investment per kilometer, an extended model joining together the decision AV subnetworks and strategic location problem for V2I communication sites (5 km of radius), as well with traffic efficiency parameters more accurate, could be solved through heuristic methods, though the optimal solution might not be guaranteed. Besides, an improvement could be taking public transport as another alternative mode of transport, but it would involve both bus routes and schedules, transforming the whole road network design problem into a massive combinatorial transit assignment problem. Moreover, it is also possible to add improvements such as other cost components involving pollution, noise reduction, or other benefits, for example, freeing space in the city center (e.g., parking and gas stations).

4

REVERSIBLE LANES FOR AUTOMATED TRAFFIC

4.1. INTRODUCTION

Reversible lanes are road car traffic lanes whose flow direction can be changed to accommodate shifting demands. Currently, this strategy is applied to median (central) lanes at multilane roads. Up until now, reversible lanes are of complex implementation because of difficult human driving adjustment and the need for investment on variable traffic signs (Cao et al., 2014). Previous research on road safety has always revealed that reversible lanes have a negative impact on road safety. However, with the promise of vehicle-to-infrastructure (V2I) communication and vehicle automation, car-to-car frontal crashes in reversible lanes can be highly mitigated (Kulmala et al., 2008).

In this sense, the new AVs paradigm clearly supports the use of reversible lanes in urban environments, as long as V2I guarantees that vehicles are informed of such changes. As reversible lanes have a direct impact on road capacity, the following research questions arise: Can reversible lanes contribute to mitigating congestion in urban areas? What impacts can one expect from this strategy?

A novel network design problem is proposed in this thesis, designated as the Dynamic Reversible Lane Network Design Problem (DRLNDP) for AVs traffic. The DRLNDP is formulated as a macroscopic mathematical model in a mixed-integer non-linear programming (MINLP) problem. It aims at replicating the upcoming benefits of reversible lanes at a network level and testing their effects in two distinct traffic assignment mechanisms: user-equilibrium (UE) versus system-optimum (SO) traffic assignment, i.e., the selfish and unselfish behavior, respectively. The number of lanes for each road direction is optimized while a traffic assignment equilibrium is computed for the given traffic demand (trips) and supply (road capacity).

The remaining of this chapter is organized as follows. Section 4.2 presents a background literature review. Section 4.4 introduces the modeling formulation of the DRLNDP problem. In Section 4.5, the application to the Delft case study is presented. Finally, Section 4.6 reports the main summary and conclusions of this chapter.

4.2. BACKGROUND

The literature around reversible lanes has been increasing in the last two decades. The benefits of such a dynamic strategy are evident in road capacity increase and are applied in many facility types (Wolshon and Lambert, 2006). However, traffic conflicts have been identified due to the human maladaptation to reversible lanes, which led to low operating efficiency and a low lane utilization rate (Cao et al., 2014). In practice, they are often applied as median reversible lanes in bridges (Bede and Torok, 2014) and freeway construction zones (Waleczek et al., 2016).

Hitherto research has been focusing on signalized intersections and median lane problems (Bede and Torok, 2014; Wang and Deng, 2015). Reversible lane problems assumed that there would be at least one lane in each road direction, but that assumption is no longer needed once vehicles become automated and a smart system is put in place to control the roadway layout. AVs' driving task will be performed automatically and autonomously and, under a connected traffic control system, be informed of the road lane configuration dynamically (Chu et al., 2017). The roadway layout would then be decided dynamically as a function of the ongoing traffic flow to achieve the maximum benefits of this strategy.

Most of the existent research related to reversible lanes involves the optimization of signalized intersections, from a microscopic perspective. Geraldes (2011) presented a methodology using genetic algorithms and micro-simulation techniques (AIMSUN) to estimate possible gains for real-time lane topological changes in a small network with eight signalized junctions while assuming an advanced traffic information system. Zhao et al. (2014) developed a single-level optimization model, formulated in mixed-integer linear programming (MILP), to design median reversible lanes while accounting for the turns and signal timing features, in an urban corridor with three signalized intersections. Wang and Deng (2015) defined a bi-level problem to optimize the capacity of the signalized road network by allocating reversible lanes in the upper level; and then performed a deterministic UE assignment, solved by genetic algorithms and applied the method to a numerical example. Zhao et al. (2015) focused on signalized diamond interchanges, presenting a binary mixed-integer linear program (BMILP) that simultaneously optimizes lane markings, dynamic usage of the reversible lane, and signal timings.

Most of the literature concerning reversible lanes has been focused on emergency rescue and evacuation in metropolitan regions threatened by hurricanes and catastrophes (Hua et al., 2015; Tuydes and Ziliaskopoulos, 2007; Williams et al., 2007; Wolshon, 2002; Zhang et al., 2019). Looking at traffic operations, Wu et al. (2009) optimized reversible lanes within a traffic network by formulating a bi-level program, minimizing the total system cost based on flow entropy at the upper-level, and on the lower level the stochastic UE assignment; this was solved by a chaotic optimization algorithm. Karoonsoontawong and Lin (2011) proposed a simulation-based optimization problem on a grid network, through a bi-level formulation for the time-varying lane-based capacity reversibility problem, and solved it by genetic algorithms and VISTA simulator that simulates traffic in UE conditions. Lu et al. (2018) proposed a bi-level model that considers queueing at signalized junctions: the upper model optimizes the reversible lane assignment that can be solved with the enumeration method or the Monte Carlo Algorithm for small and large networks, respectively; the lower level is a stochastic UE model that is solved by the method of successive averages. Within the topic of AVs, Chu et al. (2017) combined dynamic reversible lanes with AVs routing and scheduling though limited by not considering congestion (travel times are an input).

Table 4.1 briefly summarizes the literature review around the topic of reversible lanes.

Table 4.1 – Summary of the literature review.

Research	Methodological Approach		Formulation		Traffic assignment		Application	AVs
	Simulation	Optimization	Single level	Bi-level	UE	SO		
Geraldes (2011)	AIMSUN	GA		X	X		8 signalized intersections	
Zhao et al. (2014)		MILP	X		-	-	3 signalized intersections	
Wang and Deng (2015)		GA		X	X		4 signalized intersections	
Zhao et al. (2015)		BMILP			-	-	2 signalized intersections	
Wu et al. (2009)		COA		X	X		5 link network	
Karoonsoontawong and Lin (2011)	VISTA	GA		X				
Lu et al. (2018)		MCA & MSA		X	X		25 link network	
Mo et al. (2019)		Modified algorithm			-	-	26 link network	
Chu et al. (2017)		ILP	X		-	-	51 link network	X

4.3. METHODOLOGY

The decision problem regarding reversible lanes is also linked to the study of the contraflow problem, usually studied regarding evacuation operations. Reversible lanes in the context of AVs are therefore a form of network design problem both at the tactical (e.g., orientation of streets, lane allocation, and exclusive lanes) and at the operational level (e.g., scheduling problem). Typically formulated as bi-level, the upper-level decides on the lanes changing whose performance is dependent on the lower-level travelers’ routing decisions (Magnanti and Wong, 1984). The formulation of such problem transforms, therefore, two problems in a complex problem with NP-hard solving nature (Ben-Ayed et al., 1988). Heuristics, metaheuristics and iterative optimization methods usually deal with this complexity, yet a local optimum may be found instead of the global optimum.

Most of these studies have been formulated as bi-level problems to account for both the perspective of system-optimal design and travelers’ selfish routing behavior. They are generally solved in two-parts through metaheuristics (e.g., genetic algorithms), making the search for the optimal solution hard and mostly undetermined. The proposal for a single-level optimization model puts together both perspectives in a simpler formulation. It considers traffic congestion and tests the reversible lanes’ traffic strategy interaction with the traffic assignment problem in UE and/or SO conditions. The complexity of solving the problem is reduced, and global optimality can be guaranteed. Joining such interaction between the reversible lanes’ strategy and the traffic assignment method makes this problem highly combinatorial. Its calculation time is proportional to the network size and travel demand.

4.4. THE DYNAMIC REVERSIBLE LANE NETWORK DESIGN PROBLEM (DRLNDP)

The following mathematical formulation is a single-level problem, deciding on the reversible lanes while performing the traffic assignment in the same problem (Conceição et al., 2020). It admits periodic lane reconfigurations given a specific time-varying demand (origin-destination matrix for AVs for different periods of the day). It is assumed a 100% coverage of V2I communication, and all AVs are equipped with this technology so that they are informed of the lane configuration throughout the network.

This is a network optimization problem from a macro modeling perspective. All lanes are considered to be potentially reversible, and at every road intersection, the model guarantees that at least one lane converges or diverges from that node.

The interaction between the reversible lanes and intersection performance is not evaluated in this paper, as signal control in a scenario with AVs might not be needed, and such performance is still mostly unknown. Also, pedestrians' interaction with reversible lanes is not part of the main problem, though naturally there should be traffic lights managing their crossing for road safety reasons.

4.4.1. Formulation in MINLP

Sets

$\boldsymbol{I} = (1, \dots, i, \dots, I)$:	set of notes in the network, where I is the number of nodes.
$\boldsymbol{R} = \{\dots, (i,j), \dots\}\ \forall i, j \in I \cap i{\neq}j$:	set of arcs of the road network where vehicles move.
$\boldsymbol{P} = \{\dots, (o,d), \dots\}\ \forall o, d \in I \cap o{\neq}d$:	set of origin-destination pairs that represent the travel demand in the network.
$\boldsymbol{H} = \{1, \dots, h, \dots, 24\}$:	hours of the day

Parameters

$D_{od}^{h_i h_f}$:	trips from an origin node o, towards a destination node d, from period h_i to period h_f, $\forall\ o, d \in \boldsymbol{D}\ \cap\ h_i, h_f \in \boldsymbol{H}$.
t_{ij}^{min}:	minimum driving travel time in free-flow speed at link $(i,j) \in \boldsymbol{R}$, expressed in hours.
$L_{ij}^{current}$:	the current number of lanes at link $(i,j) \in \boldsymbol{R}$.
C^{lane}:	average lane capacity of link $(i,j) \in \boldsymbol{R}$, expressed in vehicles for the period of analysis.
M:	big number.

Decision variables

$l_{ij}^{h_i h_f}$:	integer variable equal to the number of lanes of each link $(i,j) \in \boldsymbol{R}$, from period $h_i \in \boldsymbol{H}$ to period $h_f \in \boldsymbol{H}$.
$f_{ijod}^{h_i h_f}$:	continuous variable that corresponds to the flow of AVs in each link $(i,j) \in \boldsymbol{R}$ and each OD pair $(o,d) \in \boldsymbol{P} \cap D_{od}^{m} > 0$, from period $h_i \in \boldsymbol{H}$ to period $h_f \in \boldsymbol{H}$.

Objective Function

The objective function (4.1) minimizes the traffic assignment function in UE conditions. The alternative objective function (4.2) reproduces the SO traffic assignment.

$$\text{Min(UE)} = \sum_{(i,j)\in R} \int_0^{f_{ij}^{h_i h_f}} t_{ij}^{h_i h_f}\, df \tag{4.1}$$

$$\text{Min(SO)} = \sum_{(i,j)\in R} f_{ij}^{h_i h_f}\ t_{ij}^{h_i h_f} \tag{4.2}$$

The BPR function (4.3) reflects the link performance functions, with α and β as parameters.

$$t_{ij}^{h_i h_f} = t_{ij}^{min}\left[1 + \alpha\left(\frac{f_{ij}^{h_i h_f}}{l_{ij}^{h_i h_f} C^{lane} + \frac{1}{M}}\right)^{\beta}\right] \tag{4.3}$$

Constraints

The objective functions are subject to the following constraints (4.4)-(4.14).

$$\sum_{j\in \boldsymbol{I}} f_{ojod}^{h_i h_f} = D_{od}^{h_i h_f}, \forall\ j \in \boldsymbol{I}, (o,d) \in \boldsymbol{P}, v \in \boldsymbol{V}, h_i, h_f \in \boldsymbol{H} \tag{4.4}$$

$$\sum_{j\in \boldsymbol{I}} f_{jdod}^{h_i h_f} = D_{od}^{h_i h_f}, \forall\ j \in \boldsymbol{I}, (o,d) \in \boldsymbol{P}, v \in \boldsymbol{V}, h_i, h_f \in \boldsymbol{H} \tag{4.5}$$

$$\sum_{j\in \boldsymbol{I}} f_{ijod}^{h_i h_f} - \sum_{j\in \boldsymbol{I}} f_{jiod}^{h_i h_f} = 0, \forall\ (o,d) \in \boldsymbol{P}, i \in \boldsymbol{I}, v \in \boldsymbol{V}, h_i, h_f \in \boldsymbol{H} \cap i \neq o,d \tag{4.6}$$

$$f_{ij}^{h_i h_f} = \sum_{(o,d)\in \boldsymbol{P}} f_{ijod}^{h_i h_f}, \forall\ (o,d) \in \boldsymbol{P}, (i,j) \in \boldsymbol{R} \tag{4.7}$$

$$l_{ij}^{h_i h_f} \geq 0\ \forall\ (i,j) \in \boldsymbol{R}, h_i, h_f \in \boldsymbol{H} \tag{4.8}$$

$$l_{jo}^{h_i h_f} \geq 1\ \forall\ j \in \boldsymbol{I}, (o,d) \in \boldsymbol{P}, h_i, h_f \in \boldsymbol{H} \tag{4.9}$$

$$l_{dj}^{h_i h_f} \geq 1\ \forall\ j \in \boldsymbol{I}, (o,d) \in \boldsymbol{P}, h_i, h_f \in \boldsymbol{H} \tag{4.10}$$

$$l_{ij}^{h_i h_f} \leq L_{ij}^{current} + L_{ji}^{current}\ \forall\ (i,j) \in \boldsymbol{R}, h_i, h_f \in \boldsymbol{H} \tag{4.11}$$

$$l_{ij}^{h_i h_f} + l_{ji}^{h_i h_f} = L_{ij}^{current} + L_{ji}^{current}, \forall\ (i,j) \in \boldsymbol{R}, h_i, h_f \in \boldsymbol{H} \tag{4.12}$$

$$l_{ij}^{h_i h_f} \in \mathbb{N}^0\ \forall\ (i,j) \in \boldsymbol{R}, h_i, h_f \in \boldsymbol{H} \tag{4.13}$$

$$f_{ijod}^{h_i h_f} \in \mathbb{R}\ \forall\ (o,d) \in \boldsymbol{P}, (i,j) \in \boldsymbol{R}, h_i, h_f \in \boldsymbol{H} \tag{4.14}$$

Constraints (4.4)-(4.6) define the traffic assignment problem. For each O-D pair, AV flows are generated (4.4) in the origin node $o \in \boldsymbol{O}$, absorbed in the destination node $d \in \boldsymbol{D}$ (4.5), and there is a flow conservation (4.6) in the intermediate nodes. Constraints (4.8)-(4.12) define the reversible lanes' problem. The first three constraints set the lower bound of the lane decision variables. In the intermediate nodes (4.8), flow is passing through and constraints (4.6) already assure that there is at least one lane converging and diverging from every node since the flow arriving must leave that node. However, in nodes (intersections) that generate or absorb trips, there must be one lane that converges and diverges to and from that node – constraints (4.9) and (4.10). Constraints (4.11) set the upper bound, i.e., the number of lanes of both road directions. Constraints (4.12) ensure that the sum of the lanes of both directions must correspond to the existent number of lanes on both sides of the road. Constraints (4.13) and (4.14) set the domain of the decision variables.

4.4.2. SCENARIOS

In order to understand the benefits of reversible lanes and their traffic implications, four scenarios were defined and the results are detailed in Table 4.2. Scenario O is the base scenario and it represents the current traffic UE situation without reversible lanes. Scenario A represents the first days of implementation, showing the immediate impacts (short-term) of reversible lanes whereby AVs could still be following their previous paths (from scenario O). In scenario B, the model optimizes the reversible lane problem while performing a UE, meaning that AVs choose their path minimizing their individual travel times (selfish behavior), i.e., a UE scenario likely to happen in the long-term if there is no centrally managed traffic system. Scenario C optimizes the reversible lane problem under a SO traffic assignment which is only possible if the system (with V2I connectivity) gives instructions to AVs during their trips, forcing them to follow the system-optimal paths (unselfish behavior). Lastly, scenario Z was introduced for comparison purposes, holding a pure SO traffic assignment without reversible lanes. In this sense, both scenarios O and Z are NLP models with continuous variables (traffic flow) within convex objective functions and vital to assure the convergence of the MINLP models (scenarios A, B and C).

UE considers two main assumptions (Sheffi, 1985): first, all users have identical driving behavior; second, users have full information (i.e. travel time on every possible path), meaning that they consistently make the correct decisions regarding path choice. The SO assumes that vehicles choose their paths in order to benefit the whole social system (Newell, 1980). These assumptions can only be made in a scenario where vehicles will be directed to choose specific paths without the intervention of human drivers – a reality in a future with fully AVs. Smart cities having a connected traffic control system with V2I being aware of the traffic situation (e.g., congested roads, accidents and construction work) can inform and instruct vehicles to make socially desirable path choices.

Table 4.2 – Scenarios description

		Traffic Assignment	Reversible Lanes Problem	Type of Mathematical Model
Scenario O	Current traffic situation without reversible lanes	UE	No	NLP
Scenario A	First days after implementing reversible lanes, AVs follow previous paths (scenario O)	No	Yes	MINLP
Scenario B	Long-term scenario with reversible lanes and UE traffic conditions. AVs choose their paths (selfish behavior)	UE	Yes	MINLP
Scenario C	Long-term scenario with reversible lanes and SO traffic conditions. The system chooses AV paths (unselfish behavior)	SO	Yes	MINLP
Scenario Z	A SO traffic situation without reversible lanes	SO	No	NLP

The pseudo-code used to run these scenarios is detailed in the following algorithms 1-3.

Algorithm 1 Scenarios O & Z: Traffic Assignment Problem without the Reversible Lane Problem

$h_i = 0$
While $h \leq \boldsymbol{H}$ do
    $h_f = h_i + 1$
    $l_{ij}^{h_i h_f} = L_{ij}^{current}$
    function OBJECTIVE FUNCTION
        $\min(UE \text{ or } SO)$
    end-function
    Solve the DRLNDP
    $h_i = h_i + 1$
    Clear all decision variables
end-do

- Sets the problem of reversible lanes to be solved periodically, i.e., per hour
- Fix the lane variables from the currently existing lane topology.
- Minimize the objective function which for scenario O is function (4.1) and for scenario Z is (4.2).

Algorithm 2 Scenario A: the Reversible Lane Problem without changing the Traffic Assignment

$h_i = 0$
While $h \leq \boldsymbol{H}$ do
    $h_f = h_i + 1$
    read $f_{ijod}^{h_i h_f}$ variables from scenario O
    function Objective Function
        $\min(UE)$
    end-function
    Solve the DRLNDP
    $h_i = h_i + 1$
    Clear all decision variables
end-do

- Sets the problem of reversible lanes to be solved periodically, i.e., per hour
- Fix the traffic flow variables to those obtained in scenario O.
- Minimize the objective function (4.1).

Algorithm 3 Scenarios B & C – Both the Reversible Lane and Traffic Assignment Problems (UE & SO)

$h_i = 0$
While $h \leq \boldsymbol{H}$ do
    $h_f = h_i + 1$
    function OBJECTIVE FUNCTION
        $\min(UE \text{ or } SO)$
    end-function
    Solve the DRLNDP
    $h_i = h_i + 1$
    Clear all decision variables
end-do

- Sets the problem of reversible lanes to be solved periodically, i.e., per hour
- Minimize the objective function which for scenario B (UE) is (4.1) and for scenario C (SO) is (4.2).

4.5. THE DRLNDP MODEL APPLIED TO THE CITY OF DELFT, THE NETHERLANDS

The DRLNDP model is exemplified for the case study city of Delft, in the Netherlands. Figure 4.1 illustrates the network of the city which has been simplified to 46 nodes and 122 links that represent 61 road segments, i.e., each link represents a direction. There are two types of road links with one (1-1) or two lanes (2-2) per direction with a free-flow speed of 50 and 70 km/h, respectively; and a lane capacity of 1441 vehicles per hour. The city center is close to node 3, while TU Delft campus, the biggest traffic generator, is close to node 31. Major residential areas are in the southern region (e.g., node 6).

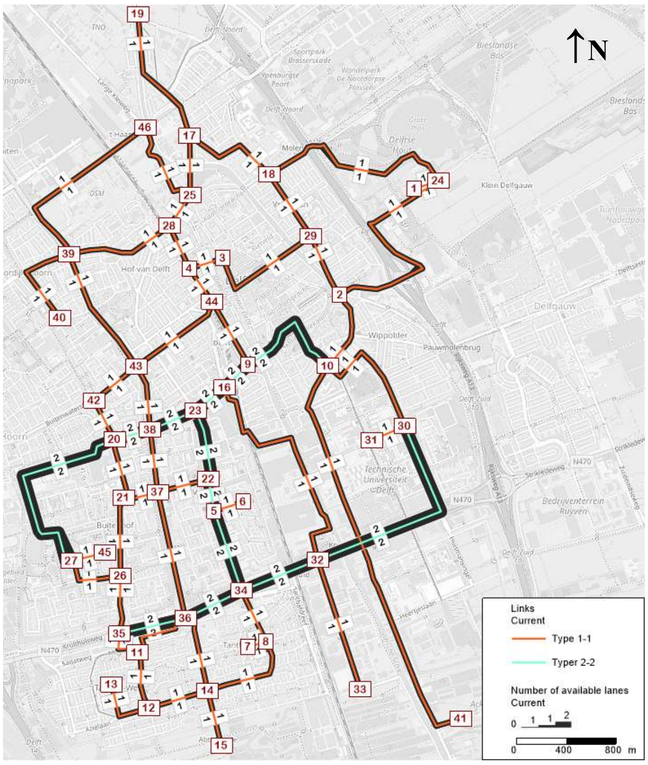


Figure 4.1 – Network representation of the city of Delft, the Netherlands (Conceição et al., 2020).

The traffic demand collected by the Dutch government (MON 2007/2008) is available for transport research. The filtered dataset contains a collection of 152 trips from 29 sampled households who travel inside the city on a working day in the year of 2008, ignoring external trips. Expansion factors were given for a typical working day, usually varying from 200 to 1300, leading to 137832 trips by 14,640 households, yielding an average sample rate of 0.2% (Correia and van Arem, 2016). The final travel demand corresponds to 120600 trips through 58 O-D pairs over the day (Figure 4.2).

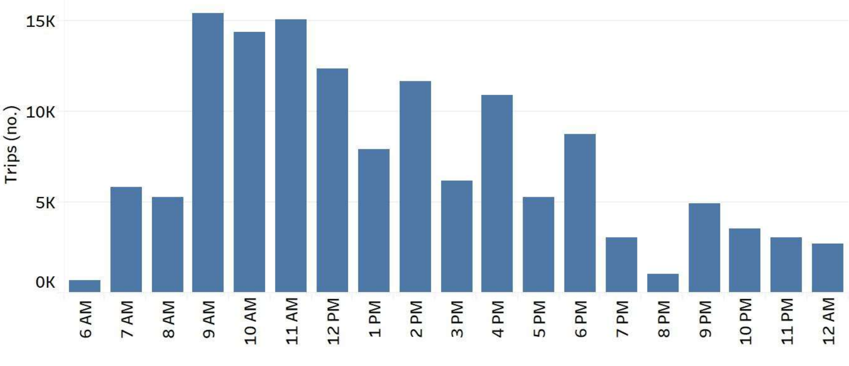


Figure 4.2 – Trips data of the city of Delft, the Netherlands (Conceição et al., 2020).

The BPR (United States Bureau of Public Roads, 1964) function (4.3) uses the reference values: $\alpha = 0.15, \beta = 4$.

The DRLNDP model is here implemented in the Mosel language and solved by Xpress 8.1 (FICO, 2017) in a computer with a processor of 4.2 GHz Intel Core i7-7700K and 16GB RAM. The MINLP problem is solved by the FICO Xpress-NLP SLP solver designed for large scale nonconvex problems that use a mixed-integer successive linear programming approach, combining branch and bound and successive linear programming.

For convex NLP problems, global optimality is guaranteed, and the same applies for MINLP problems if its continuous relaxation is convex. However, the relationship between the traffic assignment problem and the reversible lane problem is not linear; hence, the global optimality can be compromised. For more information about the Xpress Solver (Fair Isaac Corporation, 2019), and the existent solvers for convex MINLP, the reader may consult (Kronqvist et al., 2019).

4.5.1. Experiments

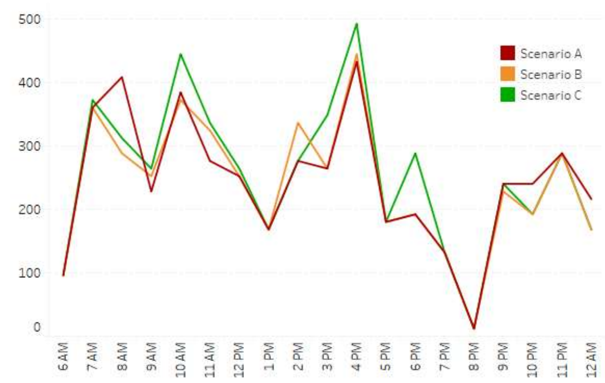
Table 4.3 summarizes the results of the experiments, showing the value of the objective function (expressed in hours vehicles) and its computation time. For the MINLP models (scenarios A, B and C), it is presented the differential of the objective function with its corresponding NLP model (scenarios O or Z).

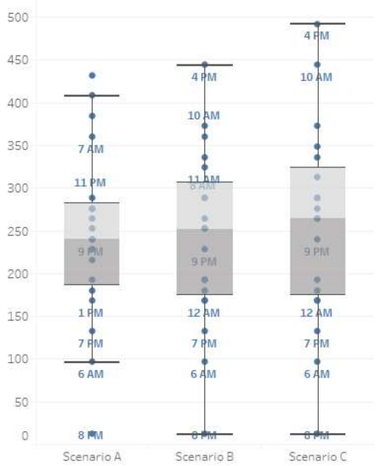
The separate problems are run in a few seconds: scenario O and Z just took 3 and 4 seconds, while scenario A took eleven seconds because of its mixed-integer nature. As Scenario B and C hold the complex RLNDP model, the calculation time rose to seventeen and fifty-three minutes, respectively.

Table 4.3 – Model results: objective function.

	Objective Function (1)								Objective Function (2)				
Period	Scenario O		Scenario A			Scenario B			Scenario C			Scenario Z	
		[s]		Δ^{O}	[s]		Δ^{O}	[s]		Δ^{Z}	[s]		[s]
6 7	105	0.1	105	*0%*	0.3	105	*0%*	0.4	105	*0%*	0.4	6346	0
7 8	729	0.2	721	*-1%*	0.4	721	*-1%*	0.9	723	*-3%*	2.1	937	0
8 9	1353	0.2	1338	*-1%*	0.4	1325	*-2%*	0.8	1374	*-3%*	4.0	2058	0
9 10	2541	0.3	2528	*-1%*	1.4	2523	*-1%*	219.6	2588	*-4%*	1768.6	4588	1
10 11	1733	0.2	1711	*-1%*	1.0	1673	*-3%*	21.6	1682	*-11%*	113.7	2140	0
11 12	2220	0.2	2217	*0%*	0.7	2193	*-1%*	14.7	2220	*-3%*	433.3	2884	0
12 13	1831	0.2	1826	*0%*	0.9	1825	*0%*	395.6	1851	*-1%*	764.1	2204	0
13 14	353	0.1	345	*-2%*	0.4	345	*-2%*	0.5	345	*-10%*	0.5	391	0
14 15	2046	0.2	2016	*-1%*	0.6	1934	*-5%*	8.8	1984	*-6%*	39.9	5330	0
15 16	843	0.1	841	*0%*	0.6	841	*0%*	6.8	843	*-1%*	8.0	863	0
16 17	2194	0.2	2124	*-3%*	0.5	2078	*-5%*	5.8	2085	*-10%*	42.7	3553	0
17 18	374	0.1	370	*-1%*	0.4	370	*-1%*	0.5	370	*-5%*	0.5	391	0
18 19	1120	0.2	1117	*0%*	0.4	1117	*0%*	6.5	1121	*-1%*	38.6	1302	0
19 20	247	0.1	247	*0%*	0.7	247	*0%*	0.4	247	*0%*	0.4	250	0
20 21	33	0.1	33	*0%*	0.3	33	*0%-*	334.4	33	*0%*	0.4	33	0
21 22	638	0.2	627	*-2%*	0.3	615	*-4%*	1.4	618	*-7%*	4.4	706	0
22 23	594	0.1	544	*-8%*	0.5	537	*-10%*	0.7	569	*-23%*	1.0	738	0
23 24	404	0.1	402	*-1%*	0.4	402	*-1%*	0.4	402	*-2%*	0.4	416	0
24 1	404	0.1	353	*-13%*	0.3	346	*-14%*	0.4	346	*-31%*	0.4	545	0
Total	19761	00:00:03	19466	*-1%*	00:00:11	19230	*-3%*	00:17:00	19475	*-6%*	00:53:43	29437	00:00:04
	[h veh]	[h:m:s]	[h veh]		[h:m:s]	[h veh]		[h:m:s]	[h veh]		[h:m:s]	[h veh]	[h:m:s]

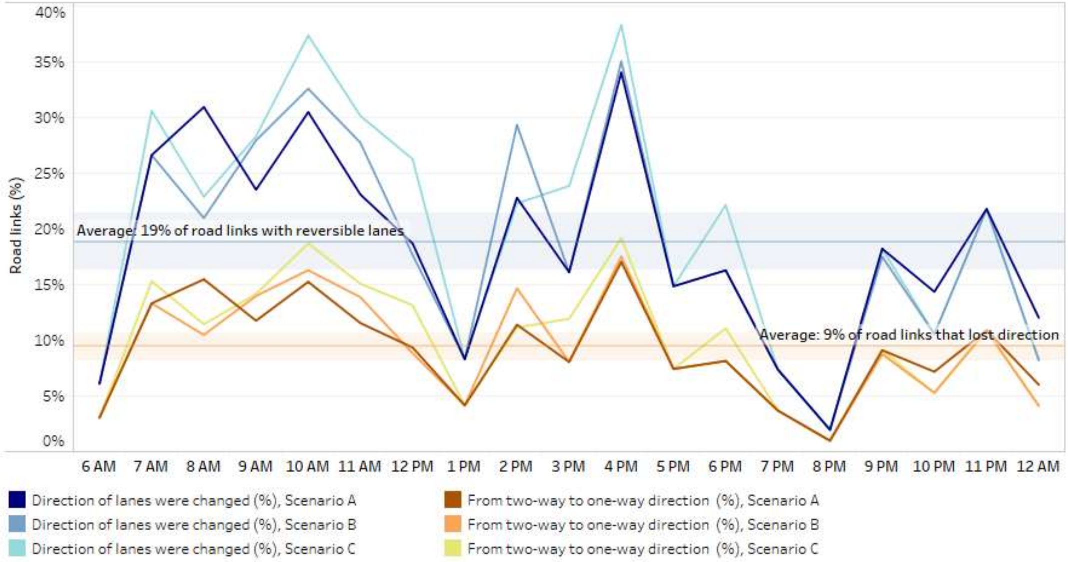
Figure 4.3 (a) analyzes the number of reversible lanes that vary every hour to the travel demand in order to optimize the overall traffic system performance. Figure 4.3 (b) depicts in box charts the variance of reversible lanes, revealing the hours that are outliers in the dataset. Figure 4.3 (c) shows the percentage of roads whose lane directions were changed throughout the day. It also shows the percentage of road links that became one-way roads. On average, 19% of the road links have reversible lanes, and 9% switch from two-way to one-way direction during the day. It is clear that reversible lanes are optimal throughout the day, even with the current driving paths (scenario A). In the long-term, such traffic rearrangement towards UE (scenario B) would need fewer reversible lanes than towards a SO traffic assignment (scenario C) (check Table 4.4).





(a) Scenario analysis.

(b) Reversible lanes (no.)



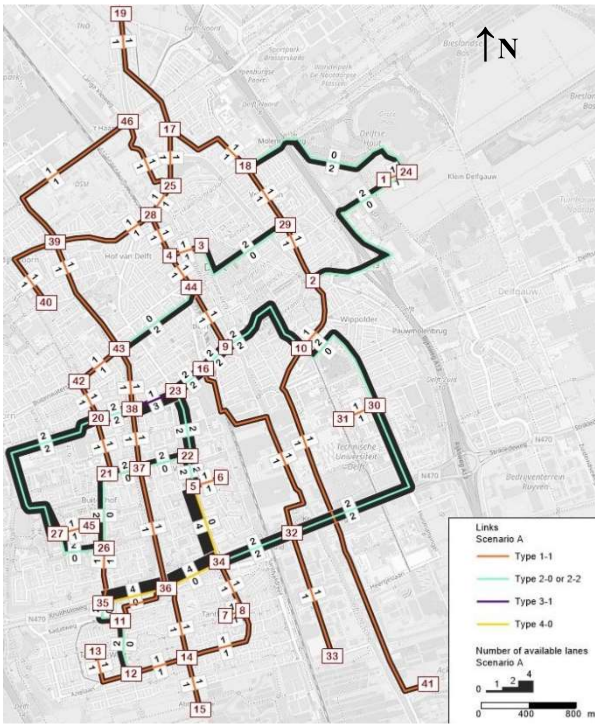
(c) Road links analysis

Figure 4.3 – Graphical analysis of the reversible lanes strategy throughout the day: (a) Scenario analysis; (b) number of reversible lanes; (c) Road link analysis.

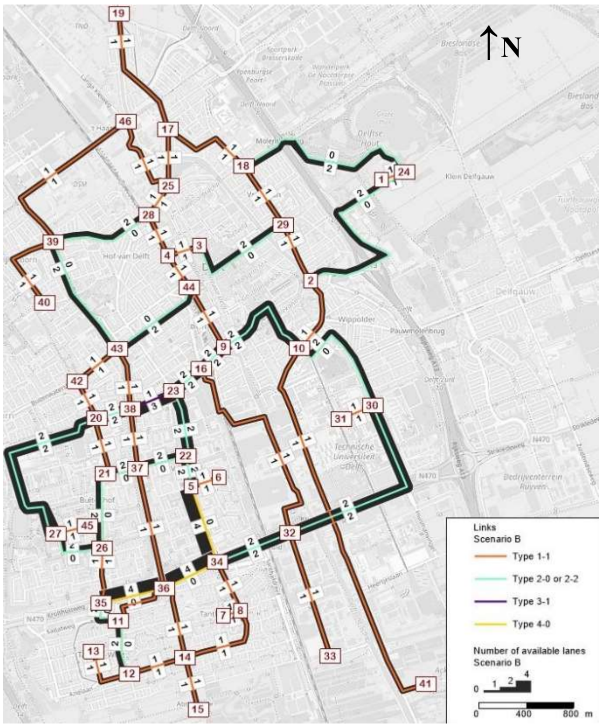
Table 4.4 – Model results: reversible lanes.

Period		Reversible lanes [no.] Scenario A	Scenario B	Scenario C	Road links with reversible lanes [%] Scenario A	Scenario B	Scenario C	Road links that lost direction [%] Scenario A	Scenario B	Scenario C
6	7	16	16	16	6%	6%	6%	3%	3%	3%
7	8	60	60	62	27%	27%	31%	13%	13%	15%
8	9	68	48	52	31%	21%	23%	15%	10%	11%
9	10	38	42	44	24%	28%	28%	12%	14%	14%
10	11	64	62	74	31%	33%	37%	15%	16%	19%
11	12	46	54	56	23%	28%	30%	12%	14%	15%
12	13	42	42	44	19%	18%	26%	9%	9%	13%
13	14	28	28	28	8%	8%	8%	4%	4%	4%
14	15	46	56	46	23%	29%	22%	11%	15%	11%
15	16	44	44	58	16%	16%	24%	8%	8%	12%
16	17	72	74	82	34%	35%	38%	17%	18%	19%
17	18	30	30	30	15%	15%	15%	7%	7%	7%
18	19	32	32	48	16%	16%	22%	8%	8%	11%
19	20	22	22	22	7%	7%	7%	4%	4%	4%
20	21	2	2	2	2%	2%	2%	1%	1%	1%
21	22	40	38	40	18%	18%	18%	9%	9%	9%
22	23	40	32	32	14%	11%	11%	7%	5%	5%
23	24	48	48	48	22%	22%	22%	11%	11%	11%
24	1	36	28	28	12%	8%	8%	6%	4%	4%
Total		774	758	812	18%	18%	20%	9%	9%	10%

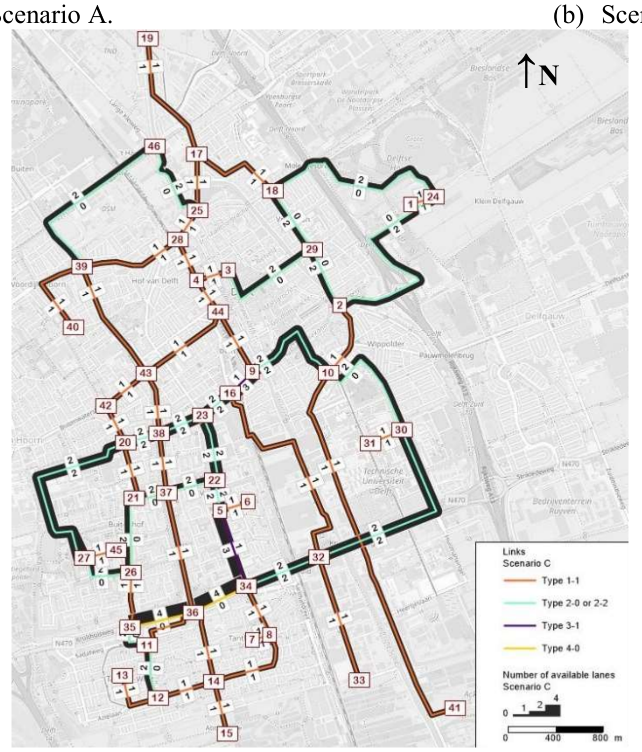
Reversible lanes are implemented hourly, so the design changes throughout the day in the network. Figure 4.4 illustrates the lane configuration for the period between 9 to 10 am. The roadway layout is colored according to types: roads with one lane per direction (type 1-1); roads with two lanes per direction (type 2-2) or one-way roads with two lanes (type 2-0); roads with three lanes in one direction and one lane in the opposite one (type 3-1); and one-way roads with four lanes (type 4-0). During this period from 9 am to 10 am it is clear that reversible lanes are mostly needed in the southern region, close to residential areas, as people commute to work. Besides, the northern part of the network highly varies amongst the scenarios A, B and C.



(a) Scenario A.



(b) Scenario B.



(c) Scenario C.

Figure 4.4 – Lane configuration for the period between 9h-10h am (Conceição et al., 2020).

Table 4.5 – Model results: traffic performance indicators

Scenario	Average Degree of Saturation [%]					Average Congestion [%]					Congested road links (≥100%) [km]				
Period	O	A	B	C	Z	O	A	B	C	Z	O	A	B	C	Z
6 7	39.3%	24.1%	24.1%	24.1%	39.3%	1.8%	1.2%	1.2%	1.2%	1.8%	0.00	0.00	0.00	0.00	0.00
7 8	73.6%	51.2%	51.3%	48.6%	64.3%	11.1%	6.0%	6.0%	5.7%	10.9%	3.68	0.87	0.87	0.87	3.68
8 9	71.6%	45.5%	57.4%	47.0%	57.2%	20.4%	14.5%	13.9%	15.0%	21.5%	15.06	8.77	8.77	7.88	9.39
9 10	94.8%	81.4%	82.3%	70.1%	85.3%	35.3%	30.4%	29.7%	30.4%	38.3%	29.60	27.19	25.94	21.21	28.82
10 11	85.1%	67.9%	65.8%	58.8%	67.9%	27.6%	21.2%	19.7%	19.9%	28.8%	17.90	15.06	8.82	8.98	16.31
11 12	82.6%	71.8%	70.7%	63.4%	73.8%	36.7%	31.9%	30.0%	31.1%	37.3%	28.96	26.66	23.62	25.93	28.72
12 13	82.9%	68.3%	67.7%	62.3%	72.8%	29.1%	23.5%	23.3%	21.7%	29.8%	20.11	16.44	16.44	12.91	15.94
13 14	57.3%	36.9%	36.9%	36.9%	51.2%	5.9%	3.7%	3.7%	3.7%	5.9%	2.41	0.15	0.15	0.15	2.41
14 15	89.2%	77.3%	70.8%	67.0%	76.3%	21.3%	17.9%	14.2%	17.0%	23.8%	13.53	10.64	5.28	10.09	11.22
15 16	56.4%	44.5%	44.5%	38.4%	47.0%	15.4%	12.5%	12.5%	12.6%	15.3%	0.15	0.15	0.15	0.15	0.15
16 17	100.4%	69.7%	68.5%	63.0%	75.2%	32.3%	23.2%	21.0%	20.1%	34.4%	26.68	15.43	11.89	10.84	23.29
17 18	63.6%	42.3%	42.3%	42.3%	63.6%	6.9%	4.3%	4.3%	4.3%	6.9%	0.00	0.00	0.00	0.00	0.00
18 19	72.5%	52.8%	52.7%	46.8%	57.7%	18.1%	12.9%	12.9%	13.2%	18.5%	1.92	1.15	1.15	1.15	1.92
19 20	42.7%	27.2%	27.2%	27.2%	42.7%	4.5%	3.6%	3.6%	3.6%	4.5%	0.00	0.00	0.00	0.00	0.00
20 21	36.1%	27.1%	27.1%	27.1%	36.1%	0.6%	0.5%	0.5%	0.5%	0.6%	0.00	0.00	0.00	0.00	0.00
21 22	63.6%	38.5%	40.2%	35.4%	49.2%	10.2%	5.7%	5.0%	5.3%	10.6%	4.02	0.57	0.57	0.57	5.77
22 23	83.4%	47.6%	55.6%	55.6%	57.6%	9.2%	5.7%	5.6%	5.6%	10.9%	3.31	0.17	0.17	0.17	3.31
23 24	53.8%	28.1%	28.1%	28.1%	42.2%	6.8%	3.4%	3.4%	3.4%	6.9%	0.00	0.00	0.00	0.00	0.00
24 1	108.1%	52.5%	67.4%	67.4%	63.3%	5.8%	2.4%	2.4%	2.4%	7.5%	3.31	0.17	0.17	0.17	3.31
Total	71.4%	50.2%	51.6%	47.9%	59.1%	15.7%	11.8%	11.2%	11.4%	16.5%	170.64	123.41	103.99	101.06	154.24

Scenario	Total Distance [km veh]					Total Travel Times [h veh]					Delay Total [h veh]				
Period	O	A	B	C	Z	O	A	B	C	Z	O	A	B	C	Z
6 7	5975	5975	5975	5975	5975	106	105	105	105	106	1	0	0	0	1
7 8	40752	40752	40694	40355	41924	945	908	908	907	937	271	233	234	229	256
8 9	66066	66066	65826	68944	67415	2094	2021	2018	2001	2058	927	854	867	784	848
9 10	102330	102330	102699	109752	110513	4833	4764	4690	4404	4588	2865	2796	2708	2271	2459
10 11	86097	86101	86171	86407	87016	2167	2059	1903	1900	2140	543	435	287	272	474
11 12	108008	108009	107118	108298	110217	2973	2957	2880	2802	2884	941	925	858	728	798
12 13	98178	98178	98190	99949	100324	2279	2256	2266	2183	2204	560	538	551	415	424
13 14	19777	19777	19777	19777	19789	391	353	353	353	391	48	9	9	9	47
14 15	60916	60914	59198	64241	71328	5581	5432	5161	4988	5330	4419	4270	4034	3755	3984
15 16	44758	44758	44758	45063	45859	870	860	860	858	863	34	24	24	20	20
16 17	101387	101393	100481	101527	109864	3690	3344	3203	3191	3553	1871	1524	1406	1383	1579
17 18	19388	19388	19388	19388	19388	391	373	373	373	391	22	4	4	4	22
18 19	63122	63122	63118	62779	63057	1310	1294	1294	1291	1302	238	222	222	213	217
19 20	13500	13500	13500	13500	13500	250	250	250	250	250	4	3	3	3	4
20 21	1670	1670	1670	1670	1670	33	33	33	33	33	0	0	0	0	0
21 22	37254	37255	36966	37056	37110	719	662	659	658	706	101	44	56	50	77
22 23	31169	31169	30822	30822	35409	826	574	569	569	738	289	37	41	41	98
23 24	23520	23520	23520	23520	23597	417	406	406	406	416	16	5	5	5	11
24 1	20495	20495	20148	20148	24735	633	379	375	375	545	287	33	36	36	96
Total	944360	944369	940019	959169	988689	30510	29031	28306	27648	29437	13436	11957	11344	10217	11414

4.5.2. Traffic Impacts

This subsection analyses traffic performance indicators (detailed in Table 4.5) in every scenario, more specifically the degree of saturation, congestion, number of congested road links, total travel distance, total travel times and total delay.

The degree of saturation corresponds to the traffic flow divided by the road capacity at each link. Currently (scenario O), the degree of saturation is on average 71.4%. Hypothetically, in a centralized system (SO) without reversible lanes, the average degree of saturation would be 59.1%.

With the strategy of implementing reversible lanes, the degree of saturation reduced to an average of 50.2% in non-equilibrium traffic conditions (scenario A). In equilibrium conditions, the degree of saturation is between 51.6% and 47.9% for UE and SO scenarios (B and C, respectively). Scenario C seems to be the best scenario in the long-term, and that happens because the minimization of the total system travel times causes a geographical dispersion of the traffic flows and, consequently, an overall reduction of the degree of saturation.

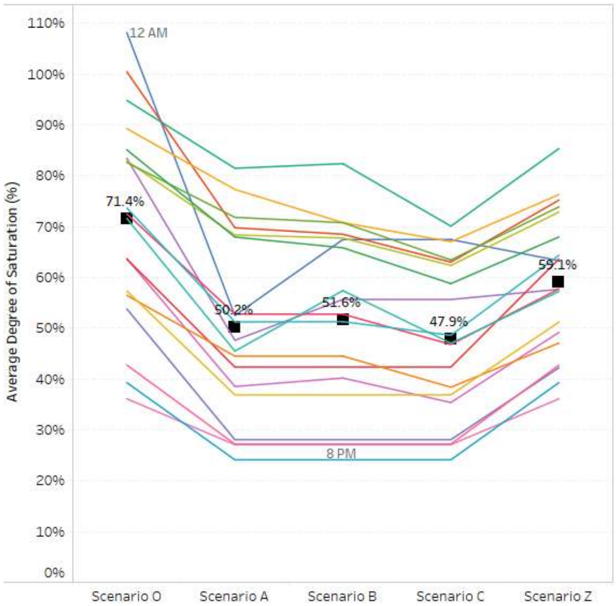
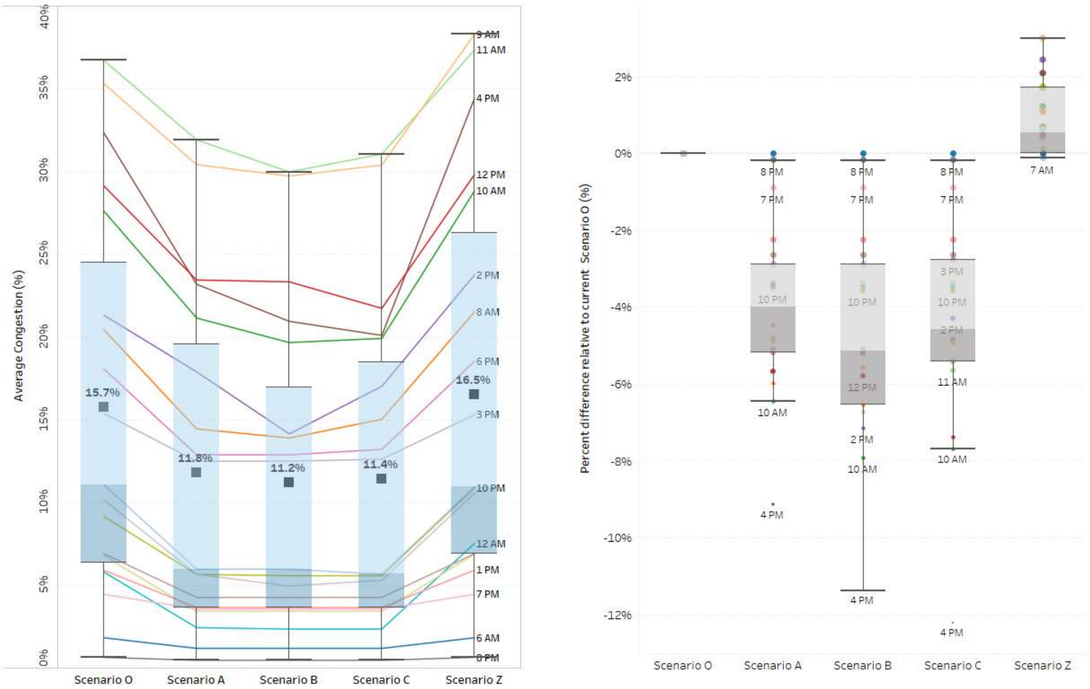


Figure 4.5 – Degree of saturation analysis.

The congestion shown in Figure 4.6 is calculated through a weighted average of the degree of saturation using the length of each link as a weighting factor. The implementation of reversible lanes revealed to have a positive impact in reducing congestion, dropping from 15.7% (scenario O) to 11.4% (variation of 4.3%) in SO conditions (scenario C). The UE scenario seems to have lower congestion at the network level than the SO scenario. However, the UE-SO difference (scenarios B and C) is just 0.2%. This “lower” congestion level in UE occurs because in SO the traffic flow dispersion reduces the degree of saturation but induces slightly longer trips.

Therefore, the congestion at the network level does not give a clear perspective about congested roads (degree of saturation equal to or higher than one). Congested roads are a major concern in urban regions, linked with queueing and delay. Figure 4.7 illustrates the length of congested links in every scenario. Currently (scenario O), there are 171 kilometers of congested roads on the whole day. The implementation of reversible lanes would help to reduce it to 123 kilometers, with the potential of reduction to 101 kilometers in the long run with the SO assignment.

It is not clear which strategy is the most beneficial: UE (selfish behavior in which every occupant chooses a path) or SO (social centralized behavior). For example, for 9 am, congested roads were initially 30 km and dropped to 21 km in scenario C (SO conditions). At 11 am this length dropped from 29 km to 24 km in scenario B (UE conditions) – here SO conditions would not be as beneficial (26 km of congested roads). Therefore, traffic demand at each hour can perform differently in UE or SO conditions as far as congested links are concerned.



(a) Average congestion. (b) Percent difference relative to Scenario O.

Figure 4.6 – Congestion at network-level.

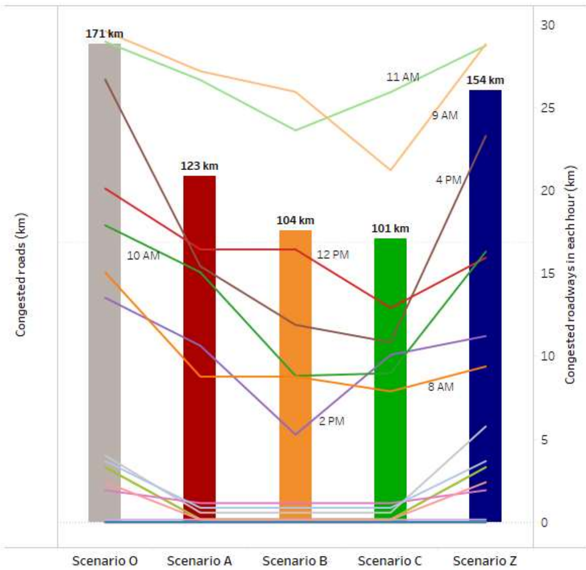
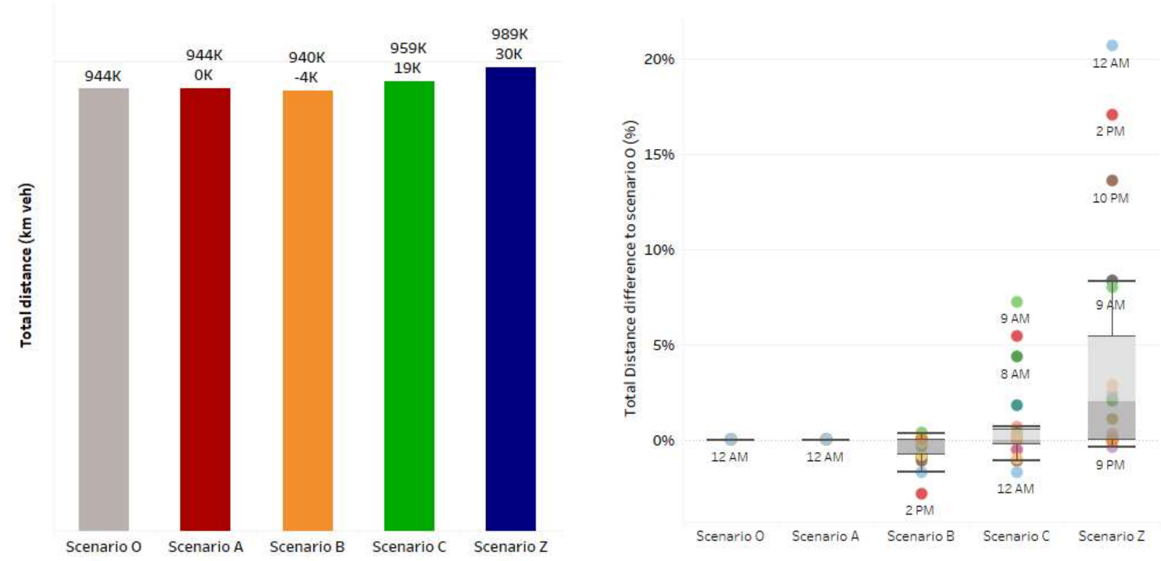


Figure 4.7 – Congested road links evolution.

The comparison of the total distance travelled amongst scenarios with scenario O is shown in Figure 4.8. As expected, reversible lanes do not have an impact on the short-term (scenario A), because the paths are the same as in scenario O. In UE conditions (scenario B), the total distance reduces 4,000 km veh. In SO conditions, AVs are forced to follow the optimal system paths, and the total distance increases 19,000 km veh.

Lastly, the total travel time and delay are depicted in Figure 4.9. Delay corresponds to the sum of the difference between the actual travel time and the minimum travel time (in free-flow conditions) in each road link. Reversible lanes already reduce travel times in the short-term (scenario A), especially in the long-term (scenario C). The SO scenario C is the most beneficial, producing lower travel times than the ones obtained in UE scenarios (A and B). There is a noticeable reduction of the total delay. In scenarios A and B (UE), the total travel time reduction is proportional to the total delay reduction. In scenario C (SO), the total travel time reduces 2,900 h veh and the total delay reduction is 3,200 h veh, which reflects the reduction of congested roads accompanied by longer trips performed in free-flow speed.



(a) Total distance with variation relative to current Scenario O

(a) Hourly total distance variation relative to Scenario O in percentage

Figure 4.8 – Total distance variation, daily and hourly, (a) and (b), respectively

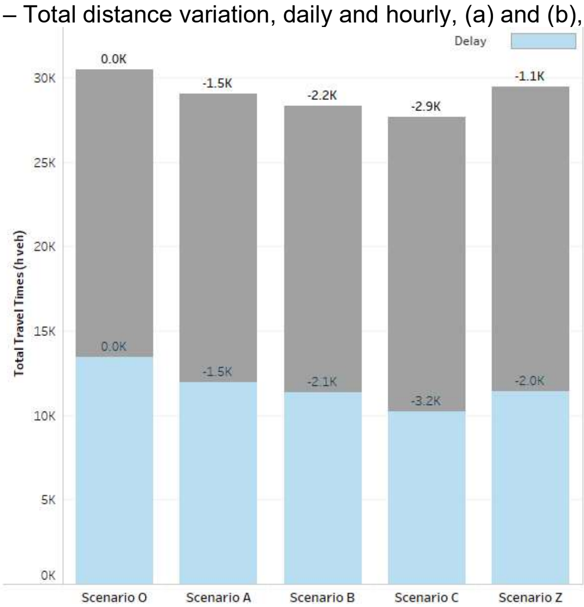


Figure 4.9 – Total travel time and total delay variation.

The following Figure 4.10 shows the percentage difference of each scenario relative to scenario O in every performance indicator for every hour. The best scenario obtained from comparing UE and the SO is depicted in black boxes. The SO is beneficial in some hours of the day (e.g., 9 am and 10 am), reducing congested roads and total delay. There are hours in which such difference is not clear (e.g., 6 am and 1 pm). Setting up a SO traffic distribution in some hours of the day while allowing AVs deciding on their own paths (UE) in the remaining part of the day – called "dual scenario" – could be beneficial. The criteria used to create the dual scenario (summarized at the end of Figure 4.10) were: first, the highest reduction of congested roads (degree of saturation equal or higher than one); then the highest reduction of total delay. In the remaining hours, the UE scenario was given preference so that AVs are free to follow their shortest paths, as the SO implies paths controlled by the centralized system.

Figure 4.11 shows the daily aggregated analysis – each hour was weighted by its travel demand. Amongst scenarios B and C, the best solution for the whole day would be scenario C, forcing SO traffic assignment conditions all day. Scenario B (UE conditions all day) still revealed a fair traffic performance but greatly reducing the total distance. The dual scenario revealed an intermediate performance between scenarios B and C in most of the traffic indicators, total travel times are reduced up to 8%, while the total delay is reduced 19%. Nevertheless, the dual scenario is the one that highly reduces congested roads by 40%, still compromising the total distance with a slight increase of 1%.

Percent difference relative to Scenario O		6 AM	7 AM	8 AM	9 AM	10 AM	11 AM	12 PM	1 PM	2 PM	3 PM	4 PM	5 PM	6 PM	7 PM	8 PM	9 PM	10 PM	11 PM	12 AM
	Scenario O	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	Scenario A	-39%	-30%	-36%	-14%	-20%	-13%	-18%	-36%	-13%	-21%	-31%	-33%	-27%	-36%	-25%	-39%	-43%	-48%	-51%
Degree of Saturation	Scenario B	-39%	-30%	-20%	-13%	-23%	-14%	-18%	-36%	-21%	-21%	-32%	-33%	-27%	-36%	-25%	-37%	-33%	-48%	-38%
-51% 0%	Scenario C	-39%	-34%	-34%	-26%	-31%	-23%	-25%	-36%	-25%	-32%	-37%	-33%	-35%	-36%	-25%	-44%	-33%	-48%	-38%
	Scenario O	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	Scenario A	-35%	-46%	-29%	-14%	-23%	-13%	-19%	-38%	-16%	-19%	-28%	-38%	-29%	-20%	-27%	-44%	-38%	-49%	-58%
Congestion	Scenario B	-35%	-46%	-32%	-16%	-29%	-18%	-20%	-38%	-34%	-19%	-35%	-38%	-29%	-20%	-27%	-51%	-39%	-49%	-59%
-59% 0%	Scenario C	-35%	-49%	-26%	-14%	-28%	-15%	-25%	-38%	-20%	-18%	-38%	-38%	-27%	-20%	-27%	-48%	-39%	-49%	-59%
	Scenario O		0%	0%	0%	0%	0%	0%	0%	0%	0%	0%		0%			0%	0%		0%
	Scenario A		-76%	-42%	-8%	-16%	-8%	-18%	-94%	-21%	0%	-42%		-40%			-86%	-95%		-95%
Congested roadways	Scenario B		-76%	-42%	-12%	-51%	-18%	-18%	-94%	-61%	0%	-55%		-40%			-86%	-95%		-95%
-95% 0%	Scenario C		-76%	-48%	-28%	-50%	-10%	-36%	-94%	-25%	0%	-59%		-40%			-86%	-95%		-95%
	Scenario O	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	Scenario A	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%		0%		0%	0%
Distance	Scenario B	0%	0%	0%	0%	0%	-1%	0%	0%	-3%	0%	-1%	0%	0%	0%	0%	-1%	-1%	0%	-2%
-3% 7%	Scenario C	0%	-1%	4%	7%	0%	0%	2%	0%	5%	1%	0%	0%	-1%	0%	0%	-1%	-1%	0%	-2%
	Scenario O	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	Scenario A	0%	-4%	-3%	-1%	-5%	-1%	-1%	-10%	-3%	-1%	-9%	-5%	-1%	0%		-8%	-31%	-3%	-40%
Total Travel Time	Scenario B	0%	-4%	-4%	-3%	-12%	-3%	-1%	-10%	-8%	-1%	-13%	-5%	-1%	0%	0%	-8%	-31%	-3%	-41%
-41% 0%	Scenario C	0%	-4%	-4%	-9%	-12%	-6%	-4%	-10%	-11%	-1%	-14%	-5%	-1%	0%	0%	-8%	-31%	-3%	-41%
	Scenario O	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	Scenario A	-40%	-14%	-8%	-2%	-20%	-2%	-4%	-81%	-3%	-29%	-19%	-83%	-7%	-19%	-51%	-56%	-87%	-67%	-89%
Total Delay	Scenario B	-40%	-14%	-6%	-5%	-47%	-9%	-2%	-81%	-9%	-29%	-25%	-83%	-7%	-19%	-51%	-45%	-86%	-67%	-87%
-89% 0%	Scenario C	-40%	-15%	-15%	-21%	-50%	-23%	-26%	-81%	-15%	-42%	-26%	-83%	-11%	-19%	-51%	-50%	-86%	-67%	-87%
	Dual Scenario	UE	SO	SO	SO	UE	UE	SO	UE	UE	UE	SO	UE	SO	UE	UE	SO	UE	UE	UE

Figure 4.10 – Hourly analysis of the main traffic performance indicators (Conceição et al., 2020).

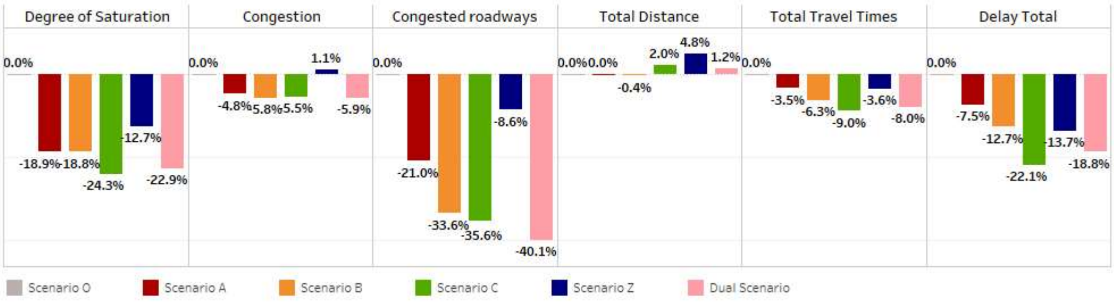


Figure 4.11 – Graphical comparison with nowadays scenario O: daily analysis (hours adjusted by travel demand).

4.5.3. NETWORK IMPACTS

An essential aspect of the network design is the location of these reversible lanes. The need for reversible lanes occurs in links where most of the traffic circulates in one direction rather than having a balance between the two directions. In the morning commute period, many lanes will turn to one direction, and in the afternoon the direction will be inverted. That might indicate that those reversible lanes will be much more dynamic in the suburbs because traffic demand is more imbalanced in those places compared to the city center. This section analyzes where the reversible lanes are being generated throughout the day in the case study city and their corresponding degree of saturation.

Figure 4.12 depicts the degree of saturation in scenario O, which corresponds to nowadays situation. The illustration shows that in the city center (close to node 3), the daily average degree of saturation is above capacity (105-110%). Close to TU Delft (node 31) and towards the northern part of the city, roads are saturated way above 50% in both directions.

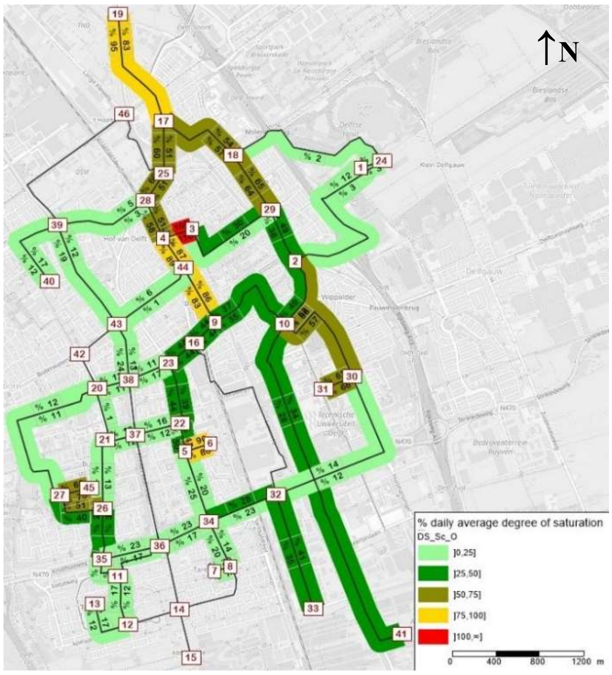
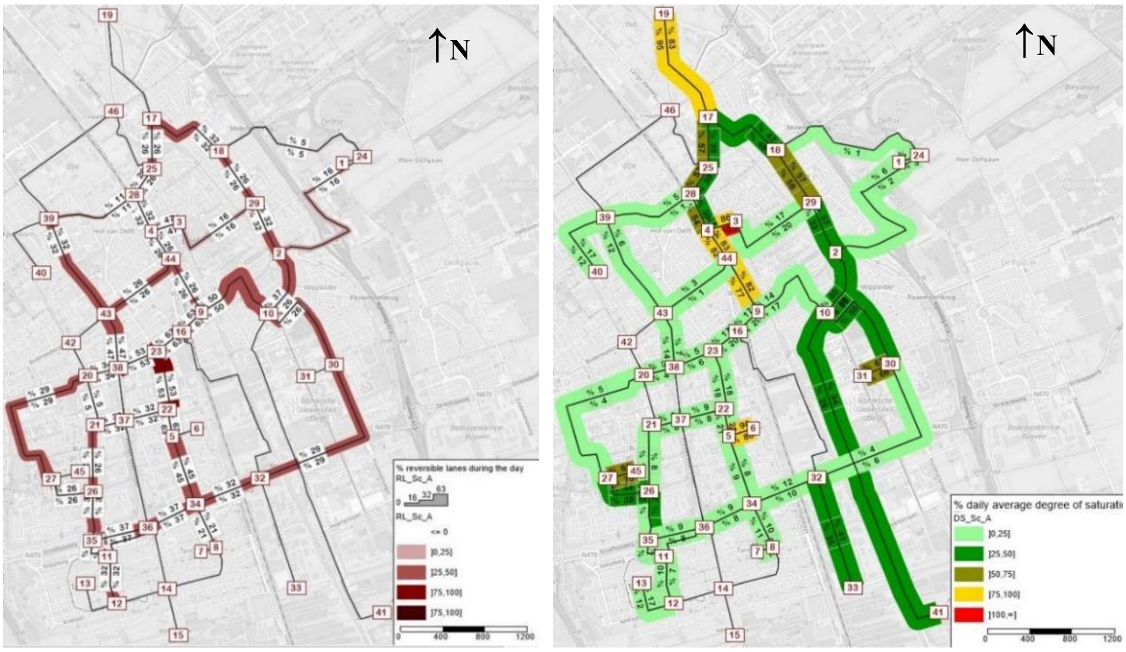


Figure 4.12 – Graphical representation of the average degree of saturation in scenario O(Conceição et al., 2020).

Figure 4.13 shows the daily variability of reversible lanes and the degrees of saturation for scenario A – the scenario that reflects the implications of implementing reversible lanes in the first days where vehicles are still following the previous paths. Reversible lanes help the city center (node 3) to reduce its degree of saturation (from 105-110% to 86-103% each way), holding a different lane layout than the initially set 47% of the day (9 hours out of 19 hours analyzed). Close to residential areas (node 27), there is an average small degree of saturation (5%), that sets 26% (5 out of 19 hours) of the day a different lane layout than the original one.



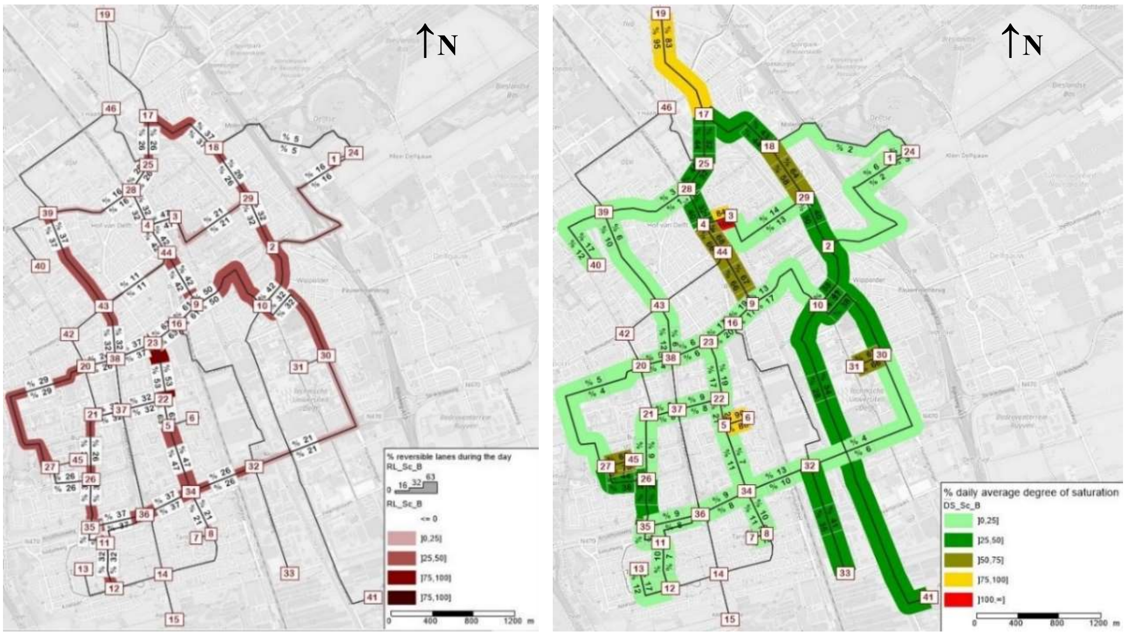
(a) Lane layout variation (b) Average degree of saturation

Figure 4.13 – Scenario A - network representation of the daily lane layout variation (a) and the degree of saturation (b) (Conceição et al., 2020).

Similarly, Figure 4.14 illustrates the results for scenario B – the scenario with reversible lanes where the system reaches equilibrium in UE conditions (AVs follow their individual selfish paths). This scenario revealed similar results as in scenario A. Reversible lanes reduce congestion in the city center, for example, looking at link 4-44 the degree of saturation in the first days (scenario A) was 83-82% each way and decreased to 68-66% each way in the long-term (scenario B). The lane layout of link 4-44 varied 42% of the day (in scenario A was 26%), reflecting an increase of variability as the average degree of saturation decreases.

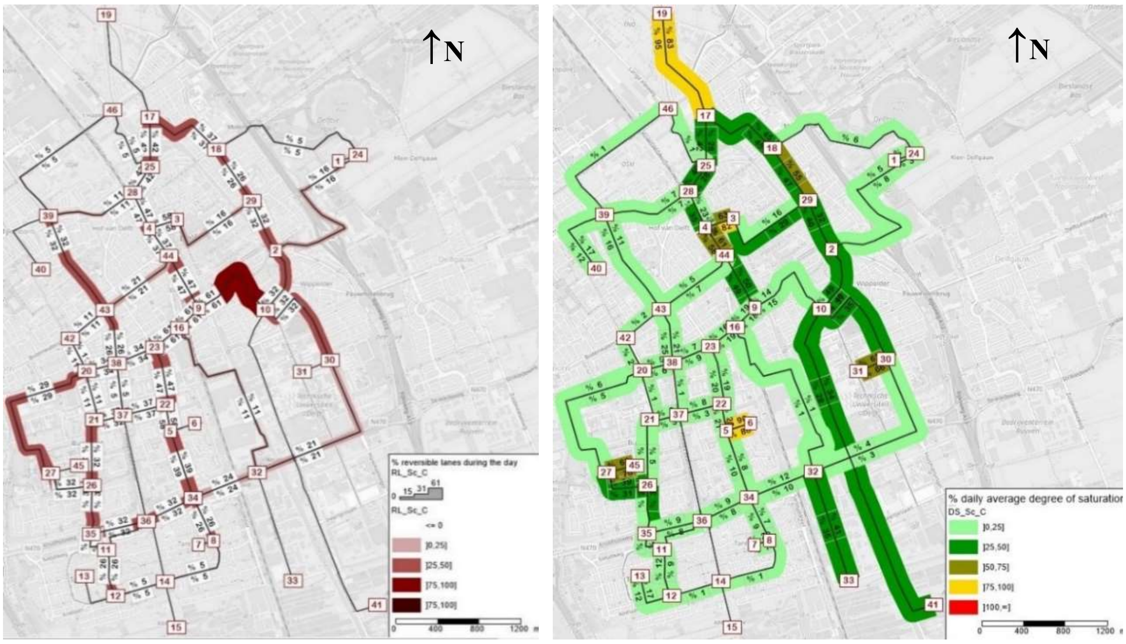
Figure 4.15 illustrates the variability of reversible lanes and the average degree of saturation for scenario C – the scenario that implies SO paths all over the day (AVs are forced to follow a paths given by the centralized system). The city center clearly sees a reduction in traffic congestion under capacity level (63-82%), with a lane layout different from the original 58% of the day, showing a higher lane layout variability.

The dual scenario – the one where SO works in some hours and UE in the remaining part of the day – revealed lower degrees of saturation all over the network, strongly reflecting the congestion reduction already mentioned. Still, in Figure 4.16, the congestion located in the city center is not so well mitigated as in the previous scenario C (SO), though it is still better than scenario B (UE). The variability of reversible lanes decreases in the suburbs (e.g., link 27-20 and 32-16), which can be positive for road safety



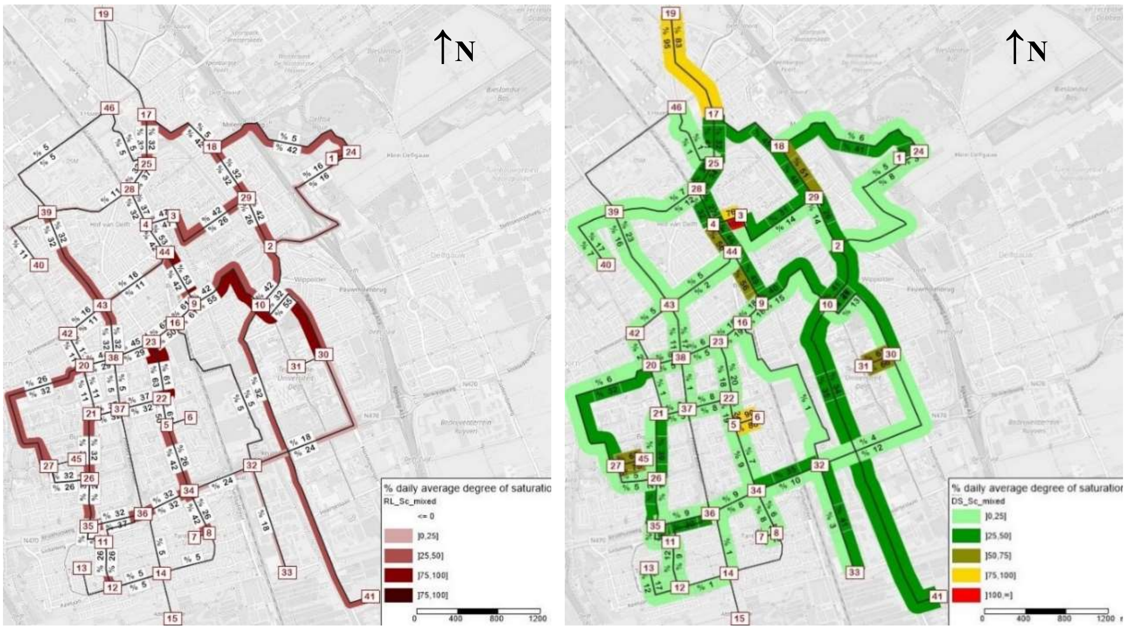
(a) Lane layout variation (b) Average degree of saturation

Figure 4.14 – Scenario B - network representation of the daily lane layout variation (a) and the degree of saturation (b) (Conceição et al., 2020).



(a) Lane layout variation (b) Average degree of saturation

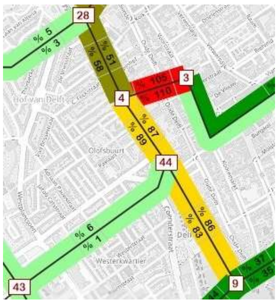
Figure 4.15 – Scenario C - network representation of the daily lane layout variation (a) and the degree of saturation (b) (Conceição et al., 2020).



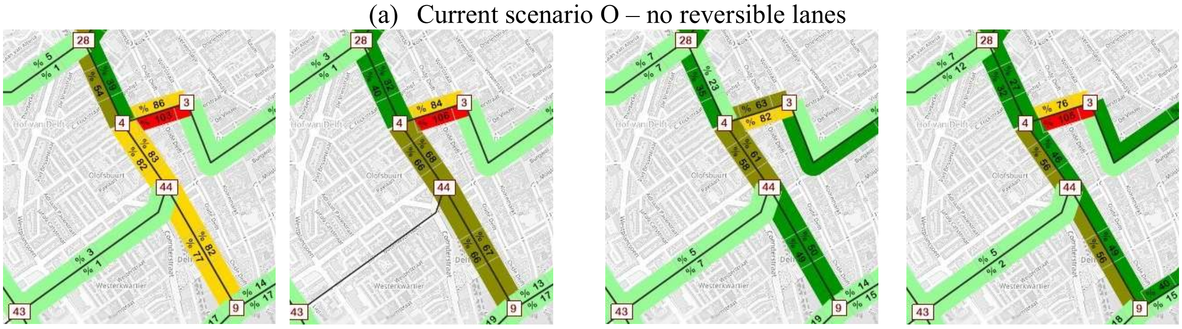
(a) Lane layout variation (b) Average degree of saturation

Figure 4.16 – Dual Scenario - network representation of the daily lane layout variation (a) and the degree of saturation (b) (Conceição et al., 2020).

Figure 4.17 zooms into the city center, showing the evolution of congestion (degree of saturation) across every scenario. Reversible lanes already help to reduce congestion in the short-term (scenario A), but congested roads only disappear in the long-term for a scenario with SO paths (scenario C). The dual scenario revealed an intermediate performance between scenarios B and C, though presenting results closer to scenario C (working in SO conditions).



(a) Current scenario O – no reversible lanes



(b) Scenario A – same previous routes (c) Scenario B – in UE conditions all-day (d) Scenario C – in SO conditions all-day (e) Dual scenario – SO in some hours of the day

Figure 4.17 – Congestion in the city center (% degree of saturation) in every scenario evaluated (a), (b), (c), (d) and (e) (Conceição et al., 2020).

4.6. SUMMARY

The mathematical model for solving the Dynamic Reversible Lane Network Design Problem (DRLNDP) optimizes the number of lanes in each road direction on an urban road network for every hour of the day and it can be run under UE or SO traffic conditions – formulated as a MINLP. The contribution is focused on studying the implementation of reversible lanes in the short and long term, analyzing the immediate impacts when traffic is not yet in equilibrium and the impacts when traffic rearranges itself reaching an user-equilibrium, as well when AVs are forced to follow a system optimal path – a condition only possible with V2I connectivity and a centralized routing system that instructs AVs to follow SO paths.

Five scenarios were calculated. Scenario O corresponds to the current situation as traffic runs under UE conditions without reversible lanes, i.e., a fixed lane layout; and Scenario Z corresponds to a hypothetical scenario with a centralized system controlling AVs' paths working on SO without reversible lanes. Three scenarios with reversible lanes were considered: scenario A, reflecting the first days of implementing reversible lanes where paths are the same as the ones experienced in scenario O; and two long-term scenarios, B and C, that consider a UE and a SO traffic assignment, respectively. A sixth scenario is derived from a comparative hourly analysis of scenarios B and C - the so-called dual scenario considers SO in some hours of the day and UE in the remaining ones, optimizing the strategy of reversible lanes on an hourly basis.

The model was applied to the network of the city of Delft, for every hour in all scenarios, and proved to be an easy tool to guide the reversible lane implementation throughout the day as a function of the travel demand and the existing road capacity. The optimal solutions were obtained within satisfactory computation times given the combinatorial nature of the problem. The simple traffic assignment problem, scenario O, took just a few seconds while scenario A, which corresponds to only deciding on the reversible lane problem, took eleven seconds. Scenarios B and C, the DRLNDP model, took eleven and fifty-four minutes, respectively.

Reversible lanes have the potential to reduce the degree of saturation, congestion at the network-level, congested roads, travel times and delay, regardless of the traffic assignment considered. However, travel distance is sensitive to the type of traffic assignment. With UE, the total distance reduces 0.4% while in SO increases by 2.0%. In peak hours, SO scenario revealed to have a better performance in most of the traffic performance indicators. The dual scenario combining UE or SO at each hour showed a total distance increase of 1.2%. In this optimal scenario, congested roads were reduced by 40.1%, total travel times and delay decreased 8.0% and 18.8%, respectively.

The study of the spatial location of congestion and variability of this strategy revealed that reversible lanes naturally vary more frequently in zones where demand is imbalanced throughout the day (residential areas). In city centers, congestion can still be reduced by the use of reversible lanes, though congested roads only disappear in the SO scenario.

Given these results, the SO scenario confirmed to be the ideal one in the future to reduce total travel times, delay, and traffic congestion located in the city center. Notwithstanding, the mixed UE-SO scenario appears to be the best on reducing congested roads all over the day.

Table 4.6 summarizes the overall benefits of implementing reversible lanes. Reversible lanes are an excellent strategy to be implemented reducing the overall degree of saturation, congestion, congested road links, total travel times and delay. The total traveled distance is very sensitive to the type of traffic assignment implemented (UE or SO).

Table 4.6 – Benefits of reversible lanes.

	Daily
Degree of saturation	19-24% reduction
Congestion at network-level	5-6% reduction
Congested road links	21-40% reduction
Distance	-0.7% or +2.0%, depending on the traffic assignment
Total Travel Time	4-9% reduction
Total Delay	7-22% reduction

The experiments showed that the difference between the assignments – UE and SO – is reduced by the presence of reversible lanes. Table 4.7 summarizes the SO-UE gap in every traffic performance indicator based on daily results.

Table 4.7 – SO and UE traffic assignment comparison.

	Behavior		SO-UE Gap	
	UE	SO	Without Reversible Lanes	With Reversible Lanes
Degree of saturation	↑	↓	-12.7%	-5.1%
Congestion at network-level	↓	↑	+1.1%	+0.3%
Congested road links	↑	↓	-8.6%	-2.0%
Distance	↓	↑	+4.8%	+2.7%
Total Travel Time	↑	↓	-3.6%	-2.5%
Total Delay	↑	↓	-13.7%	-9.3%

Municipalities are mostly concerned with congested road links and their influence on air pollution and energy consumption. Therefore, a future with SO paths that might be a reality with automated traffic and a smart traffic control system can have a positive impact and contribute to achieving sustainability goals. The application of the DRLNDP model points for the need for investment to inform AVs of their required SO paths and make the SO traffic assignment a reality.

Table 4.8 shows how much money can be saved by using the reversible lanes' strategy. Nowadays the value of travel time in the Netherlands is ten euros per hour approximately (Yap et al., 2016), which means that the total travel time cost savings per day are between 10.7k € in the short-term and 27.4k € on the long-term. Even considering a reduction in the value of travel time in an AVs scenario of six euros per hour (Correia et al., 2019), the total travel time cost savings per day would be between 6.5k € on the short-term and 16.4k € on the long-term for the Delft case-study.

Table 4.8 – Daily total travel time cost savings from implementing reversible lanes.

	Short-term	Long-term	
	3.5% reduction (scenario A)	6.4% reduction (scenario B)	9.0% reduction (scenario C)
Value of travel time in a car nowadays:10€/h	10 764.67 €	19 644.09 €	27 388.99 €
Value of travel time with AVs if work is possible: 6€/h	6 458.80 €	11 786.45 €	16 433.40 €

The DRLNDP model can be adjusted to some of the prospective benefits of the automated driving features, such as the chance to have smaller lanes that will raise the overall existing road capacity. Nevertheless, the model was formulated with the introduction of some simplifications and assumptions; for example, the time for the lane adjustment between the different hours is not considered; and mobility patterns are considered to be the same as today. Also, the model simplified the dynamic of the reversible lanes' strategy in every intersection, ignoring the number of turns which could generate a delay in the nodes. As future work, adding the delay in every node in a scenario with AVs at a macroscopic perspective (i.e., network level) and studying the impacts on pollution.

5

A SIMULATION-OPTIMIZATION FRAMEWORK FOR THE REVERSIBLE LANE PROBLEM ON REAL CITY SIZE NETWORKS

5.1. INTRODUCTION

A road network design problem (RNDP) usually involves two levels: the main design decision and the subsequent network performance that derives from that network design. In real-world cities, solving these two levels together in a single-level framework through mathematical methods (optimization) increases the overall numerical complexity of the problem, turning the problem very computationally expensive and the solving process becomes cumbersome (most of the times).

The previous chapters introduced two network design problems, the subnetworks and the reversible lanes for automated traffic. Both problems were tested in a case study that involved a road network of 61 road segments (that turn into 122 directional links) which allowed to be solved through single-level mathematical programming. Yet, the road network of the city case study has been formerly simplified to reduce the complexity of the RNDP.

For larger case studies, single-level optimization is not the most advisable method to solve these problems. Simulation methods appear as a method to reduce the complexity of the mathematical problem by solving one part of the issue. In RNDP, simulation solves the lower-level problem by estimating the performance of the network for a given network design solution in a much faster way than the mathematical methods (at larger road networks). Yet, joining optimization together with simulation requires an interface and a framework that can be very computationally expensive; plus, the methodology for solving the higher-level problem through optimization is usually through (meta)heuristics that generate ("random") design solutions not through mathematical programming. Joining simulation and optimization is challenging in terms of programming, software interfaces and time resources; yet a feasible solution (the global optimal solution is not guaranteed) can be obtained even when the solution process does not reach the end.

Therefore, this chapter explores simulation and optimization methodologies in theory and practice through the application of a RNDP – the reversible lanes problem – in a case study with a much larger road network than the one previously tested. Section 5.2 presents a background literature review. Section 5.4 presents the simulation-optimization framework for solving the RL-NDP that uses genetic algorithms and macro-simulation. Section 5.5 sets up the dataset and the conditions in which the case study is based – the city of Porto, Portugal. Section 5.6 presents the results of the experiments. Section 5.7 withdraws the summary and conclusions of this chapter.

5.2. BACKGROUND

A brief literature review regarding reversible lanes was introduced in the previous chapter, section 4.2. According to the preceding **Table 4.1**, two studies solved this problem through simulation and optimization techniques: Geraldes (2011) and Karoonsoontawong and Lin (2011).

Geraldes (2011) used simulation and optimization for intelligent/advanced traffic incident management system purposes to control reversible lanes in eight signalized intersections with time signal settings. Their framework used microscopic simulation (AIMSUN software) and genetic algorithms (GA).

Karoonsoontawong and Lin (2011) used a simulation-based optimization problem for the time-varying lane-based capacity reversibility problem, through a bi-level formulation that, in the upper-level problem (reversible lanes decision), is solved by GA; and, in the lower-level problem (traffic flow distribution), it uses the Visual Interactive System for Transportation Algorithms (VISTA) simulator developed by Ziliaskopoulos and Waller (2000) which corresponds to a mesoscopic simulator based on an extension of the cell transmission model that propagates traffic and satisfies capacity constraints as well as the first-in-first-out traffic property. Their main contribution focuses on comparing the performance and convergence of GA on a grid network. Four GA variations are proposed. GA1 is a simple GA. GA2, GA3, and GA4 are developed with the jam-density factor parameter, employing time-dependent congestion measures in their decoding procedures, and increasing degrees of randomness. GA3 performed best on the three criteria on a grid test problem, whereas the simple GA appears second. The performance comparison considered three criteria: solution quality, convergence speed, and CPU time. Their study showed that the GA with appropriate inclusion of problem-specific knowledge and parameter calibration can provide better results than the simple GA.

5.3. METHODOLOGY

The integration of simulation and optimization is particularly useful when the problem is extremely difficult to solve by mathematical linear models, as the raw complexity of the problem does not permit to represent complex systems and stochastic effects. In fact, almost all real-world systems generate problems that are too complex to be mathematically expressed either because it is not possible to solve linearly (unfeasible) or because it takes unreasonable calculation times to perform the search process for a solution. Nevertheless, the nature of the problem can raise questions of functionality that surpass the mathematical difficulty.

According to Allaoui and Artiba (2004), the complexity of a problem might arise from two natures: algorithmic complexity, plus structural and functional complexity. When a problem presents both characteristics, simulation and optimization reveal to be a good methodology to solve. Whereas optimization deals with algorithmic complexity and is intended for NP-hard problems, simulation deals with structural and functional complexity and is intended for dynamic complex systems. When NP-hard problems and complex systems nature collide, the solving methods integrate simulation and optimization.

In fact, real problems are often too complex in order for them to be deal with only mathematical programmingplus also some performance measures can only be obtained by simulation rather than with a linear function. Therefore, the integration of simulation and optimization embraces two approaches:

- *Simulation-optimization*, that gives more "importance" to the simulation process and thus can be called *optimization for simulation* (Fu, 2002).
- *Optimization-simulation,* where simulation is an add-on to the main optimization tool whereby inputs are generated for the soving of multiple instances, for example the Monte Carlo simulation. This method is also called *simulation for optimization* (Fu, 1994).

The distinction between these two methods is represented in Figure 5.1.

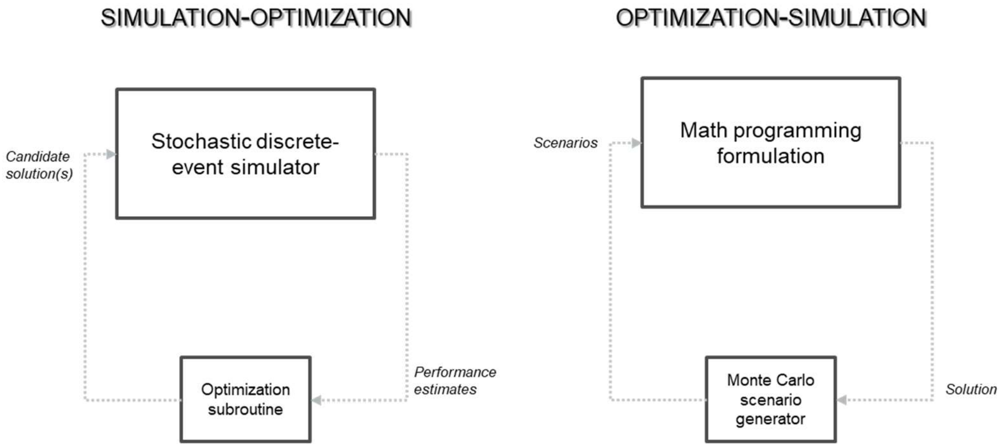


Figure 5.1 – Integration schemes of simulation and optimization approaches: simulation-optimization and optimization-simulation, adapted from Fu (2002)

The methodological approach used in this chapter is the simulation-optimization. This methodology consists of two sub-routines under a feedback process: the simulation model runs creating an output that the optimization algorithm analyzes and returns another solution to be an input to the simulation model again. In other words, the optimization model runs, creating a set of feasible decision variables (simulation input). The simulation model returns performance estimates to the optimization sub-routine which adjusts the algorithm towards the optimal searching process (calculation of the objective function) and henceforth creates again a new set of feasible solutions – creating a feedback loop process. When the stop criterion is reached, the best "optimal" solution is found (Fu, 2002).

Carson and Maria (1997) define Simulation-Optimization as "the process of finding the best input variable values from among all possibilities without explicitly evaluating each possibility". In this methodology, the resources spent while maximizing the information obtained in a simulation experiment are minimized. In this process, the inputs of this methodology can be called: controllable parameter settings, values, variables, (initial proposed solutions), designs, configurations or factors. Outputs can be called: performance measures, criteria, or responses. Some of these outputs can be part of the objective function (Carson and Maria, 1997).

In the optimization sub-routine, depending on the complexity of the problem, the solution search process might take a long time to solve. Heuristics appear as a good solution to shorten the time needed for the process, as they allow to determine near-optimal solutions by evaluating only part of the combinatorial possible solutions. Meta-heuristics are better tools to integrate into simulation tools, since they can be applied to a major number of problems and evaluate more efficiently an optimal or near-optimal set of parameters which relieves the computational cost. The metaheuristics include algorithms such as (Fu et al., 2005):

- *Simulated Annealing* is a variant of local iterative search, proposed by Kirkpatrick et al. (1983). The solution search process reminds the annealing cooling process through a temperature function. In other words, it aims to find the global optimum of a given function and at each step, a probability function is applied to decide whether to move to the new solution or not.
- *Tabu Search* introduces an adaptive memory into the metaheuristic search. It evaluates all solutions in the neighborhood. It involves an attribute-based focus to evaluate solutions and impose restrictions on a set of attributes (Glover and Laguna, 1997).
- *Genetic Algorithm (GA)* is a metaheuristic that randomly creates solutions through different processes (reproduction, crossover and mutation). It starts with initial solutions that iteratively are associated/combined to form other solutions with better objective values.
- *Scatter Search* is similar to the genetic algorithm because it involves an evolutionary population-based algorithm that constructs solutions by combining others. The main difference from the genetic algorithm is that it chooses more intelligently by incorporating history, e.g. past evolutions (Glover, 1999). According to Fu et al. (2005), scatter search consists of five methods: a diversification generation method, an improvement method, a reference set update method, a subset generation method and a solution combination method.
- *Neural networks* often are combined to function approximation, such as forecasting and curve-fitting role. Basically, they accelerate the search by predicting results as bad or inferior relative to the others (Fu et al., 2005). Since it requires iterations to achieve information that trains the model, it is applied to greater complexities.

Moreover, while the optimization model is running, the simulation sub-routine might evolve to add more elements (Glover et al., 1996).

The simulation sub-routine is important because each solution given from the optimization sub-routine is tested and the results from the simulation results are very crucial for an efficient computational cost. The performance results come from this sub-routine process.

In traffic simulation, there are three types of performing the simulation subroutine: micro, macro or meso simulation. Examples of micro-simulation software are AIMSUN, VISSIM, INTEGRATION and Paramics. DYNASMART is a software that performs meso-simulation. For macro-simulation, there is VISUM, CUBE and EMME/2. While micro-simulation focus on the mobility of each individual vehicle, involving more details and parameters that characterize the specificities of roads (geometry, traffic lights delay, etc.); macro-simulation focus on the complete road traffic flow, taking into account the general traffic density, vehicles distribution, different specificities (road capacity, free-flow speed, etc.).

Besides micro, macro or meso simulation, agent-based models are also a good approach to settle traffic simulation. The agent-based models have been studied only since the 1980s and were created within the field of artificial intelligence. This method can also be called as multi-agent simulation, where the agents belong to a class of computational models that attribute behaviors and actions to each agent. In this way, the interactions of the "autonomous" agents (individual or collective entities) will allow assessing their effects on the whole system. These classes of behaviors that each agent is assigned can be managed as: a rule-based decision making, discrete choice modeling, game theory, optimization, among others. This last, optimization, corresponds to the aim of our research proposal. The agent-based models may contain stochastic effects (randomness) introduced by Monte-Carlo methods, for example (Marik et al., 2001).

The integration of simulation and optimization methodologies has only begun around the 2000s. This hybrid methodology was only possible with the research advancement in operations research and artificial intelligence areas (Allaoui and Artiba, 2004).

Fu et al. (2005) presented some of the software routines for performing simulation optimization. At the time, the two most popular optimization sub-routines were AutoStat and OptQuest. Currently, integrating optimization and simulation can be easily implemented, for instance, in python or Matlab interfaces, that connect both the optimization (e.g., metaheuristics such GA or simulated annealing) and the simulation routines (e.g., traffic simulator such VISUM or VISSIM).

5.4. A Simulation Optimization Framework (SOF) for solving the RL-NDP

5.4.1. Formulation of the RL-NDP-SOF

The simulation-optimization methodological approach that addresses the RL-NDP problem is schematized in four subgroups. This scheme represents the methodological scheme using a simulation-optimization approach to our RL-NDP problem. The optimization routine (blue color) represents the solution search process whereas the simulation routine (red color) represents the performance evaluation of the system. The stopping criteria (green box) is a crucial step of this methodology to compare if the solution that was found is better than the previous one and to restrain the improvement stage (loop). The SOF was implemented in the Matlab interface.

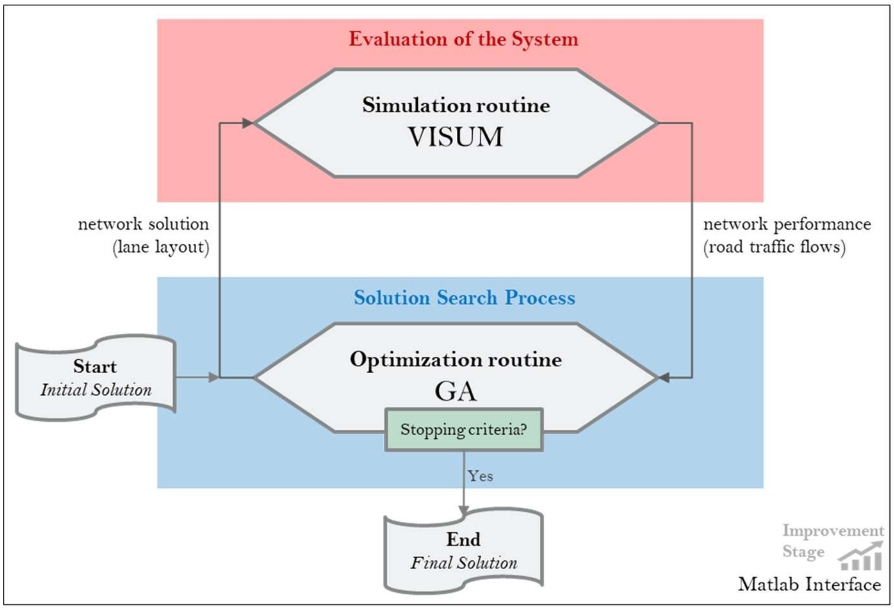


Figure 5.2 – Methodological scheme used for solving the RL-NDP-SOF.

If given, the initial network solution is always a benchmark on comparing the following solutions found in the GA method. In the RL-NDP, the initial solution is the current fixed road lane layout. The simulation routine (VISUM software) receives the lane layout and performs the traffic assignment procedure to estimate the distribution of the traffic flow (network performance), ending reporting those road flows to the optimization routine (GA implemented in Matlab). The GA first calculates the value of the objective function and checks with the stopping criteria whether to continue generating and evaluating new solutions of lane configurations of the urban network. If the stopping criteria are not reached, the process will return. This loop ends when one of the stopping criteria is attainable. In the following subsections, these processes are detailed.

There are three types of requirements for implementing the RL-NDP-SOF:

- Interfaces and connectivity: COM script to link Matlab-VISUM software; internet to verify licenses.
- Database integration: network data from VISUM is read as a cell and is transformed into numerical.
- Modeling needs: time-consuming. It is very computationally expensive to run VISUM at every solution generated from the GA.

5.4.2. OPTIMIZATION ROUTINE

As argued before, the linearization of the problem is not suitable for large networks and variables that best reflect the problematic and performance measures – the complexity rises exponentially. As the RL-NDP embraces a non-linear objective function, the optimization routine implemented a metaheuristic - the GA due to its evident efficiency and effectiveness in the literature (Adeli and Cheng, 1994a, 1994b; Teklu et al., 2007; Unnikrishnan et al., 2009).

The following outline summarizes how the genetic algorithm works (Mathworks, 2019a):

- In the first stage (*generation 1*), the GA creates several random network solutions/lane layouts (first *population*). In the RL-NDP, it is given the fixed lane layout as a starting point as a feasible network solution to help the creation of the first set of network solutions (first *population*) that will be tested in the simulation routine in order to calculate their value of the objective function (so-called *fitness function*).
- The GA performs a sequence of new *generations*, each one with new network solutions (several lane layouts) that are called *populations*.
- In every stage (*generation)*, the GA uses the network solutions (current *population*) of the current stage (*generation)* to create the next set of solutions (next *population)* as the following:
    - Scores each network solution of the current *population* by computing its value of the objective function (*fitness* value).
    - Scales the values previously obtained and converts them into a range of values called the expectation values.
    - Selects the network solutions (*parents*) based on their expectation values.
    - The network solutions with the best (*fitness)* values are called *elite* and automatically pass to the next stage (next *generation*).
    - The prior best network solutions (*parents*) will be combined with the entries of their vectors (*genes*) to create new network solutions (*children*). The new network solutions *(children)* are created either by *mutation* (random changes of a single network solution/*parent*) or *crossover* (the combination of the vector entries of the pair of network solutions/*parents*).
    - Replaces the current *population* with the new set of network solutions (new *population*: *elite* plus *children*) to initiate the next *generation*.
- The algorithm stops when one of the stopping criteria is met: maximum number of *generations*, maximum number of *stall generations* (a GA performance indicator that describes the improvement of the best fitness values and indicates the stagnation in the evolution process), Time limit, *stall* time limit (the maximum time limit for the stagnation process), *fitness* (objective) function limit, *fitness* (objective) function tolerance, among others.

The following notation is introduced for the RL-NDP-SOF:

Sets

$\boldsymbol{N} = (1, \ldots, i, \ldots, I)$:	set of notes in the network, where I is the number of nodes.
$\boldsymbol{R} = \{\ldots, (i,j), \ldots\}\ \forall i, j \in I \cap i \neq j$:	set of arcs of the road network where vehicles move.

Parameters

$V_{(i,j)}^{true}$: binary parameter that indicates whether reversible lanes can be implemented in link $(i,j) \in \boldsymbol{R}$. Note that in roads networks, there are roads that are assigned to different modes of transport like pedestrians, cyclists, public transport; therefore, $V_{(i,j)}^{true}$ might have be different of $V_{(j,i)}^{true}$.

$t_{(i,j)}^{min}$: minimum driving travel time in free-flow speed at link $(i,j) \in \boldsymbol{R}$, expressed in hours.

$L_{(i,j)}^{road}$: the total number of lanes of the road, including both directional links $(i,j), (j,i) \in \boldsymbol{R}$. Note that $L_{(i,j)}^{road} = L_{(j,i)}^{road}$.

$C_{(i,j)}^{lane}$: average lane capacity of link $(i,j) \in \boldsymbol{R}$, expressed in vehicles for the period of analysis.

M: big number.

Decision variables

$l_{(i,j)}$: integer variable equal to the number of lanes of each link $(i,j) \in \boldsymbol{R}$.

$f_{(i,j)}$: continuous variable that corresponds to the flow of AVs in each link $(i,j) \in \boldsymbol{R}$ – note that this variable is obtained through the simulation routine.

Objective Function

The fitness function used in the GA is similar to the previously non-linear objective function introduced for the RL-NDP, reproducing a user-equilibrium traffic assignment. In this experiment, the minimization of the total travel time of all passengers is reflected by the following expression (5.1) – α and β are the parameters of the BPR function.

$$\text{Min(Total Travel Time)} = \sum_{(i,j)\in R} \int_0^{f_{ij}^{h_i h_f}} t_{ij}^{min} \left[1 + \alpha \left(\frac{f_{ij}^{h_i h_f}}{l_{ij}^{h_i h_f} C^{lane} + \frac{1}{M}} \right)^{\beta} \right] df \tag{5.1}$$

Constraints

The previous constraints (4.8)-(4.12) are now formulated differently. Constraints (4.8) represent a lower-bound of the integer variable, while constraints (4.11) are an upper-bound of the variable. Constraints (4.9)-(4.10) and the flow constraints are removed, since the traffic flow distribution amongst the lane layout is solved by the simulation routine. Yet, in order to run the simulation software, a path for each O-D pair is required. In cases that the solution given by the GA did not present a feasible path for a certain O-D pair, the connection between Matlab (GA) and VISUM is stopped and the GA stops. Therefore, in order to overcome this issue, the following constraints (5.2) indicate that the lower-bound is 1, meaning that there still must exist one lane in every direction – two-way to one-way will not occur. As upper-bound, constraints (5.3) indicate that the number of lanes can go up to the total existent number of lanes in the whole road (both directions) minus one lane for the opposite direction.

Constraints (5.4) define the integer constraint of the main decision variable. Note that only one direction of the road link is considered for this problem, to simplify the solution search process of the GA. Theoretically, there would be an equality constraint to ensure that the lanes assigned for both directions would be equal to the total amount of lanes of that road. The genetic algorithm method that solves mixed-integer optimization does not allow equality constraints – check Mathworks (2019a) and Deep et al. (2009) for details. In such case, inequality constraints would be used, and the minimization of the problem would likely solve this issue as it tries to increase the road capacity, and therefore, the number of lanes. However, the penalty algorithm used for evaluating the value of the objective functions of the solutions allows that these constraints might be broken by adding a penalty term to the function when such constraints are not satisfied which will increase the value of the objective function. In other to overcome this issue that would take much longer to find a feasible solution that satisfied all the constraints, the opposite direction was neglected in the GA algorithm only. In other words, this means that the GA will only try to decide the number of lanes in one direction of the road, and while transferring the data from GA to VISUM, these constraints are added to the opposite direction on every road link. This "trick" allows to transform an initial mixed-integer constrained problem (previous chapter) to an integer problem only, while maintaining the structural form of the initial problem.

Lower-bound

$$l_{(i,j)} \geq V_{(i,j)}^{true} \; \forall \, (i,j) \in \boldsymbol{R} \tag{5.2}$$

Upper-bound

$$l_{(i,j)} \leq \; L_{(i,j)}^{road} \; \forall \, (i,j) \in \boldsymbol{R} \tag{5.3}$$

Integer constraints

$$l_{(i,j)} \; \in \; \mathbb{N}^0 \; \forall \, (i,j) \in \boldsymbol{R}, (i,j) {\neq} (j,i) \tag{5.4}$$

Nevertheless, solving integer programming through GA involves modifications of the basic algorithm – see (Mathworks, 2019a, 2019b). For instance, the creation, crossover, and mutation functions must enforce variables to be integers (Deep et al., 2009). For integer optimization, the GA attempts to minimize a penalty function, not the objective function, as it might include an extra term for infeasibility. When the solution is feasible, the penalty function corresponds to the objective function. When the solution is infeasible, the penalty function is the maximum value of the objective function among the feasible solutions, plus a sum of constraint violations of the infeasible solution (Deb, 2000). The GA does enforce linear constraints when there are integer constraints but incorporates linear constraint violations into the penalty function.

Figure 5.3 shows the workspace of Matlab software, moreover the simulation (VISUM) call inside the objective function defined inside the optimization routine (GA). The integration of VISUM is done through a VISUM COM script.

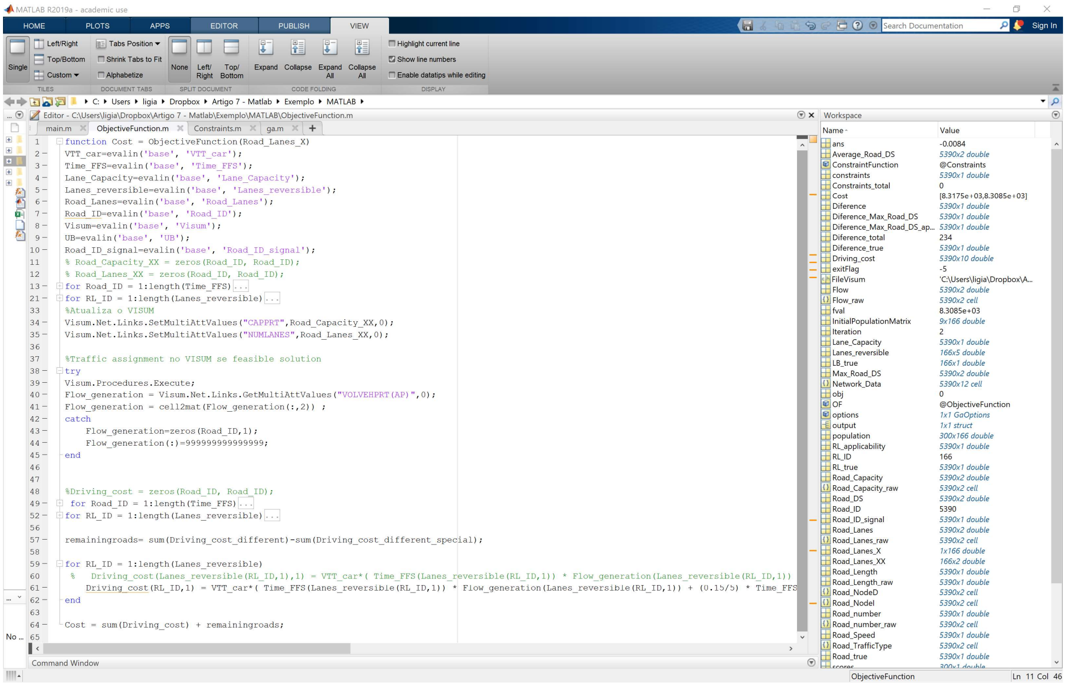


Figure 5.3 – Example of a Matlab workspace.

5.4.3.SIMULATION ROUTINE

The simulation subroutine evaluates each solution given by the optimization routine and estimates the traffic effect of the whole road network. The VISUM macroscopic simulator was chosen since it is easier, quicker and, at the light of the problem, the microscopic variables (such geometric characteristics) won't have a significant influence in this problem. The traffic flow can be characterized without microscopic variables.

The inputs of this simulation gather the design of the road network, represented by road links where each direction must be defined individually. Each link requires the definition of the number of lanes, road capacity, speed, length, transport systems permitted to use the directional link. After drawing the road links, the allowed turns in each node must be defined.

Another input is the demand (OD matrix) that must be set for each transport system existent in the network (bus, cars, pedestrians). This OD matrix is defined in zones that correspond to a specific area of the network. In order to link zones with the nodes where traffic will arrive/depart, the so-called connectors must be defined beforehand.

Following, the procedure sequence in the academic license of VISUM allows several types of traffic assignment: incremental assignment, equilibrium assignment, equilibrium assignment LUCE, equilibrium assignment bi-conjugate Frank-Wolf, equilibrium Lohse, Assignment with ICA, Stochastic assignment, dynamic user-equilibrium DUE, dynamic stochastic assignment and simulation-based dynamic assignment. In conformity with the objective function used in the GA, the user equilibrium was chosen together with the BPR function (same reference parameters). As explained before, in order to the procedure succeed there must be a feasible path for every

The results from the user-equilibrium procedure reflect the distribution of the traffic flow for a specific configuration of the network. The VISUM software uses the capacity in the denominator of the BPR functions, yet the integer lane variables are needed to reduce or increase capacity in a realistic way.

Figure 5.4 The workspace of VISUM software with the network of Porto

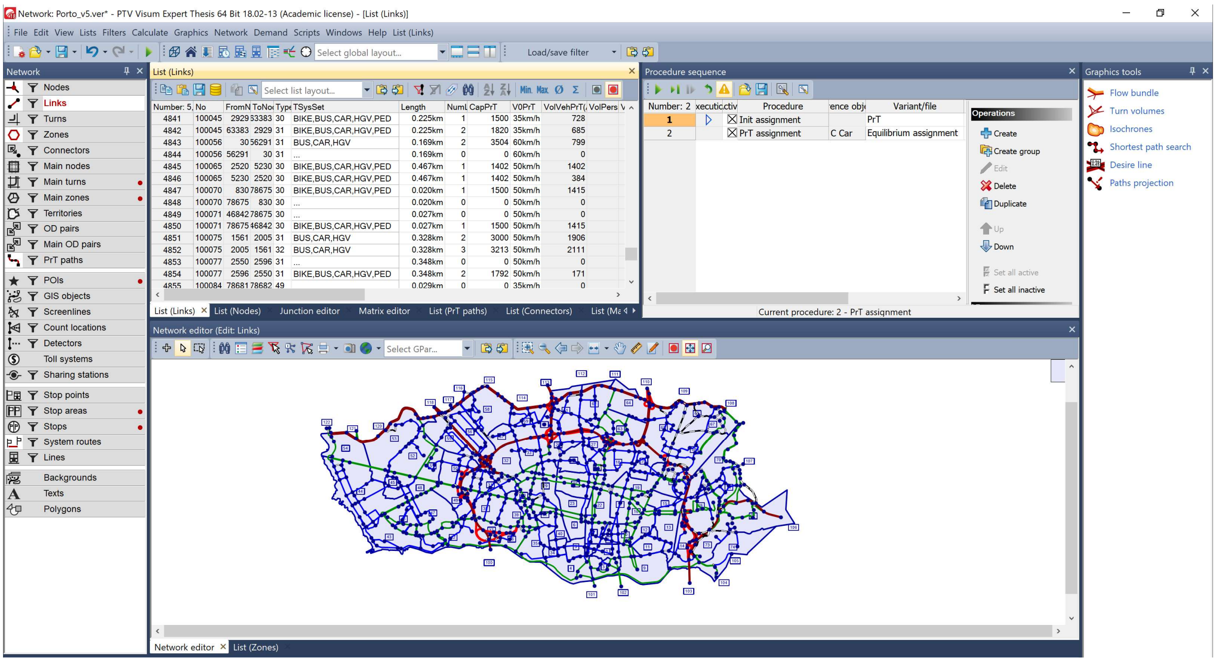


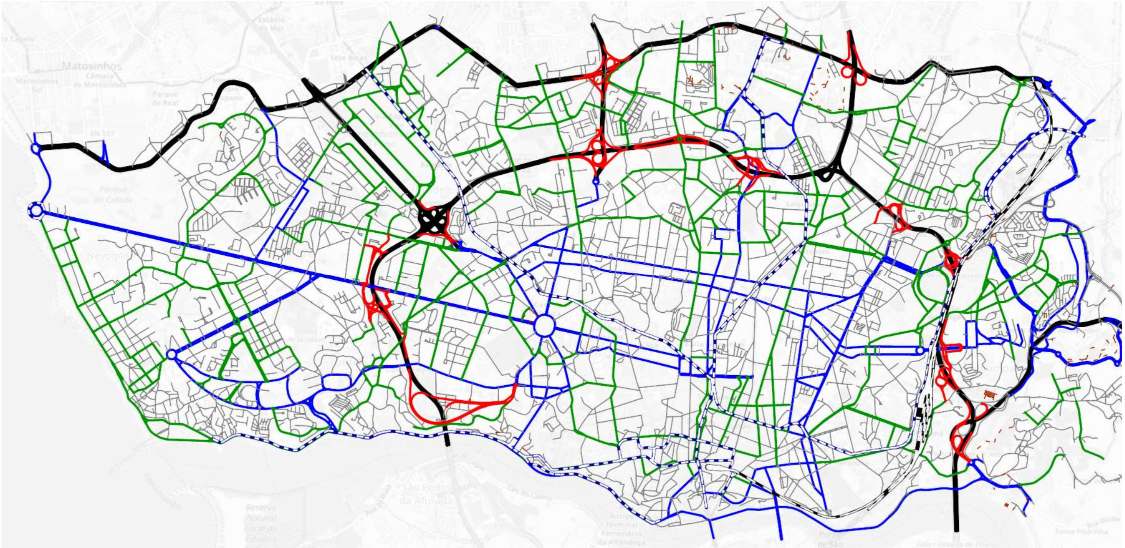
Figure 5.4 – Example of a VISUM workspace.

5.5. SETTING UP THE CASE STUDY OF THE CITY OF PORTO, PORTUGAL

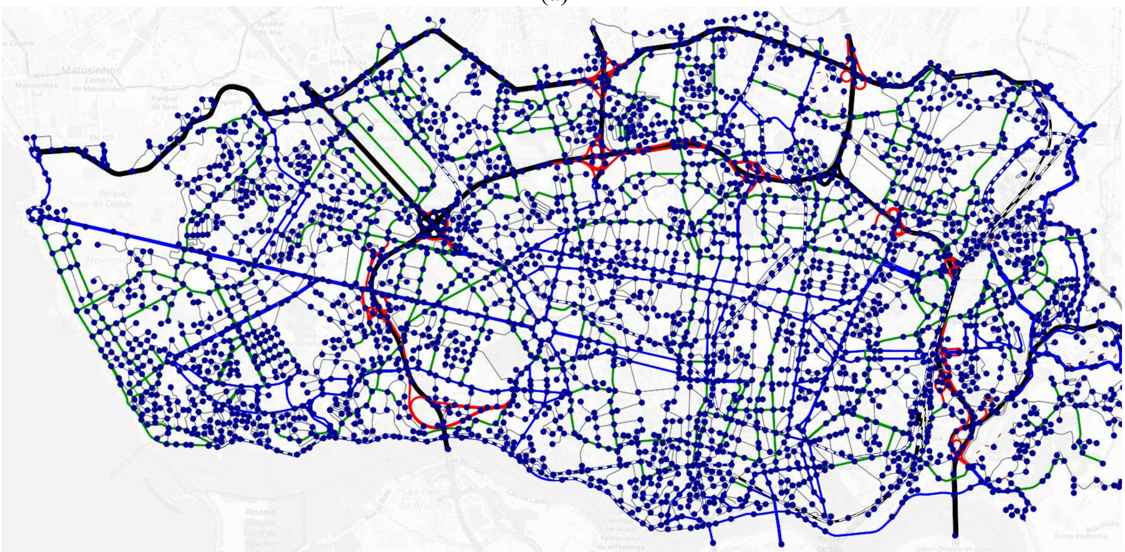
The application of the RL-NDP-SOF is exemplified in a case study of the city of Porto, in Portugal. The original database was developed by FEUP and Porto's municipality and is used for transport planning and research purposes. Figure 5.5 shows the initial dataset with more than 8000 nodes and 21000 links. The road hierarchy is characterized by: freeways (black color) that surround the city center and connect in six points to the traffic coming from a neighboring city across the river (south); freeway interchanges (red color); principal arterials (blue color), vital for traffic distribution across the city; collectors (green color) are roads that distribute the traffic flow inside the city, connecting with the local roads (grey color).

The original travel demand database was also provided together with the network file. The O-D Matrix represents the peak-hour with traffic estimations for the year 2018. The travel dataset contains a demand of 125700 trips across 122 zones – see Figure 5.6.

As previously introduced, the user-equilibrium uses a BPR function. The reference values ($\alpha = 0.15$; $\beta = 4$ when the degree of saturation is ≤ 1, otherwise $\beta = 8$). The user-equilibrium procedure uses an initial solution calculated by an incremental assignment. The OD demand share per iteration step is 30%,20%, 10%, 10%, 10%, 5%, 5%, 5%, 2%, 2% and 1%. No impedance functions are used in the nodes.



(a)



(b)

Figure 5.5 – Map of the city of Porto (a) and graph representation (b) (links and nodes from VISUM).

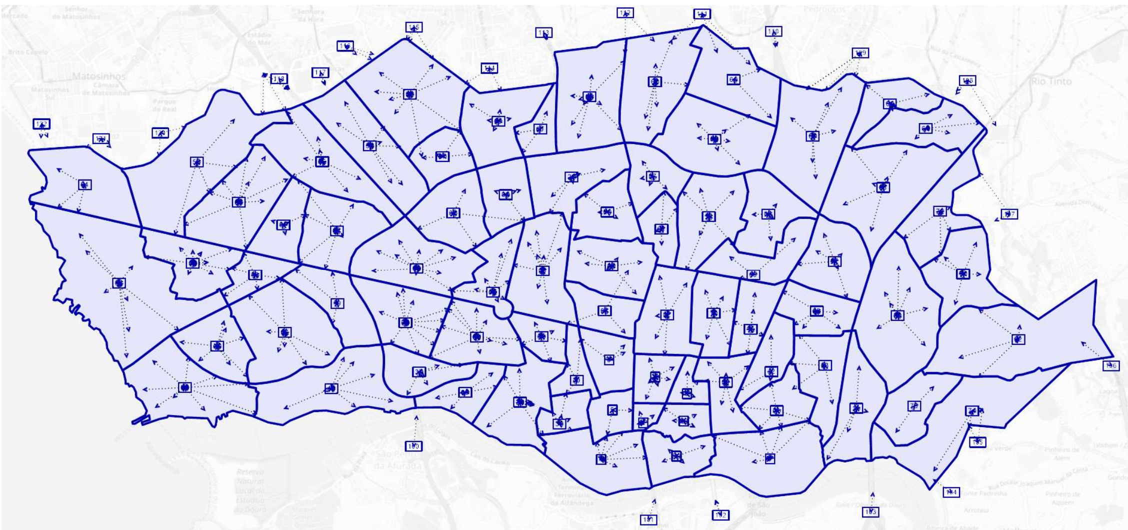


Figure 5.6 – Map of the zones and connectors considered in the Porto case study (from VISUM).

Based on the existent highway hierarchy, a simplified network of Porto in a map of the region was created as illustrated in Figure 5.7, ignoring local roads while trying to maintain the main intersections and connectors to represent the connection with the local neighborhoods. This is the network used for the following experiments that include 5390 links and 1189 nodes. The initial O-D matrix and the number of zones are maintained.

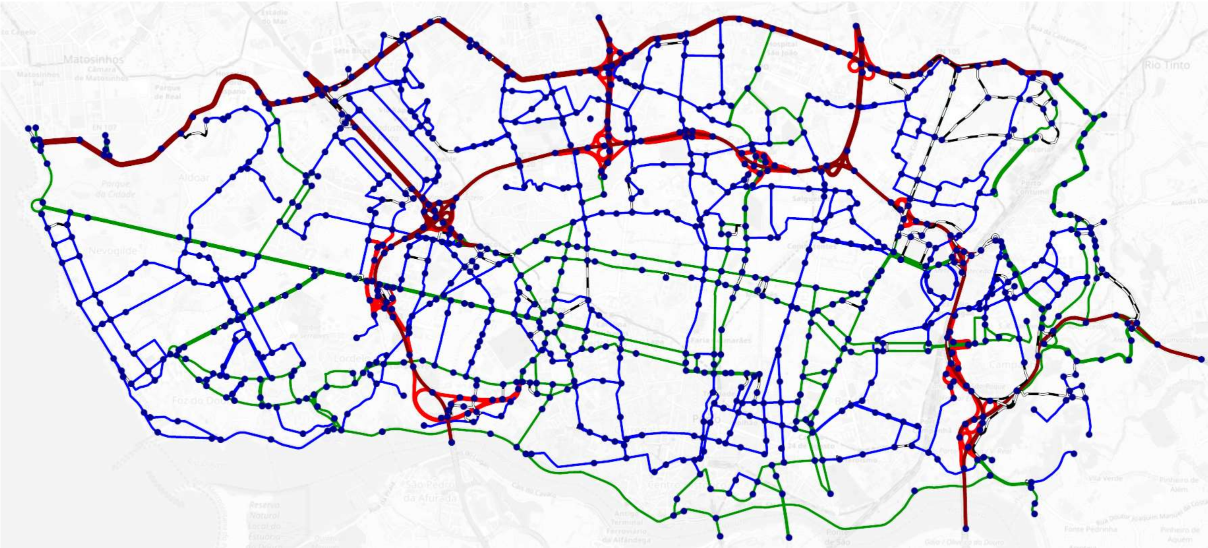


Figure 5.7 – Simplified map of the Porto case study: links and nodes representation (from VISUM).

Additionally, a design rearrangement in the Porto case-study was done in the freeways surrounding the city center. The previously freeway layout required physical separation of both flow directions. Once vehicles become connected AVs and reversible lanes are inside freeways, there's no physical barriers. Therefore, the design modeling in VISUM software changes to a design as the one presented in Figure 5.8 (b).

(a) (b)

Figure 5.8 –Rearrangement of the Porto case study: from (a) physical to (b) non-physical separation of both directions freeway (from VISUM).

Figure 5.9 illustrates the applicability of reversible lanes in the Porto case study. Reversible lanes are applied in two-way roads that have three lanes or more. Roads with one lane per direction (total of two lanes) were not considered in this experiment. The total number of roads where reversible lanes are accepted was 166 roads, each one with two directions (leading to 332 road links).

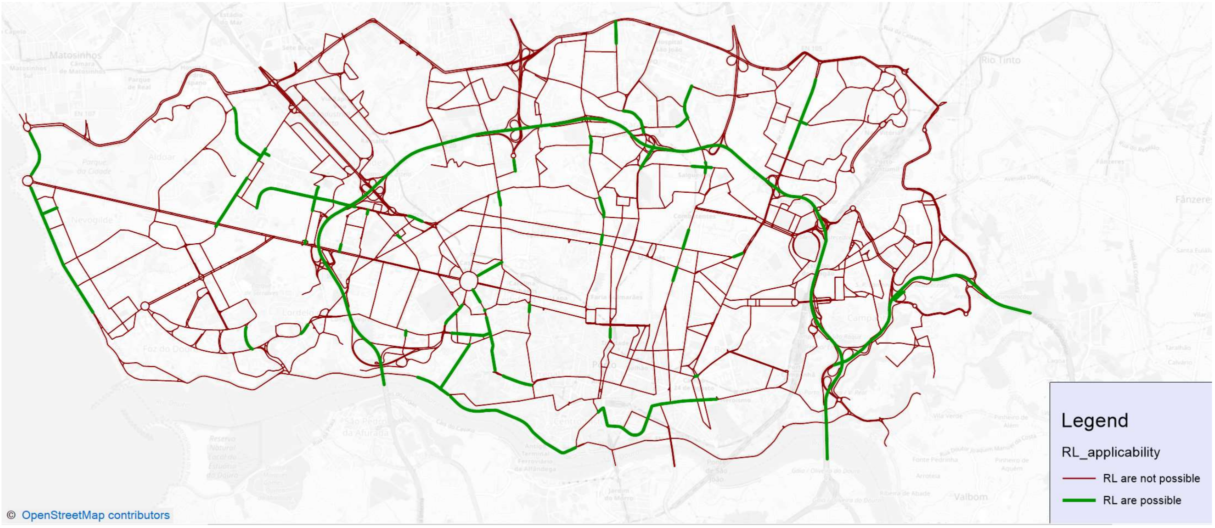


Figure 5.9 –Applicability of reversible lanes in the Porto case study (from VISUM).

5.6. Experiments

The RL-NDP-SOF is applied for the Porto case study in two scenarios: scenario O and scenario I, without and with optimized lane layout (reversible lanes strategy). For scenario I, three experiments were performed to test the convergence of the GA:

- Experiment I: GA does not consider random mutation in the generation of populations; plus, the stopping criteria are a maximum run time of 12h and a maximum number of stall generations of 5.
- Experiment II: GA considers both crossover (80%) and random mutation (20%) in the generation of populations; plus, the stopping criteria are a maximum run time of 12h and a maximum number of stall generations of 5.
- Experiment III: GA considers both crossover (90%) and random mutation (10%) in the generation of populations; plus, the stopping criteria are a maximum run time of 24h and a maximum number of stall generations of 5.

The RL-NDP-SOF has been implemented in Matlab (R2019a-academic use) together with VISUM (version 18.02- academic thesis license) in a laptop with a processor of 2.11 GHz Intel Core i7-8650U and 16GB RAM. The next two subsections explore the experiments from the application of the RL-NDP-SOF to the Porto case-study.

5.6.1. Previous lane layout: scenario O

Scenario O was only simulated in VISUM software and its flow outputs transferred to the Matlab interface in order to calculate the value of the objective function, which represents the total travel time of all vehicles that travel under user-equilibrium ,i.e., replicating a selfish-behavior where each vehicle minimizes its individual travel time. For scenario O, the value of the objective function is 8332.4 hours. In this case-study, VISUM takes about 33 seconds to perform a traffic assignment.

The assignment of all vehicles performed in VISUM software led to the results graphically presented in Figure 5.10 that shows the degree of saturation in every link considered. The traffic assignment performed by VISUM takes, on average, 33 seconds. The freeway surrounding the city center of the city of Porto presents high levels of degree of saturation, between 50-75%. In particular, there is one link whose flow is over 75% of road capacity.

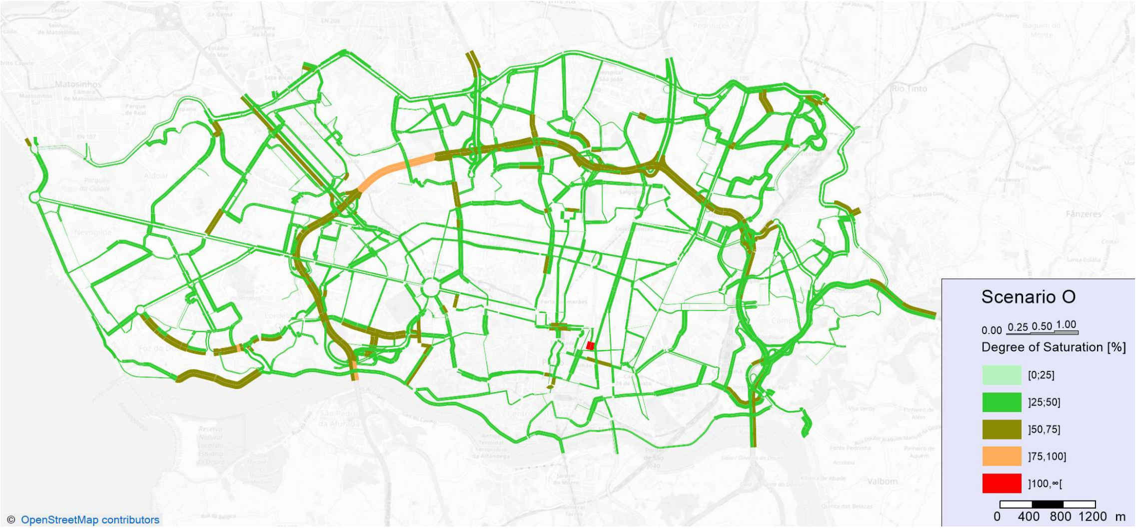


Figure 5.10 – The degree of saturation of Scenario O without reversible lanes (VISUM).

5.6.2. OPTIMIZED LAYOUT: SCENARIO I – EXPERIMENT I

This section evaluates the application of the RL-NDP-SOF in a scenario that holds reversible lanes in some road links of the network. This section analyses the results of the first experiment, where the GA was run under a stopping criterion of 12 hours, a maximum number of stall generations of five and an objective function tolerance of $1e^{-6}$ between the stages (*generations*).

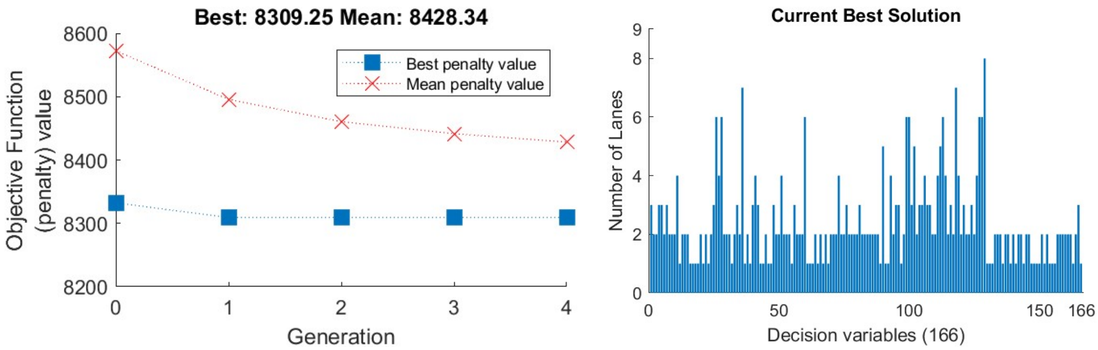
For twelve hours, the GA performed 4 stages (*generations*) that created 1500 network solutions (lane layouts) which took twelve hours to solve (43294 seconds). Each stage (*generation*) includes a set of network solutions (i.e., a *population*) that is created from the previous ones. The current (fixed) lane layout was given to create the initial set (*population*) of 600 solutions that takes five hours to complete, which, subsequently, at each following stage (*generation)* creates a new set of 300 individual solutions (*children – next population*) that takes two and half hours to complete. The feasible network solutions (the ones that satisfy the constraints) are tested by VISUM to return the road flows to the GA for calculating the values of the objective function of every network solution. The number of *elite* solutions is 10% of the *population* size at each *generation*, i.e., the best 30 solutions with the least values of objective function pass directly to the next *generation*. In this example, no random *mutation* from a single *parent* was allowed for creating the *children* solutions. Instead, the only *crossover* function was allowed, combining the entries of a pair of *parents*.

Table 5.1 shows the output of the GA for every generation. As previously introduced, the penalty function is the objective function plus a term for infeasibility. The best solution found in the experiment I revealed a value of the objective function of 8309.25 hours – meaning a reduction of 23 hours on all vehicles travel paths from Scenario O from the use of the optimal lane layout through reversible lanes implementation. These 23h of reduction represent an average 0.28% benefit in terms of travel cost reduction throughout the network, and an average local benefit of 2.60% in the roads where reversible lanes are possible (with a maximum local maximum of 6.58%). The best solution found in this experiment was already found in the first generation, i.e., after 5 hours of running calculations. Note that the process is becoming stagnate overtime, endorsed in the *stall generations* indicator from Table 5.2

Table 5.1 – Matlab output of the GA generation process: experiment I.

Generation	Func-count	Best Penalty	Mean Penalty	Stall Generations
1	600	8309	8496	0
2	900	8309	8461	1
3	1200	8309	8442	2
4	1500	8309	8428	3
Optimization terminated: time limit exceeded.				

Figure 5.11 illustrates the output from the process of finding the best lane layout under the GA solution search process. Figure 5.11 (a) shows the evolution of the best value of the penalty funcion found at each generation. The mean objective (penalty) value includes all solutions of that set (*population*). The values of the penalty function given for each infeasible solution is a sum of the worst value of the objective function (worst feasible solution found) plus a penalty value that is calculated by the constraints violations. This means that, as all the solutions are feasible, the best penalty value corresponds exactly to the objective function. Figure 5.11 (b) reveals the integer value of the decision variable, i.e., the number of lanes of each road link, of the best network solution found in this experiment I.



(a) (b)

Figure 5.11 – RL-NDP_SOF: experiment I output of the Porto case study: (a) GA objective (penalty) function; (b) best network solution.

Figure 5.12 (a) depicts the fitness scaling of the GA that converts the raw fitness scores that are returned by the fitness function to values in a range that is suitable for the selection function. Each network solution is scored as shown in Figure 5.12 (b). Along the process (*generations)*, the differences among the best, worst and mean values tend to reduce – see Figure 5.12 (c). The average distance between the solutions is somehow reducing over time – see Figure 5.12 (d).

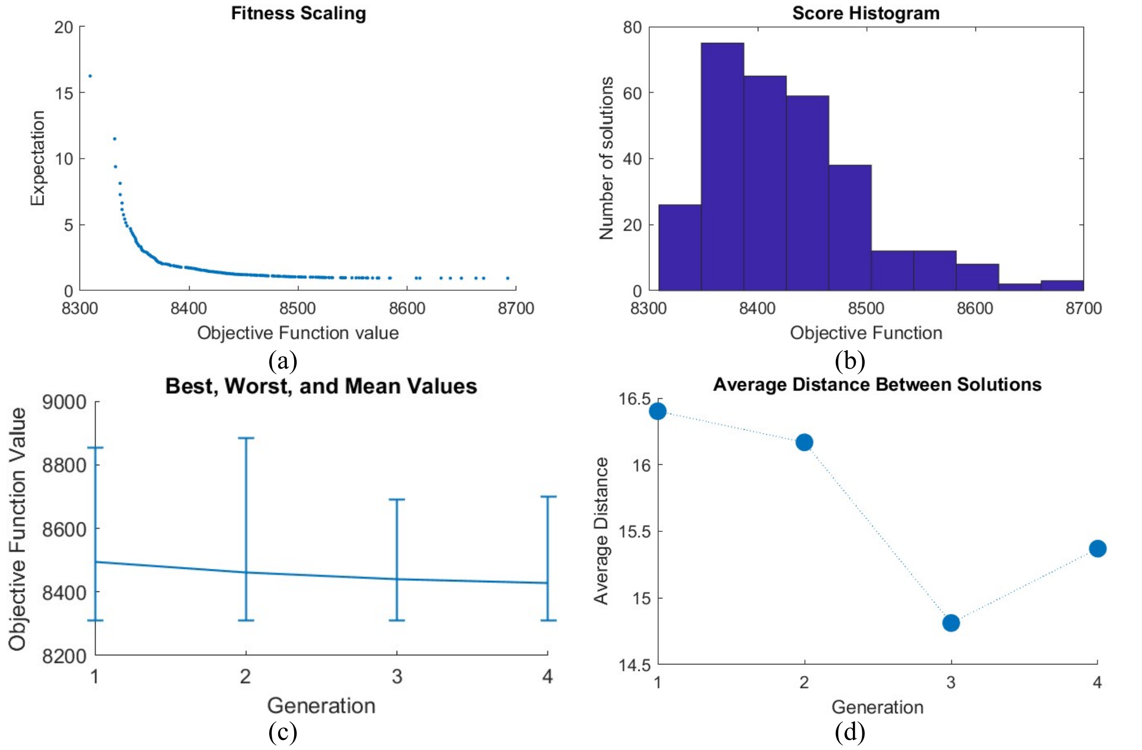


Figure 5.12 – RL-NDP_SOF: experiment I output of the Porto case study: (a) fitness scaling; (b) score histogram (c) best, worst and mean values of every *population*; (d) average distance between solutions.

Figure 5.13 (a) shows the number of network solutions (*children*) created from each previous network solution (*parent*) from the preceding stage. Figure 5.13 (b) shows the genealogy of the solutions during this process.

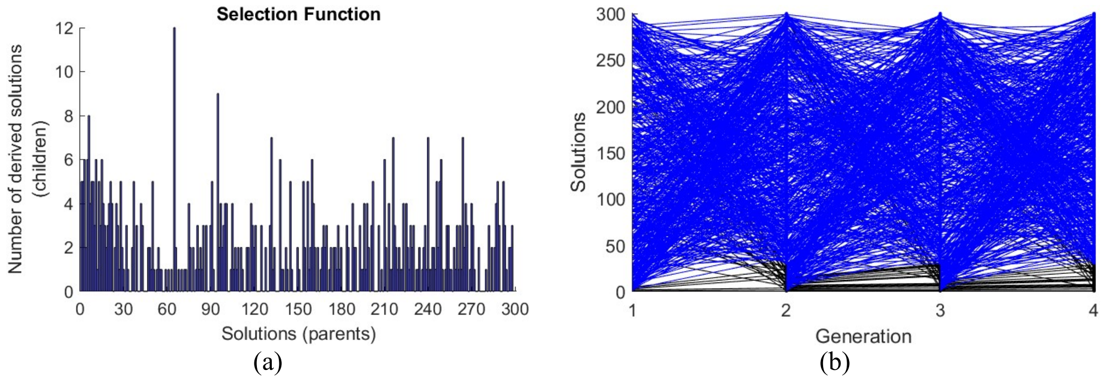


Figure 5.13 – RL-NDP_SOF: experiment I output of the Porto case study: (a) selection function; (b) genealogy of the solutions.

In this sense, Figure 5.14 compares the optimal lane layout found with the previous lane layout. Reversible lanes were implemented in the main freeway, and the RL-NDP-SOF revealed that the algorithm makes use of this possibility to implement a different layout. Therefore, green color illustrates the road links where a lane layout change happened by using reversible lanes. Red color reveals the links where reversible lanes were not implemented, even though it was possible to do so. Grey color are the roads that did not implement reversible lanes and have the same previous lane layout.

Figure 5.14 – Lane layout of the RL-NDP_SOF experiment I of the Porto case study (VISUM).

Figure 5.15 and Figure 5.16 illustrate the improvements in the traffic flow distribution in terms of the degree of saturation. Figure 5.15 shows where the traffic assignment (degree of saturation) improved and the links who experienced more improvement are drawn in thicker lanes. Figure 5.16 details the percentages of such degree of saturation improvement throughout the network. On average, the improvement of the degree of saturation was 1.82% in the entire road network, while in roads that used reversible lanes the degree of saturation reduced 14.45%. The total number of reversible lanes was 196.

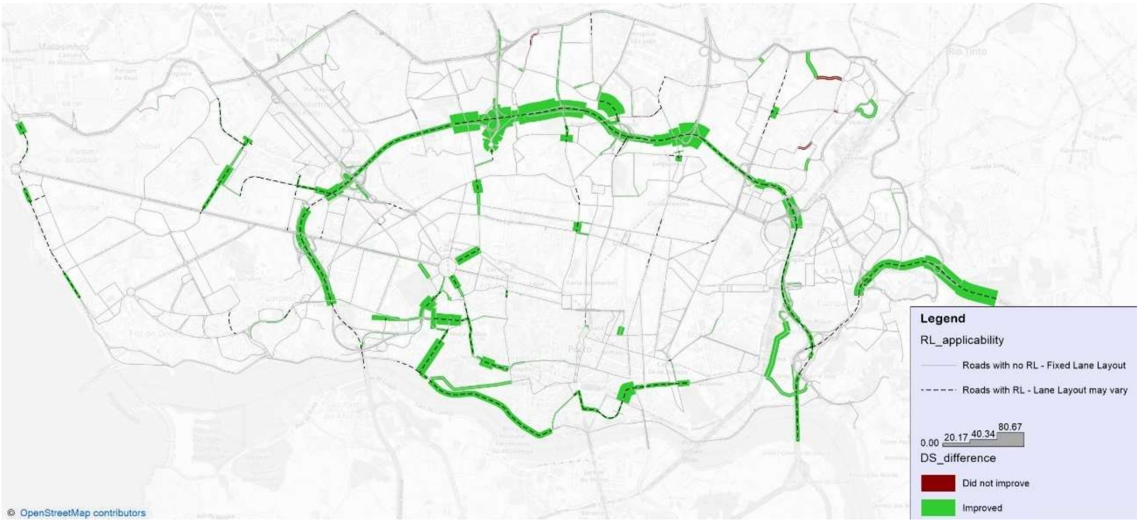


Figure 5.15 – Analysis of the traffic improvement in terms of the degree of saturation in the RL-NDP_SOF experiment I of the Porto case study (VISUM).

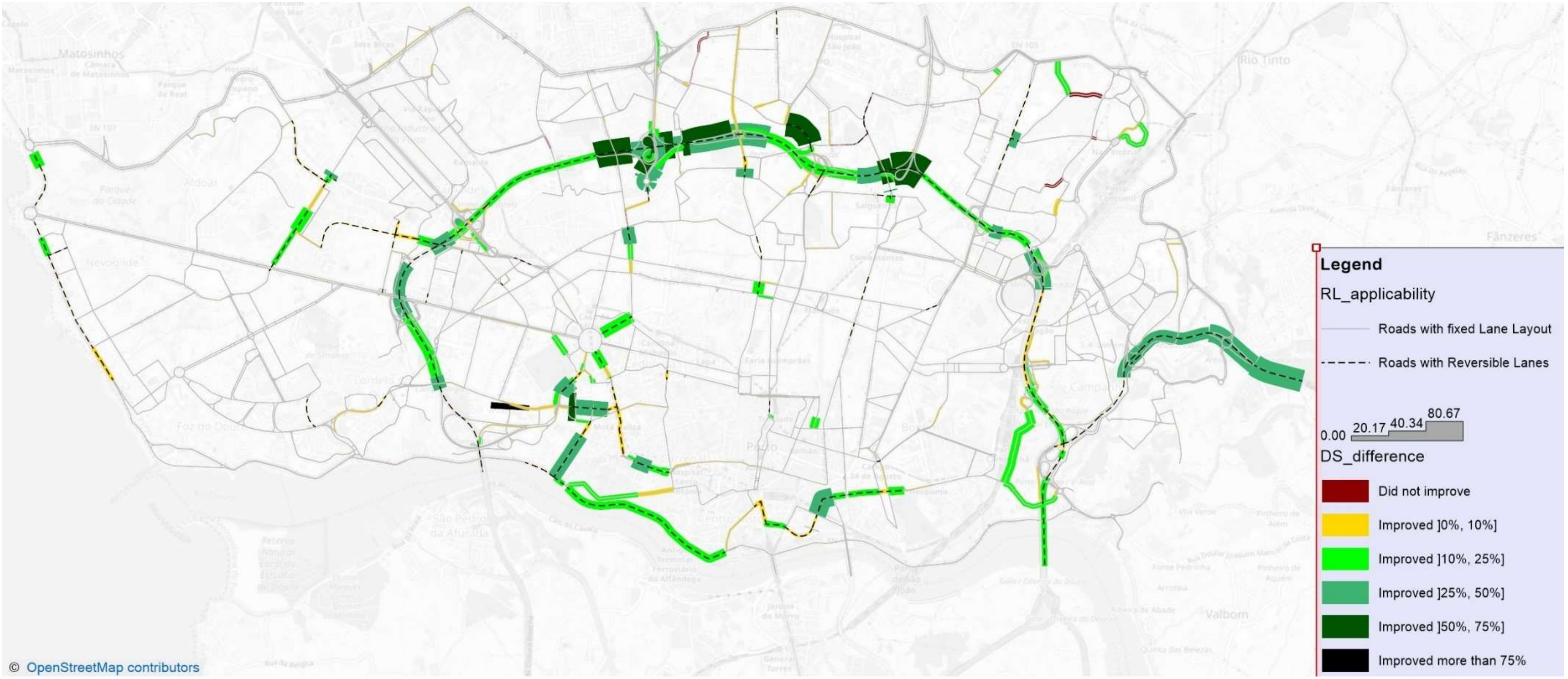


Figure 5.16 – Analysis of the percentage of the degree of saturation improvement in the RL-NDP_SOF experiment I of the Porto case study (extracted from VISUM).

5.6.3. OPTIMIZED LAYOUT: SCENARIO I – EXPERIMENT II

This section presents application of the RL-NDP-SOF in the same scenario I in a second experiment that tests different GA configurations, moreover a stopping criterion of 12 hours, a maximum number of *stall* generations of 5, and a *mutation* factor of 20%.

The GA evolved through five stages (5 *generations*) that corresponds to 1800 network solutions, which took about fourteen hours (51187 seconds) – the 5th generation had started before the 12h stopping criterion. In this example, a random *mutation* from a single network solution (one *parent)* was allowed; as well as *crossover* to combine the entries of a pair of network solutions (*2 parents*). The proportion for *mutation* and *crossover* was 20% and 80%, respectively.

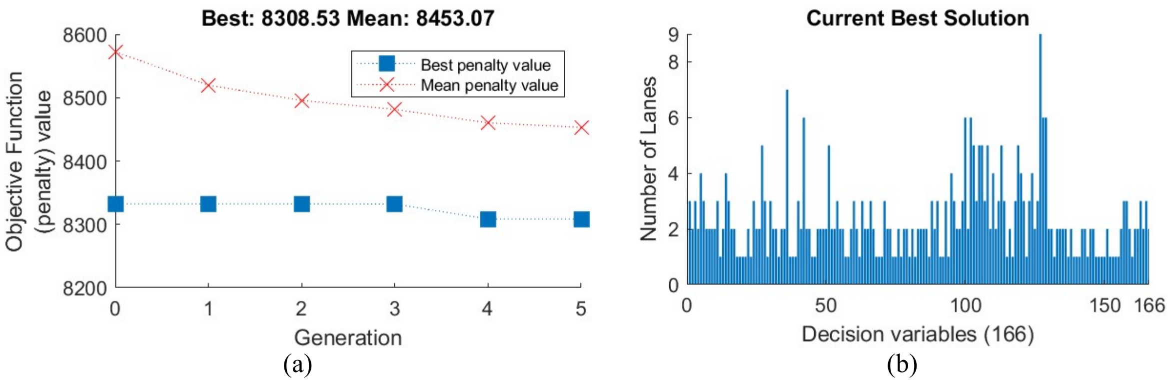
Table 5.2 shows the output of the GA for every stage (*generation*). The best solution found in the experiment IIrevealed a value of the objective function of 8308.53 hours – a reduction of 24 hours from the initial lane layout. Note that the previous experiment I had already found a fair solution in the first generation (5 hours later), while this experiment only found a similar solution in the 4th generation (12 hours later) – indicating that the *mutation* factor is not helping the experiment. The best solution (24h of travel time reduction) benefits on average 0.11% benefit in terms of travel cost reduction throughout the network, and an average local benefit of 3.66% in the roads where reversible lanes are possible (with a maximum local maximum of 5.06%).

Table 5.2 – Matlab output of the GA generation process: experiment II.

Generation	Func-count	Best Penalty	Mean Penalty	Stall Generations
1	600	8332	8520	0
2	900	8332	8496	1
3	1200	8332	8481	0
4	1500	8309	8460	0
5	1800	8309	8453	1

Optimization terminated: time limit exceeded.

Figure 5.17 illustrates the process of finding the best lane layout under the GA framework throughout the generations. Figure 5.17 (a) shows the evolution of the best objective function value found at each generation. The convergence of the values in the objective (*penalty*) function is very slow, and the optimal network solution (local optimal solution) is very close to the initial fixed lane layout. Yet, the mean (*penalty*) value is decreasing overtime, which means that the process is converging overtime. Figure 5.17 (b) shows the vector of the best network solution found in this experiment.



(a) (b)

Figure 5.17 – RL-NDP_SOF: experiment II output of the Porto case study: (a) GA objective (penalty) function; (b) best network solution.

Figure 5.18 (a) shows the fitness scaling of the solutions found in the last iteration of the GA. Most solutions are concentrated around 8450 which indicates that the distance between solutions is decreasing overtime – see Figure 5.18 (d). Figure 5.18 (b) reveals that the scores are very similar to each other. Figure 5.18 (c) shows the best, worst and mean values range in every generation – note that the *mutation* factor might have an impact on the convergence of the process. The 5th generation found a higher worst score than the one found in the previous generation which is explained by the random *mutation* factor that revokes the tendency depicted in Figure 5.12 (b).

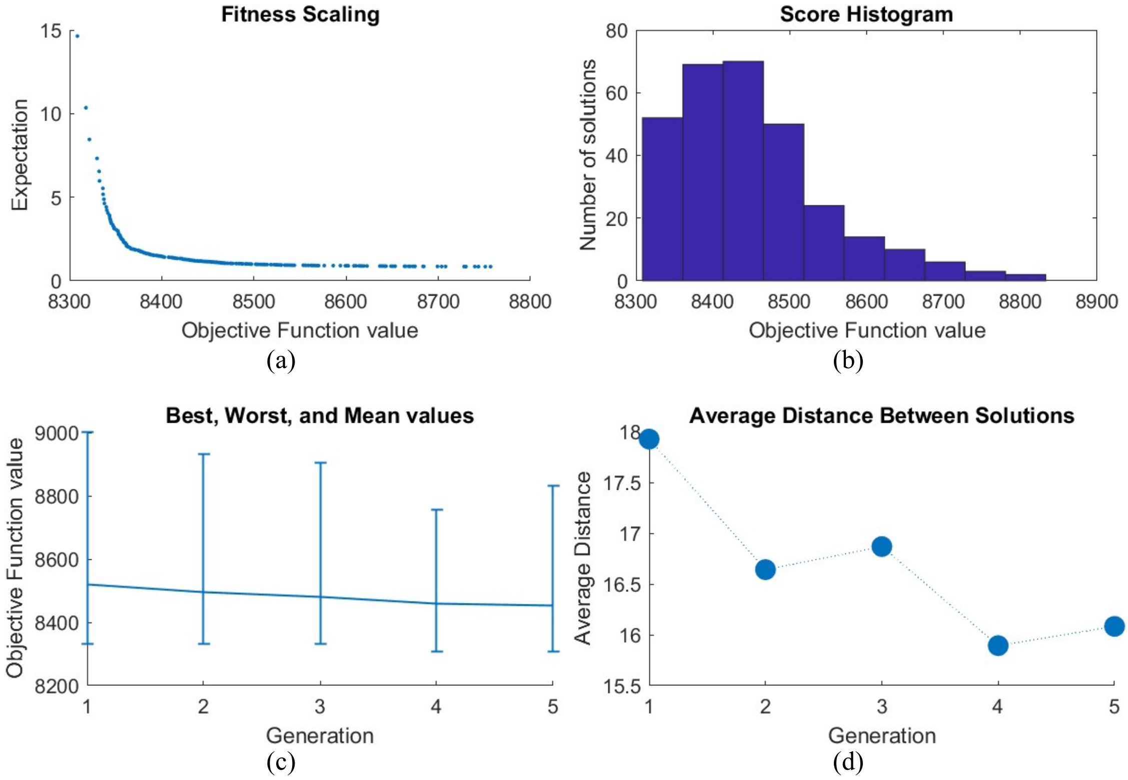


Figure 5.18 – RL-NDP_SOF: experiment II output of the Porto case study: (a) fitness scaling; (b) score histogram (c) best, worst and mean values of every *population*; (d) average distance between solutions.

Figure 5.19 (a) depicts the number of network solutions (*children*) that derived from a previous network solution (*parent*). Figure 5.19 (b) shows the genealogy of the solutions during this process: blue color are the solutions created by *crossover*, black color are the *elite* solutions, while red color are the solutions created by *mutation*.

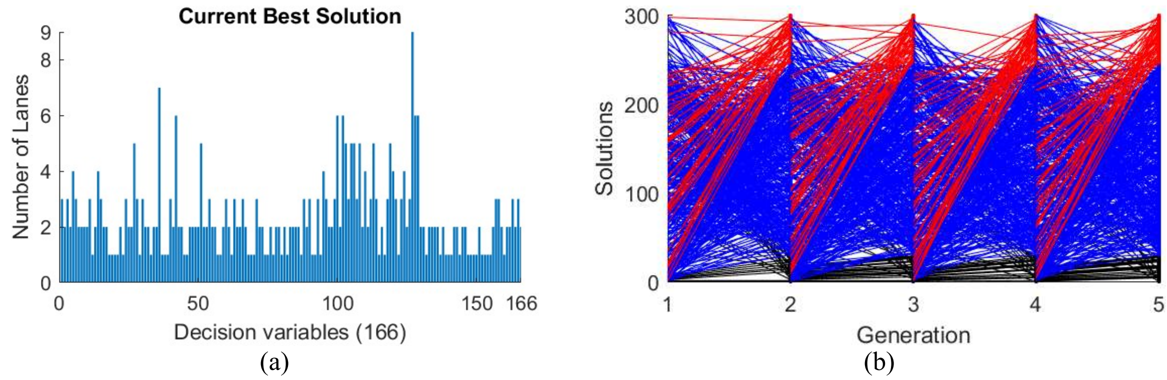


Figure 5.19 – RL-NDP_SOF: experiment II output of the Porto case study: (a) selection function; (b) genealogy of the solutions.

Figure 5.20 illustrates the lane layout found for the best solution found in this experiment II. Reversible lanes were implemented in part of the road network. The RL-NDP-SOF revealed that this strategy is used in almost every road link that could implement reversible lanes. Green color illustrates the road links where a lane layout change happened. Red color reveals the links even though reversible lanes were possible, the previous lane layout was already optimal. Grey color reveals that the links with a fixed lane layout where reversible lanes could not be implemented.

The main difference between the solutions found in the experiments I and II is that the GA explored more links with reversible lanes. The major difference between Figure 5.14 and Figure 5.20 is the arterial located on the left, next to the sea, as well more sections of the main freeway. The experiment II found a better solution that uses more reversible lanes than the experiment I best solution.

Figure 5.20 – Lane layout of the RL-NDP_SOF experiment II of the Porto case study (VISUM).

Figure 5.21 and Figure 5.22 illustrate the improvements in the traffic flow distribution in terms of the degree of saturation. Figure 5.21 tells whether the traffic assignment (degree of saturation) was improved or not. The road links who experienced improvement are drawn proportionally in thicker green lanes.

Figure 5.22 details the percentages of the degree of saturation improvement all over the network. Even though only some roads allow the implementation of reversible lanes, overall the traffic flow distribution was improved with a degree of saturation reduction up to 25%. The major improvements are in the major freeway that surrounds the city center, with improvements up to 76%. On average, the improvement of the degree of saturation was 2.17% in the entire road network, while in roads that used reversible lanes the degree of saturation reduced on average 15.24%. The total number of reversible lanes with changed direction was 234.

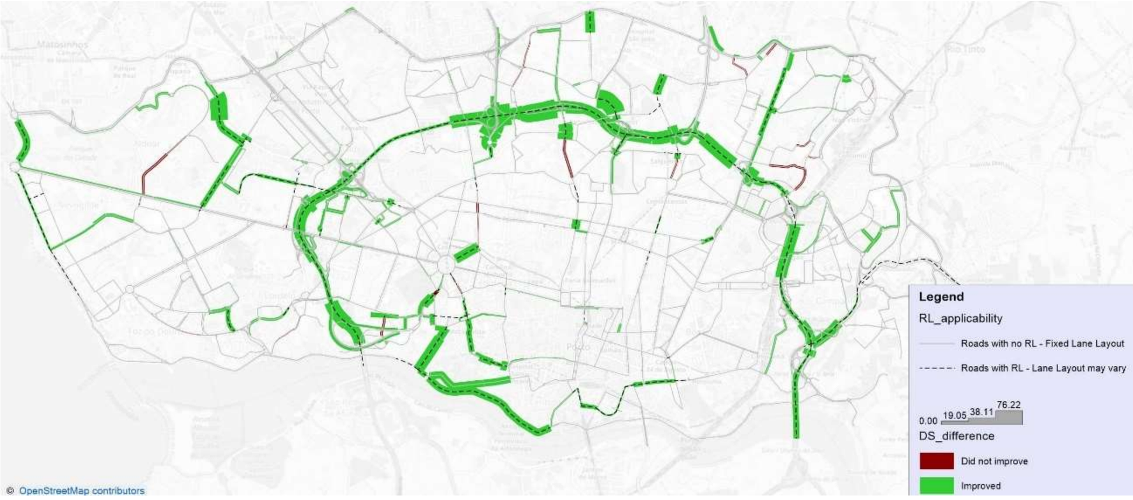


Figure 5.21 – Analysis of the traffic improvement in terms of the degree of saturation in the RL-NDP_SOF experiment II of the Porto case study (VISUM).

5.6.4. Optimized layout: Scenario I – experiment III

This section presents the results for the experiment III that involved the following GA characteristics: a stopping criterion of 24 hours, a maximum number of stall generations of five, and a *mutation* factor of 10%. This third experiment was aimed to depict the convergence of the model and evaluate the influence of the mutation factor in the solution search process.

The GA evolved through eight stages (8 *generations*) that corresponds to 2700 network solutions, which took about twenty-two hours (80588 seconds) – the maximum number of stall generation was the stopping criterion. In this example, the proportion for *mutation* and *crossover* was 10% and 90%, respectively.

Table 5.3 shows the output of the GA for every stage (*generation*). The best solution found in the experiment III revealed a value of the objective function of 8300.72 hours found at the third generation (after 10 hours) – which means a travel time reduction of 32 hours from the initial lane layout. Note that a very similar solution to the optimal was found in the second generation (after 7.5 hours). The best solution (32 hours of travel time reduction) benefits on average 0.20% benefit in terms of travel cost reduction throughout the network, and an average local benefit of 4.36% in the roads with reversible lanes.

Table 5.3 – Matlab output of the GA generation process: experiment III.

Generation	Func-count	Best Penalty	Mean Penalty	Stall Generations
1	600	8326	8509	0
2	900	8301	8470	0
3	1200	8301	8453	0
4	1500	8301	8448	1
5	1800	8301	8448	2
6	2100	8301	8432	3
7	2400	8301	8419	4
8	2700	8301	8420	5

Optimization terminated: average change in the penalty fitness value less than options.FunctionTolerance and constraint violation is less than options.ConstraintTolerance.

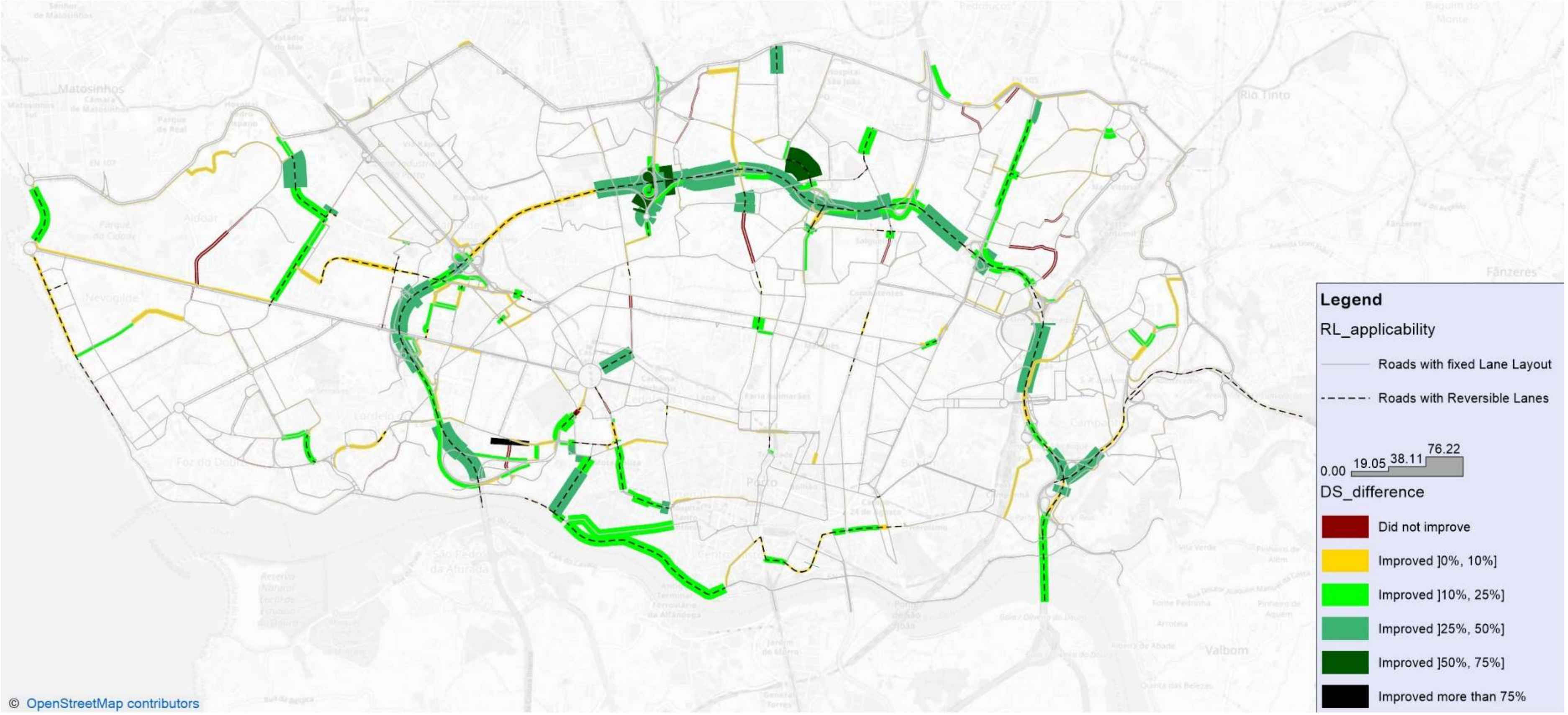
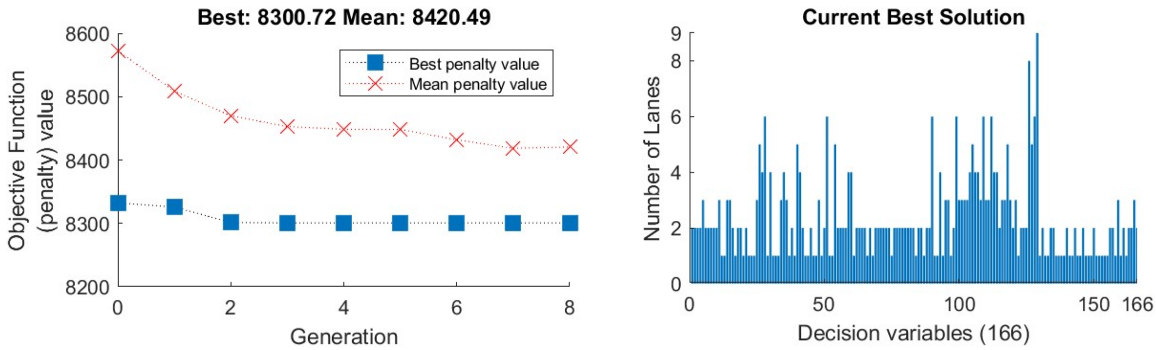


Figure 5.22 – Analysis of the percentage of the degree of saturation improvement in the RL-NDP_SOF experiment II of the Porto case study (extracted from VISUM).

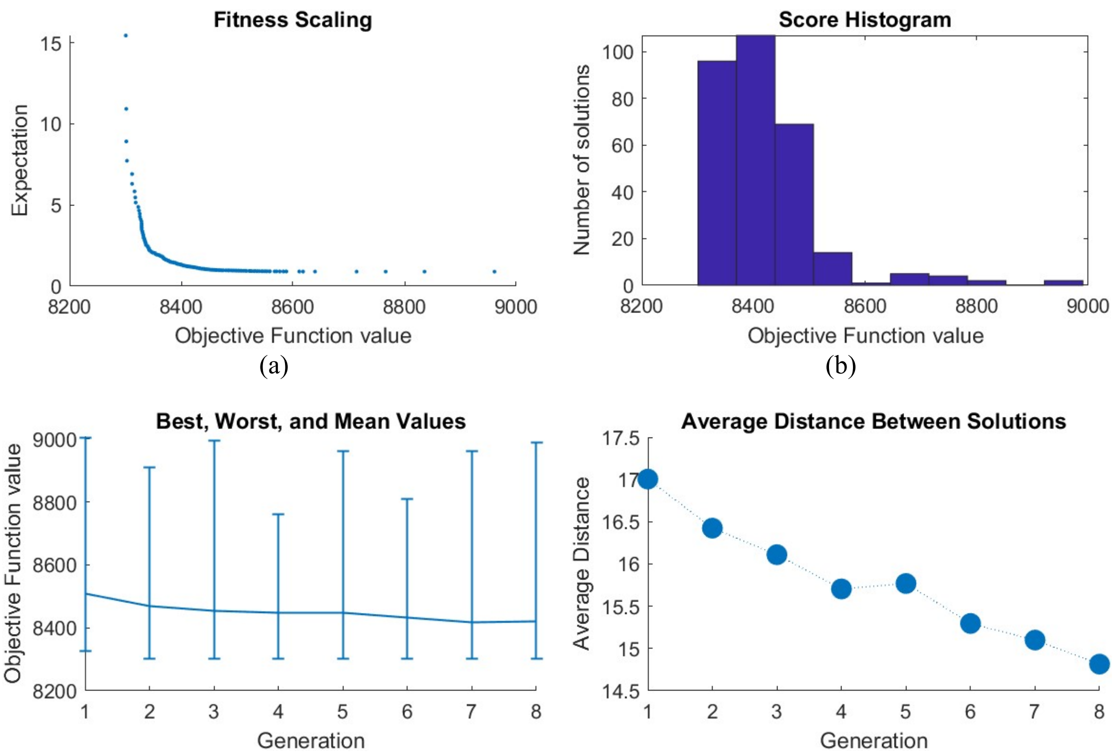
Figure 5.23 illustrates the process of finding the best lane layout under the GA framework throughout the generations. Figure 5.23 (a) shows the evolution of the objective function value – showing a very slow convergence - the process is stagnate overtime which the *stall* generations indicator from Table 5.3 corroborates. Yet, the mean (penalty) value is decreasing overtime. Figure 5.23 (b) shows the vector of the best network solution found in this experiment.



(a) (b)

Figure 5.23 – RL-NDP_SOF: experiment III output of the Porto case study: (a) GA objective (penalty) function; (b) best network solution.

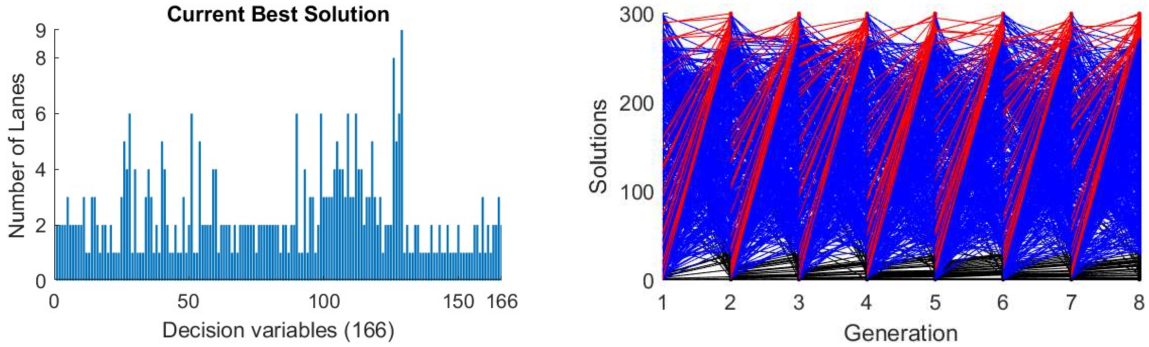
Figure 5.24 (a) shows the fitness scaling of the solutions found in the last iteration of the GA. Figure 5.24 (b) reveals that most solutions are concentrated around 8400 which indicates that the distance between solutions is very short – see Figure 5.24 (d). Figure 5.24 (c) shows the best, worst and mean values range in every generation – the non-convergence of the worst values is explained by the random *mutation* factor.



(a) (b) (c) (d)

Figure 5.24 – RL-NDP_SOF: experiment III output of the Porto case study: (a) fitness scaling; (b) score histogram (c) best, worst and mean values of every *population*; (d) average distance between solutions.

Figure 5.25 (a) depicts the number of network solutions (*children*) that derived from a previous network solution (*parent*). Figure 5.25 (b) shows the genealogy of the solutions during this process: blue color are the solutions created by *crossover*, black are the *elite* solutions, whereas red color are the solutions created by *mutation*.



(a) (b)

Figure 5.25 – RL-NDP_SOF: experiment III output of the Porto case study: (a) selection function; (b) genealogy of the solutions.

Figure 5.26 illustrates the lane layout found for the best solution found in this experiment III. Contrary to what happened in the previous experiments, this experiment tried less variations of the initial lane layout – as there are more red lines than in the previous figures Figure 5.14 and Figure 5.20. Green color illustrates the road links where a lane layout change happened. Red color reveals the links with reversible lanes where the previous lane layout was maintained. Grey color reveals that the links with a fixed lane layout where reversible lanes could not be implemented.

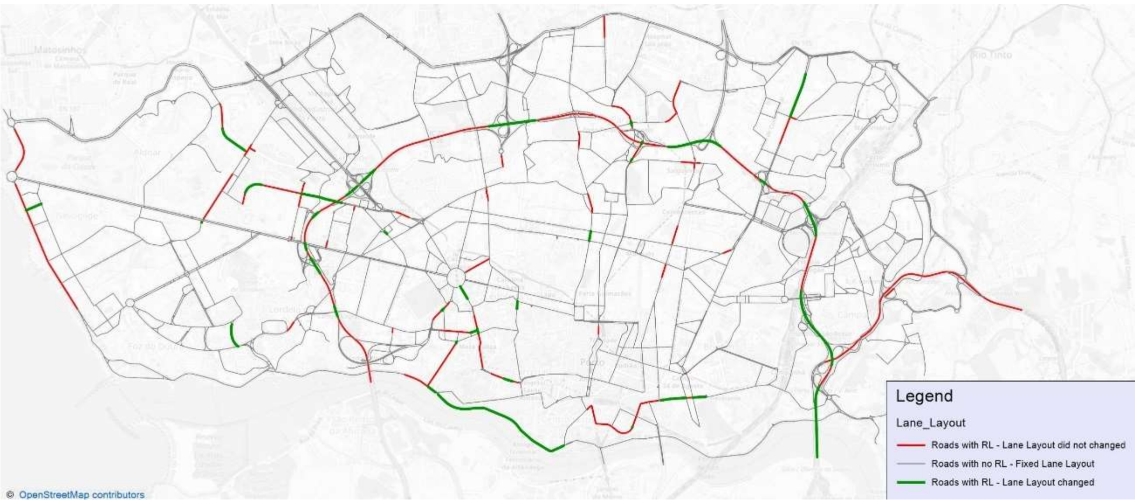


Figure 5.26 – Lane layout of the RL-NDP_SOF experiment III of the Porto case study (VISUM).

Figure 5.27 and Figure 5.28 illustrate the improvements in the traffic flow distribution in terms of the degree of saturation. Figure 5.27 tells whether the traffic assignment (degree of saturation) was improved or not. The road links who experienced improvement are drawn in thicker green lanes, which in this case are located in the main freeway and some major arterials.

Figure 5.28 illustrates the percentages of the degree of saturation improvement throughout the network. Overall the traffic flow distribution was improved with a degree of saturation reduction up to 25%. The major improvements are located in some nodes of the major freeway, with improvements up to 65%. On average, the improvement of the degree of saturation was 1.34% in the entire road network, while in roads that used reversible lanes the degree of saturation reduced on average 8.98%. The total number of reversible lanes was 130.

Figure 5.27 – Analysis of the traffic improvement in terms of the degree of saturation in the RL-NDP_SOF experiment III of the Porto case study (VISUM).

5.7. SUMMARY

This chapter proposed a simulation-optimization framework (SOF) for solving the previous RL-NDP in large road networks. The SOF was implemented in the Matlab environment with COM scripts establishing the connection with a macro-simulator (VISUM software) whose outputs are analyzed by GA. The contribution is focused on studying the implementation of reversible lanes in a large complex network with different hierarchy levels that limit the implementation of reversible lanes and several O-D pairs for travel demand.

Two scenarios were tested. Base Scenario O corresponds to the current situation as traffic runs under UE conditions without reversible lanes, i.e., there is no optimization routine. Scenario I with reversible lanes in some roads of the network is considered. The model was applied to the network of the city of Porto, for a single hour which is the most congested. However, given the complexity of case-study, the performance of the SOF performed three experiments with different GA configurations.

The network solutions were obtained with a satisfactory performance, especially when compared with Scenario O. The experiment I found a solution that reduced the overall total travel time of 23 hours, the experiment II found a solution that reduced 24 hours, and the experiment III found a solution that reduced 32 hours. The performance of the GA revealed that the experiment III found a very good solution in the 2nd generation – the problem did not converge much afterwards.

This chapter also revealed a new dimension of reversible lanes in the traffic system: overall the traffic flow distribution was improved, even in links where reversible lanes didn't exist. On average, the degree of saturation was reduced 9%, up to 65% in some roads, which corroborates with the results found in the numerical experiment of the previous chapter. On average, the improvement of the degree of saturation was 1.34% in the entire road network.

Overall, the SOF proved to be an easy tool to guide the reversible lane implementation, yet more advancements in the methodology are advisable to optimize the solution search process. As future work, more tests with randomness parameters, different shares of *mutation* and *crossover*, various number of solutions for the populations, and even different algorithms are suggested. Hybridizing the SOF by adding a neighborhood search algorithm in the local solution search process would be an asset for increasing the performance of the framework. Additionally, adding the delay in

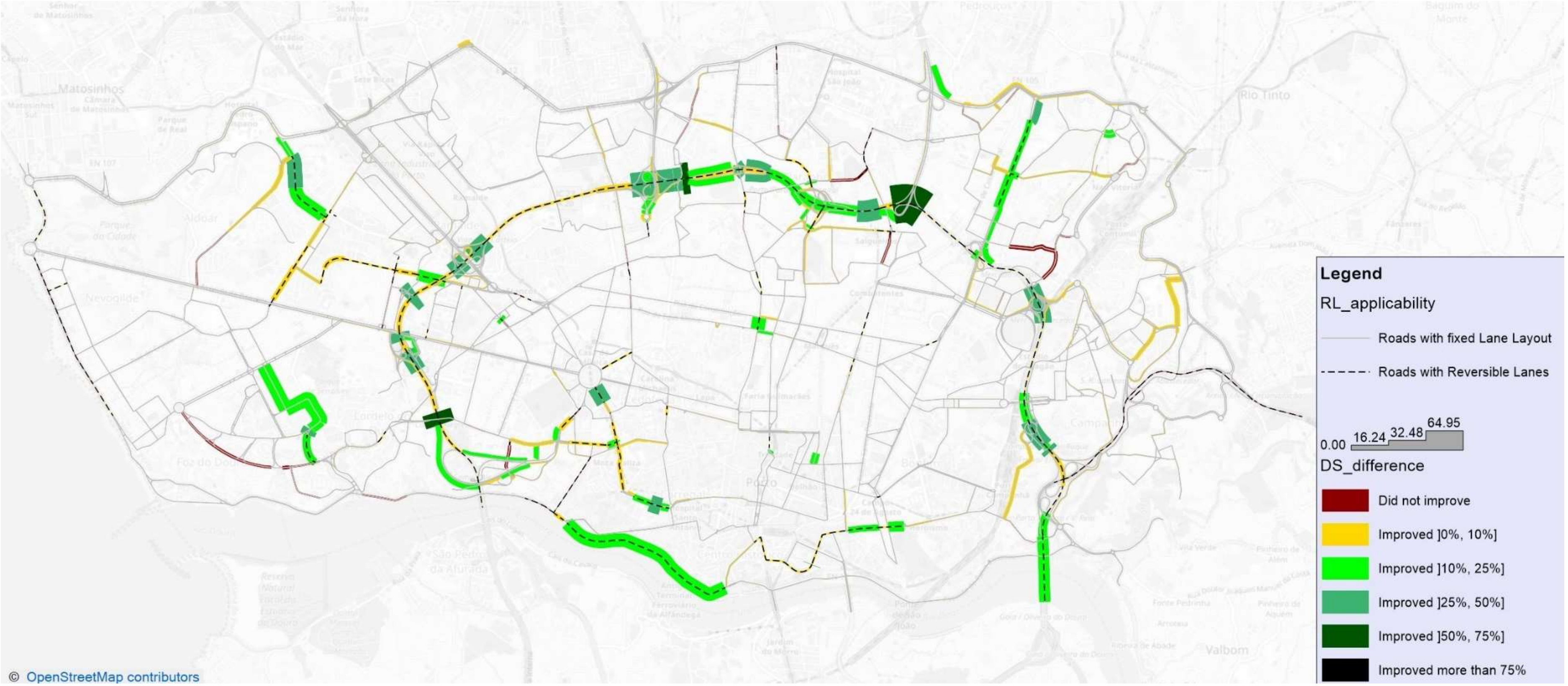


Figure 5.28 – Analysis of the percentage of the degree of saturation improvement in the RL-NDP_SOF experiment III of the Porto case study (extracted from VISUM).

every node in a scenario with AVs at a mesoscopic perspective (i.e., network-level) through impedance functions and studying its impacts on pollution.

In real-time, a similar framework to the one proposed could be applied only in several individual small scales to reduce the number of variables and the complexity of the problem and solve it in seconds or minutes. For instance, if each road (freeway) with V2I and reversible lanes received traffic data from the other hierarchical levels. Traffic assignment distribution would not be needed in real-time problems. In such a case, the flow variables provided by the VISUM software would be replaced by other traffic data sources.

6

CONCLUSIONS

6.1. KEY-FINDINGS

The main goal of this thesis is to aid the transport planning of urban metropolitan areas to engage in AVs technology and tackle urban congestion by improving the overall traffic system. The research goal acts on two levels: one supporting transport planners in the design of AV subnetworks and the other on supporting traffic engineers with a novel traffic control system centered on reversible lanes for automated traffic only. The general objectives of this thesis were set out to be the following: to study whether the segregation of mixed and automated traffic through dedicated roads is valuable for the system; to estimate the AVs' impact on traffic and congestion levels during the transition period; to evaluate the benefits of having a dynamic reversible lane approach applied in AV dedicated roads; to analyze the utility of centralized (system-optimal) AV paths on mitigating congestion. Henceforth, the main conclusions and key-findings from each chapter are introduced.

Chapter 2 «State of the art» presented the existent research developed around the topic of AVs. First, a brief presentation on the several AVs concepts and the explanation of the reasons why the term "automated vehicle" is considered the most accurate nowadays, reflecting the highest levels of automation (levels 4 and 5). Following, a literature review on the forthcoming impacts of AVs is presented which is divided into impacts on traffic, mobility, and urban environments. Finally, the deployment of AVs in urban areas is briefly reviewed for a transition period that revealed an increasing need for transport policy and the network design is seen as valuable for the future planning of AV traffic operation. The key-findings of this chapter are the following:

- Over the last decades, automated driving technology has developed at a fast track, and several levels of automation distinguish AVs. Research related to AVs upcoming impacts is quite dispersed, although far more developed on the traffic topic than on the mobility and urban environments topics. The conclusions have been somewhat consensual on AVs over level 3, positively impacting the traffic system from their platooning and efficiency skills. The literature review on the mobility impacts revealed that once AVs reach levels 4 and 5, increased travel demand is likely to happen that would eventually worsen congestion. The urban environmental impacts are highly vulnerable to these previous effects (traffic and mobility), although recent studies show that AVs might help road safety and reduce carbon emissions in urban areas.

- The literature review on the deployment of AVs in urban areas reinforces that it must be assumed a transition period to outline the best deployment until the full dissemination of AVs (levels 4 and 5). The level 4 automation reflects the most likely automation level in this "transition period" and that means that this would be the turning point when AVs might drive automatically yet requiring a human driver inside the vehicle. The place of non-AVs (human-driven vehicles) cannot be forgotten. Regulations promoting the deployment of AVs in urban areas are missing, especially at a transport planning by a smart traffic operation perspective – the existent regulations are mostly focused on the definition of AVs levels of automation and guidance for testing AVs in real environments.
- It is notorious the need to study the AVs topic in urban areas at the network level to improve mobility and tackle the congestion problem accrued by higher travel demand and high population density. As AVs level 4 and 5 are not yet a reality, academia represents the opportunity to study and evaluate future transport policy alternatives to help the governments state proactive directives for policy actions in the future.
- Network design is a viable methodology to first study transport policy in the context of AVs in a proactive way. Two levels are embedded in this methodology, the municipality decision (policy action/strategy) and the consequential network performance that accrues from the citizens' behavior (traffic assignment).

Chapter 3 «Subnetworks for Automated Vehicles» introduced a transport planning problem of designing AV subnetworks during a transition period where AVs coexist with CVs – AV penetration rate evolves from 0% to 100%. A road network design problem (RNDP) is presented, selecting dedicated roads for AVs inside an urban network. The road investment effect on the RNDP is discussed. The model is applied to a case study of the city of Delft, in the Netherlands. The design for the peak hour and the whole day is debated. The key-findings of this chapter are the following:

- In the peak-hour analysis, AVs subnetworks first appear in zones that are highly demanded (residential areas) and in which there is a compromise between the AV benefits, in terms of travel time cost savings, and CV detours. Through the experiments done at each penetration rate, it was found that for the considered peak-hour, AV subnetworks are a useful strategy to reduce the overall congestion and generalized costs, while degrading congestion in the surroundings of the AV subnetworks. From the experiments on the planning approaches designed for the peak-hour, the following conclusions can be drawn: when road investment for infrastructure improvement is part of the problem, the incremental planning strategy seems the best strategy; the hybrid planning strategy is preferred when road investment is irrelevant. The long-term planning strategy should only be initiated when at least 25% of the vehicle fleet is automated in order to avoid extra generalized costs and CV detour in the early stages of AVs deployment. CV detour might be considered the tie-breaking criteria regarding the decision of the best planning strategy - incremental planning is the strategy that mitigates the most this problem.
- The implications of the peak-hour design in the remaining hours of the day were tested. Since the travel demand of the peak-hour does not coincide with the remaining demand throughout the day, the design for the peak hour implied that CV owners with other trips routines and would be constrained to enter or leave AV subnetworks, so an alternative mode of transport is required - walking was evaluated in this sense. Nevertheless, this situation (alternative mode required) only happened for significant shares of AVs (75% onwards) from the large AV subnetworks at this stage.
- The design for the whole day revealed a substantial decrease in the total travel costs for the whole day, as it optimizes the road network configuration for the daily demand. From the experiments on the planning approaches, the following conclusions can be drawn:
    - When road investment for infrastructure improvement is part of the problem, the hybrid planning is very satisfactory as it is the strategy that most mitigates the CV detour problem. It should be applied mainly if AV subnetworks only appear after AVs have already a significant share of the vehicle fleet (over AV penetration rates of 25%). Nevertheless, the long-term planning strategy is preferred because it distributes the road investment throughout the period since the early stages of deployment (10%).

- When road investment is not evaluated, the LTP is indicated when AVs subnetworks first start to be designed in the second half of the transition period (50% of AVs onwards). At that stage, i.e., when AVs and CVs are equally balanced (50%), CVs experience more congestion (30% increased delay). The hybrid here revealed a good performance and can be used since the first half of the transition period, but then CV detour occurs when AVs are 90% of the fleet.

▪ AV subnetworks have an essential role in segregating automated from mixed traffic and its design first start in lower capacity roads, deviating AVs to shorter routes (lower distances) on lower speed roads (higher travel times as the AVs value of travel time reduces). The reduction of the AVs value of travel time might conduct the dispersion of the AVs traffic, leaving highway arterials and driving in smaller urban roads. In this sense, the creation of AV subnetworks in these zones might be welcomed, since it "takes out" AVs from regular roads where CVs are used to drive and lower speeds could be positive at a road safety perspective in urban areas, especially when the first AVs level 4 start to be deployed. Overall, we may conclude that AV subnetworks should be designed once AVs reach 25%, but the performance of the system will only show positive results when AVs are over 50% of the vehicle fleet.

▪ Nevertheless, the RNDP-AVs also depends on the AV demand diffusion over time because it will pressure the road network with more traffic flow and push forward/accelerate the creation of AV subnetworks by influencing the time lag between design stages. For instance, if the time lag from 1% to 50% of AVs is much longer than the time lag from 50% to 90% of AVs, the CV detour would be very present, which turns the incremental the best strategy to be considered regardless the road investment consideration.

Chapter 4 «Reversible Lanes for Automated Traffic» discusses the traffic operation of AVs working in dedicated infrastructure that carries V2I connectivity – only possible in smart cities. An optimization problem of reversible lanes applied at the network level is presented. In addition, it is debated whether a centralized traffic control system should (not) take control over AVs paths. The model is applied to a case study of the city of Delft, in the Netherlands, for a penetration rate of 100% of AVs. The key-findings of this chapter are the following:

▪ Reversible lanes have the potential to reduce the degree of saturation, congestion, congested roads, travel times and delay, regardless of the traffic assignment considered. However, travel distance is sensitive to the type of traffic assignment. Within UE, the total distance reduces 0.4% while within SO it increases by 2.0%. In peak hours, the SO scenario revealed to have a better performance in most of the traffic performance indicators. The dual scenario combining UE or SO at each hour showed a total distance increase of 1.2%. In this optimal scenario, congested roads were reduced by 40.1%, total travel times and delay decreased by 8.0% and 18.8%, respectively.

▪ The study of the spatial location of congestion and variability of this strategy revealed that reversible lanes naturally vary more frequently in zones where demand is imbalanced throughout the day (residential areas). In city centers, congestion can still be reduced by reversible lanes, though congested roads only disappear in the SO scenario.

▪ In terms of reducing total travel times, delay, and traffic congestion located in the city center, the SO scenario confirmed to be the ideal one. Notwithstanding, the mixed UE-SO scenario appears to be the best on reducing congested roads throughout the network all over the day.

▪ As municipalities are mostly concerned with congested road links and their influence on air pollution and energy consumption, a future with SO paths that might be a reality to achieving sustainability goals. The application of the RL-NDP model points for the need for investment to inform AVs of their SO paths and make the SO traffic assignment a reality.

▪ The RL-NDP model can be adjusted to some of the prospective benefits of the automated driving features, such as the chance to have smaller lanes that will raise the overall existing road capacity.

Chapter 5 «A Simulation-optimization Framework for the Reversible Lane problem on real city size networks» presents a framework that joins both simulation and optimization in a single framework to solve road network design problems in large urban areas. The main difference of this chapter from the others in that the main aim of the chapter is to verify how road network design problems can be solved when larger and complex networks exist. Contrariwise, chapters 3 and 4 tested and estimated novel ideas of road network design problems in a case study that mathematical programming was able to solve. This chapter proposed a simulation-optimization framework (SOF) for solving the previous RL-NDP (chapter 4) in a larger case study: the city of Porto in Portugal. The key-findings of this chapter are the following:

- The SOF, implemented in the Matlab environment with VISUM COM scripts and GA, proved to be an easy tool to guide the reversible lane implementation, yet more advancements in the methodology are advisable to optimize the solution search process (e.g., randomness in the creation of solutions).
- SOF establishing a connection between simulation (VISUM software) and optimization (GA) routines imply extended calculation times since the simulation routine is called every time a solution is generated to calculate the objective function of that solution.
- Given the running time as stopping criteria and an adjustable *mutation* factor, the solutions obtained in all three experiments were satisfactory. The experiment I found a solution that reduced the travel time of 23 hours comparatively with scenario O, the experiment II found a solution that reduced total travel time of 24 hours, while the last experiment II found a solution that reduced total travel time of 32 hours. The analysis of the GA outputs revealed that, in the experiment III, the problem was found in stagnation, and the solution found until that point was probably very close to a local optimum.
- By implementing reversible lanes in a part of the network, the overall traffic flow distribution induced a lower degree of saturation even in links where reversible lanes didn't exist, improving the overall traffic in the road network. This might indicate that an increase of capacity in the main freeways might have an influence on the paths for each O-D pair.
- On average, the degree of saturation was reduced by 1.34%, up to 65%. In roads that implemented reversible lanes, the reduction was on average 8.98%. These results corroborate with the ones from the numerical experiment of previous chapter 4.

Overall, this thesis offered a new perspective on how to deal with the deployment of AVs and potentiate their benefits in urban areas. The first of this thesis supports the transport planning of urban areas through a model that designs AV subnetworks inside urban road networks throughout this transition period (i.e., CVs are present in the road network). Then, the second part of this thesis supports the traffic operation and management through a model that decides for each period (i.e., hour) how many lanes each direction should have. While the first part is intended for the whole transition period, the second part is intended to be applied inside AV subnetworks only – and the experiments done in this thesis present the results for the full deployment of AVs (penetration rate of 100%). The thesis ends with a framework that joins simulation and optimization techniques to solve larger road network design problems.

The first main conclusion of this thesis is that AV subnetworks will be particularly useful in the second half of the transition period (AVs penetration rate over 50%), in order to reduce travel costs that includes also a road investment on every dedicated road for AVs. The road investment clearly constraints the development of AV subnetworks. The devaluation of the value of travel time in AV passengers will allow starting designing AV subnetworks in shorter roads that have lower speeds (higher travel times) and transfer AV traffic out of the main arterials where CVs will continue to circulate.

The second main conclusion of this thesis is that reversible lanes have enormous potential for reducing travel times up to 9% at the end of the deployment period (100% of AVs). Through chapters 4 and 5, it has been demonstrated that reversible lanes can be put in practice and improve traffic efficiency all over the network, influencing the paths chosen for each O-D pair.

As one might conclude, the contributions of the thesis are mostly directed on benefiting society at the transportation level, by giving a scientific viewpoint for supporting policymakers with two promising strategies, the segregation of AVs circulation from the remaining traffic, and the implementation of reversible lanes, that could be applied in the next decades to embrace the deployment of AVs in urban areas.

6.2. Limitations and Future research perspectives

Although AVs level 4 and 5 are not yet a reality, this thesis focuses on problems that will likely occur in the next few decades. In the first part of the thesis, the application of the RNDP-AVs model to the Delft case study points to the need of designing a subnetwork for AVs. In the second part of the thesis, the application of the RL-NDP model to the Delft case study also points to the need of implementing reversible lanes in dedicated infrastructure to conduct AVs traffic in the most efficient way.

In chapter 3, the RNDP-AVs model related to AV subnetworks creation was formulated with the introduction of some simplifications and assumptions, for example, a constant mixed traffic efficiency coefficient and a constant road investment per kilometer, an extended model joining together the decision AV subnetworks and strategic location problem for V2I communication sites (5 km of radius), as well with traffic efficiency parameters more accurate, perhaps could be solved through heuristic methods, though more computationally costly to solve and the optimal solution might not be guaranteed. An improvement could be taking public transport as another alternative mode of transport, but it would involve bus routes and its scheduling problem, transforming the whole road network design problem into a massive combinatorial transit assignment problem. Moreover, it is also possible to add improvements such as other cost components involving pollution, noise reduction, or other benefits, for example, freeing space in the city center (e.g., parking and gas stations).

In chapter 4, the RL-NDP model related to the reversible lanes traffic operation decision was formulated with the introduction of some simplifications and assumptions; for example, the time for the lane adjustment between the different hours is not considered. Also, the model simplified the dynamic of the reversible lanes' strategy in every intersection, ignoring the number of turns which could generate a delay in the nodes. Also, as future work, adding the delay in every node in a scenario with AVs at a macroscopic perspective (i.e., network level) and studying the impacts on pollution. Nevertheless, the RL-NDP model can be adjusted to some of the prospective benefits of the automated driving features, such as the chance to have narrower lanes that will increase the overall existing road capacity.

In chapter 5, the simulation-optimization framework applied a RNDP in a larger and complex case-study, the city of Porto, and that framework was applied to the reversible lanes problem. As future work, more tests with randomness parameters in the GA with different shares of *mutation* and *crossover*, and testing different algorithms are suggested. Hybridizing the SOF by adding a neighborhood search algorithm in the local solution search process would be an asset for increasing the performance of the framework. Additionally, studying the performance of the reversible lanes' strategy with and without the effect of impedance functions in every node (e.g., the delay from traffic lights) would validate the numerical experiment done in the previous chapter 4 that didn't consider that effect.

Correspondingly, studying the AV subnetworks problem together with the reversible lanes would be very advantageous, especially in the beginning of the transition period. The application of the RNDP-AVs model revealed that even considering an AVs increasing traffic efficiency, the creation of AV subnetworks that focused on the minimization of total travel costs takes advantages of the decreasing value of AVs travel time to induce longer AV trips (time) at the beginning of the deployment transition period. Perhaps implementing together dedicated infrastructure for AVs with reversible lanes would mitigate this travel time increase for both CV and AV passengers in the early stages of AVs deployment.

The whole problem would be more complex to be solved – only possible through a simulation-optimization framework like the one that has been proposed.

With respect to the methodologies implemented in this thesis, two approaches were taken to solve RNDPs: optimization that used mathematical programming and simulation-optimization that used a macroscopic simulator and metaheuristics.

The complexity of any RNDP is due to the non-linearity characteristics of the problem and the dimension of the road network, which influences the decision upon the appropriate methodology. Methodologies involving optimization-only, like mathematical programming and (meta)heuristics, are limited when one of these two factors occur. Yet, when the problem is non-linear, mathematical programming is able to guarantee a global optimum whereas (meta)heuristics don't. Furthermore, methodologies involving simulation and optimization involve two methods that work together to find the best optimal solution and usually do not guarantee a global optimal. In this case, the optimization routine is only possible to use (meta)heuristics that generates solutions to be tested in the simulator that returns the outputs needed to estimate the value of the objective function of that solution. Nevertheless, in both methodological approaches, the computer capacity has a crucial role in the calculation time.

Therefore, from a practical point-of-view, optimization-only is only possible to use for the simplest and parsimony RNDP models. For smaller or simplified road networks with a fair numerical structure of the problem, optimization is more advisable since it solves the RNDPs faster than simulation-optimization, as it calls the simulation routine each time a feasible solution is generated. However, for larger and complex road networks, simulation-optimization is the only alternative. Optimization-only is unreasonable (almost impossible) and computationally expensive for large numerical structures – especially the traffic assignment problem that would lead to unreasonable calculation times. In such cases, the simulation routine solves this lower-level problem in a much faster way than mathematical programming. Yet, the upper-level problem is the one that generates the solutions to be tested in the simulation and the iterative process might be taking to much time. Several trials are needed to improve the generation of solutions process from the optimization routine.

The main limitations found while doing this thesis were: the computer capacity, software licenses, compatibility amongst software, transference, and interpretation of data, and time.

6.3.PUBLICATIONS SUMMARY

Most of the research developed in these last 4 years resulted in several scientific publications and was discussed in several international and national conferences, between 2016 and 2019. These are listed below:

Journals – Articles

- **Article 1**
  Conceição L., Correia G., Tavares J.P. "A road network design problem for the deployment of automated vehicles in urban networks: a nonlinear programming mathematical model" 2019 (submitted to the Journal of Intelligent Transportation Systems: Technology, Planning, and Operations) – *Chapter3*
- **Article 2**
  Conceição L., Correia G., Tavares J.P. "The reversible lane network design problem (RLNDP) for smart cities with automated traffic" published in 08-02-2020 Sustainability Journal 2020. 12 1226 (DOI: 10.3390/su12031226) – *Chapter4*

- **Article 3**
  Conceição L., Correia G., Tavares J.P. “Reversible lanes in large-scale road network design problems: a simulation-optimization framework” 2020 (to be submitted) – *Chapter5*
- Article 4
  Conceição L., Tavares J.P. “Envisioning transport policy in a future with autonomous vehicles: a brief overview” accepted on 10-04-2020 to IEEE Potentials – *Chapter2*

Table 6.1 corresponds to the hypothesis tested on each major article, each focusing on answering the corresponding research questions introduced in previous Chapter 1, section 1.2.3.

Table 6.1 – Articles and research questions correlation

	Article 1	Article 2	Article 3
RQ1	X		
RQ2		X	X
RQ3		X	

Conference Presentations – Full paper

1. Conceição L., Rossetti R.. "Multivariate modelling for autonomous vehicles: Research trends in perspective." 2016 IEEE Intelligent Transportation Systems Conference (ITSC) Rio de Janeiro, Brazil. DOI: 10.1109/ITSC.2016.7795536 – *Chapter 2*
2. Conceição L., Correia G., Tavares J.P. “The deployment of automated vehicles in urban transport systems: a methodology to design dedicated zones” EWGT conference. Budapest, Hungary. Transportation Research Procedia 27, 230-237, EWGT 2017 DOI: 10.1016/j.trpro.2017.12.025 – *Chapter3*
3. Conceição L., Correia G., Tavares J.P. “Inconveniences from the design of AV subnetworks: when walking is the only alternative” *(accepted for the 2020 EWGT conference) – Chapter3*

Conference Presentations – Abstracts, Short Papers and Posters

1. Conceição L., Correia G., Tavares J.P. “The Deployment of Automated Vehicles in Urban Transport Systems” CITTA General Assembly and 1st PhD Student Workshop, University of Coimbra, Portugal, November 17th, 2016 *(Abstract) – Chapter1*
2. Conceição L., Correia G., Tavares J.P. “The Deployment of Automated Vehicles in Urban Transport Systems” 14º Encontro do Grupo de Estudos em Transportes, Fatima, Portugal, February 21st, 2017 *(Abstract) – Chapter2*
3. Conceição, L. “The deployment of automated vehicles: a model to design dedicated roadways in urban centers”, TRAIL PhD Congress 2017, Utrecht, November 9th, 2017 *(Abstract) – Chapter3*
4. Conceição L., Correia G., Tavares J.P. “The Deployment of Automated Vehicles: Dedicated Zones as a Urban Planning Strategy”, SYSORM 2017, University of Granada, November 13th, 2017 *(Abstract)* URL: https://congresos.ugr.es/sysorm17/wp-content/uploads/sites/15/2017/12/ProceedingsSYSORM17.pdf – *Chapter3*
5. Conceição L., Correia G., Tavares J.P. “Automated Vehicles and the Transport Planning in Urban Environments” CITTA 11th Annual Conference on Planning Research: o Espaço Lusófono e o Futuro das Cidades, University of Porto, Portugal, October 24th, 2018 *(Short Paper) – Chapter3*

6. Conceição L., Tavares J.P., Correia G. “The Deployment of Automated Vehicles in Urban Environments: Traffic Strategies in a Safety Perspective”, 31ST ICTCT conference, University of Porto, October 25th, 2018 *(Abstract)* URL: https://www.ictct.net/wp-content/uploads/ICTCT_Book_of_abstracts_Porto.pdf – *Chapter2*

7. Conceição L., Correia G., Tavares J.P. “Automated vehicles in urban environments: dedicated roads as a transport planning strategy” GET – 16th Conference, Penela, Portugal, January 8th, 2019 *(Abstract) – Chapter3*

8. Conceição L., Correia G., Tavares J.P. “How transport planning in urban regions shall be addressed to integrate automated vehicles reality: a mixed traffic analysis” NECTAR conference, Towards Human Scale Cities – Open and Happy, University of Helsinki, Finland June 6th, 2019 *(Short Paper)*URL: https://www.helsinki.fi/sites/default/files/atoms/files/nectar2019_abstract_book.pdf – *Chapter3*

9. Conceição L., Correia G., Tavares J.P. “The future of smart cities with automated vehicles: benefits from reversible lanes in a connected traffic control system” MIT Portugal conference September 2019, University of Azores, Portugal September 30th, 2019 *(Poster) – Chapter4*

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APPENDIX A

A.1. THE MIXED INTEGER PROGRAMMING (MIP) MODEL

This section presents the first formulation to solve the RNDP-AVs by mathematical programming (Conceição et al., 2017). Here, the objective function maximizes the benefits based on a traffic performance indicator, the average travel time at each road link. A walking penalty might occur when CVs trespass AV zones and a road investment is considered at each AV dedicated road.

The assumptions of the MIP model are:

- The trips performed are either done by AVs or CVs, according to their penetration rate;
- Each trip is assigned to one car (a person by car);
- An AV is considered to be level 4 (SAE, 2018) which means that inside dedicated areas they drive automatically;
- In a trip done in a CV, when the car reaches the boarders of the dedicated area, the traveler may walk toward the destination;
- AVs travel more efficiently than CVs, allowing an increase of capacity of the roadway;
- No external trips to the city are considered in the network.

The model is formulated as a discrete integer programming problem, as follows:

Sets

$\boldsymbol{I} = (1, \ldots, i, \ldots, I)$:	set of notes in the network, where I is the number of nodes.
$\boldsymbol{R} = \{\ldots, (i,j), \ldots\}\ \forall i,j \in I \cap i{\neq}j$:	set of arcs of the road network where vehicles move.
$\boldsymbol{V} = \{AV, CV\}$:	type of vehicles (mode) in the network: AV and CV

Parameters

ρ: penetration rate of AVs on the vehicle fleet, between 0 and 1.

α: coefficient that reflects the efficiency of automated traffic on the road capacity, i.e. the number of CVs to which an AV corresponds to. Defined between 0 (an AV has no effect on traffic) and 1 (an AV is as efficient as a CV).

τ: walking speed, expressed in kilometers per hour.

μ parameter that reflects the "walking capacity" of the network

VOT:	value of travel time in monetary units per hour.
$TT^{\rho=0}$:	travel times when penetration rate is null, expressed in hours.
VOI:	value of investment for road upgrade in each dedicated road link, in monetary units.
D_{ij}^{v}:	trips of mode $v \in \boldsymbol{V}$ from an origin, node i, towards a destination, node j, $\forall\ i,j \in \boldsymbol{I}$.
t_{ij}^{min}:	minimum driving travel time in free-flow speed at each link $(i,j) \in \boldsymbol{R}$, expressed in hours.
t_{ij}^{max}:	maximum driving travel time from 10% of the free-flow speed at each link $(i,j) \in \boldsymbol{R}$, expressed in hours.
L_{ij}:	length of each link $(i,j) \in \boldsymbol{R}$, expressed in kilometres.
C_{ij}:	capacity of each link $(i,j) \in \boldsymbol{R}$, in vehicles for the period of analysis.

Decision variables

x_{ij} :	binary variable equal to 1 if link $(i,j) \in \boldsymbol{R}$ is assigned for AV only driving.
f_{ij}^{v} :	integer variable that corresponds to the flow of vehicles $v \in \boldsymbol{V}$ in each link $(i,j) \in \boldsymbol{R}$ and each pair $(o,d) \in \boldsymbol{P} \cap D_{od}^{m} > 0$.
w_{ij} :	integer variable that indicates the flow of CV trips which are not allowed in dedicated roads, and therefore, it represents the people who are walking towards their destination, in each link $(i,j) \in \boldsymbol{R}$
t_{ij}^{car}:	continuous variable that reflects the total car travel time (AV and CV) in each link $(i,j) \in \boldsymbol{R}$.
t_{ij}^{walk}:	continuous variable that reflects the total walking travel time in each link $(i,j) \in \boldsymbol{R}$.

Objective Function

$$\text{Max(Benefits)} = VOT * (TT_{\rho=0} - \sum_{(i,j)\in R} t_{ij}^{car}) - VOT \sum_{(i,j)\in R} t_{ij}^{walk} - VOI \sum_{(i,j)\in R} x_{ij} \tag{A.1}$$

The objective function (A.1) maximizes the benefits, expressed in monetary units, from having dedicated roads for AVs. The first component considers the travel time savings which is computed from a scenario where only CVs circulate and a scenario where a ratio of AVs and CVs exist. The second and third component compute penalties from having dedicated roads: extra walking travel times for CV users and road investment for municipalities.

Constraints

$$\sum_{j\in I} f_{ij}^{v} = \sum_{j\in I} D_{ij}^{v} \ , \forall\ i \in \boldsymbol{I} \tag{A.2}$$

$$\sum_{i\in I} f_{ij}^{v} = \sum_{i\in I} D_{ij}^{v} \ , \forall j \in \boldsymbol{I} \tag{A.3}$$

$$\sum_{i\in I} f_{ij}^{v} - \sum_{i\in I} f_{ji}^{v} = 0 \ , \forall\ j \in \boldsymbol{I} \tag{A.4}$$

$$f_{ij}^{AV} * \alpha + f_{ij}^{CV} \leq C_{ij} + x_{ij} * M \ , \forall\ (i,j) \in \boldsymbol{R} \tag{A.5}$$

$$f_{ij}^{AV} * \alpha \leq C_{ij} + (1 - x_{ij}) * M \ , \forall\ (i,j) \in \boldsymbol{R} \tag{A.6}$$

$$f_{ij}^{CV} \leq C_{ij}(1-\rho) \ , \forall\ (i,j) \in \boldsymbol{R} \tag{A.7}$$

$$f_{ij}^{AV} \leq C_{ij} * \rho \ , \forall\ (i,j) \in \boldsymbol{R} \tag{A.8}$$

$$w_{ij} \geq f_{ij}^{CV} - (1 - x_{ij}) * M \ \ , \forall\ (i,j) \in \boldsymbol{R} \tag{A.9}$$

$$w_{ij} \leq f_{ij}^{CV}, \forall (i,j) \in \boldsymbol{R} \tag{A.10}$$

$$w_{ij} \leq C_{ij} * x_{ij}, \forall (i,j) \in \boldsymbol{R} \tag{A.11}$$

$$x_{ij} \leq f_{ij}^{v}, \forall (i,j) \in \boldsymbol{R} \tag{A.12}$$

$$t_{ij}^{car} = t_{ij}^{min} + \frac{f_{ij}^{AV} * \alpha + f_{ij}^{CV} - w_{ij}}{C_{ij}} * \left(t_{ij}^{max} - t_{ij}^{min}\right), (i,j) \in \boldsymbol{R} \tag{A.13}$$

$$t_{ij}^{walk} = \frac{w_{ij}}{\mu} \cdot \frac{L_{ij}}{\tau} \tag{A.14}$$

$$x_{ij} \in \{1,0\}, \forall (i,j) \in \boldsymbol{R} \tag{A.15}$$

$$f_{ij}^{AV}, f_{ij}^{CV}, w_{ij} \in \mathbb{N}^0, \forall (i,j) \in \boldsymbol{R} \tag{A.16}$$

$$t_{ij}^{car}, t_{ij}^{walk} \in \mathbb{R}, \forall (i,j) \in \boldsymbol{R} \tag{A.17}$$

The objective function is subject to the constraints expressed between (A.2) and (A.17). Constraints (A.2) assure that trips are generated in the centroid nodes where trips start. Constraints (A.3) assure that trips are absorbed in the destination nodes. Constraints (A.4) assure the equilibrium in the nodes, i.e. the balance between the flow that arrives and departs must be null. Constraints (A.5) and (A.6) assure the capacity limitation in each link in the network for regular and dedicated road links, respectively. Constraint (A.7) assures that there is no CVs flow when the AV penetration rate is equal to 1. Constraints (A.8) assure that there is no AVs flow when the penetration rate is null. From constraints (A.9) to (A.11) the existence of a walking flow is assured when CVs that are not allowed to circulate inside AV zones and passengers are forced to park the vehicle and walk towards their destination. In detail, constraints (A.9) state that walking flow must be higher than CVs flow in dedicated road links, while constraints (A.10) forces to take that exact value as the conventional flow. Constraints (A.11) assure that walking flow only happens in AVs links, beyond those links it is null. Constraints (A.12) assure that dedicated roads only make sense where flow circulates. Equations (A.13) and (A.14) calculate the link travel times by car and walking, respectively. Constraints (A.15) to (A.17) set the domain of the decision variables.

NUMERICAL EXPERIMENTS IN A TESTING NETWORK

The MIP model was applied to a grid symmetrical network, composed of 49 nodes and 84 arcs with two ways of circulation. The trips were equally distributed in eight nodes (1,4,7,22,28,43,46,49) with the sole destination in the central node (25). In order to give some realism to the network, speed and capacity decrease towards the centre of the network. Since the central node is surrounded by just 4 links, the maximum number of trips was limited to the sum of those capacities for the traffic assignment period being considered

In the MIP model, the travel time function is linear. The minimum travel time in each link is calculated in free flow speed whereas the maximum travel time in each link occurs when capacity is reached and speed turns 10% of the free flow speed. Regarding the efficiency coefficient (α) that details the effect of AVs on traffic, it was considered that AVs benefit capacity of 25% all over the network. Calvert et al. (2011) found a benefit around 22 when penetration rate is 50%. The value of travel time was considered 10 monetary units per hour. The walking time considered a pedestrian speed of around 4 km/h. Note that walking capacity (μ) is needed to compare at the same units both car travel and walking time, which was considered 4000 persons. The cost for V2I infrastructure in each link was considered 300 monetary units.

The model was implemented in the Mosel language and solved using Xpress 7.7, an optimization tool that uses branch-and-bound for solving MIP problems (FICO, 2017). Each scenario was run in a computer with a processor of 2.9 GHz Intel Core i5 and 8GB RAM.

In a first experiment, the model minimizes the link travel times in the network, only considering car traffic, as expression (A.18) details.

$$\text{Min(sum of link travel times)} = \sum_{i,j \in I} t_{i,j} \tag{A.18}$$

Table A.1 – The effect of the penetration rate on the sum of link travel times

Penetration Rate	Sum of link travel times (min)	No. of dedicated links for AVs
0.00	208.83	0
0.10	116.07	15
0.25	128.16	15
0.50	148.33	16
0.75	168.50	17
0.90	180.60	19
1.00	188.67	0*

* In this scenario, all network is already for AVs only.

Table A.1 presents the results for different penetration rates. Congestion happens when there are no AVs in the network. Two patterns on the results can be distinguished. The first regards the scenario where the AVs percentage is 10% where the existence of dedicated links reduce significantly the travel times. Subsequently, that value slightly increase as more AVs enter in the network and the travel times inside dedicated zones slightly rise. The second pattern shows that when the penetration rate becomes significant, the need for AV dedicated links is obvious. It is also noticeable that the number of links for AV rises alongside with the penetration rate.

The second experiment, defined by the objective function (A.1), maximizes the benefits by selecting dedicated zones for AVs. Several stages were created varying the ratio of the number of AVs and CVs and Table A.2 presents the results.

Table A.2 – The effect of penetration rate on the societal benefits.

Penetration Rate	Benefit cost (monetary units)	No. of dedicated links for AV
0.00	6,666.67	0
0.10	2,498,227.70	14
0.25	2,216,831.15	14
0.50	1,747,602.67	14
0.75	1,278,407.32	14
0.90	996,800.00	14
1.00	813,333.33	0*

* In this scenario, all network is already for AVs only.

Similar to what happened in traffic analysis, the scenario with the highest benefits were achieved in the beginning of the AV deployment. Therefore, the pattern of travel times shown in the previous model are also present here. However, the number of links selected for AVs was lower in comparison with the previous experiment. Moreover, it seems that the penetration rate does not have effect on the number of links selected for AVs like in the previous experiment. Both situations were expected to happen since other costs, such as walking time and V2I communication, are part of the objective function. Figure 1 presents the network for a scenario when ρ=0.75.

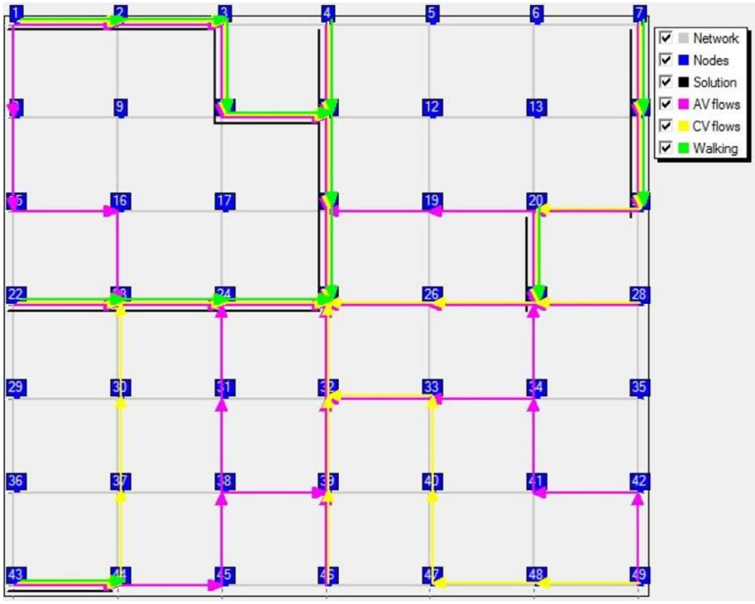


Figure A.1 – Optimal solution for the scenario with a high AV penetration rate ($\rho = 0.75$).

A.2. THE MIXED-INTEGER QUADRATIC PROGRAMMING (MIQP) MODEL

In this section, a MIQP mathematical model is proposed to solve the RNDP-AVs. The model decides the road links in which only fully-AVs are allowed to circulate for each deployment stage (penetration rate). The objective function comprises the minimization of generalized costs, which includes travel times for all the Origin-Destination (O-D) pairs of all travellers while driving and walking, plus a road investment for each dedicated road link. A system-optimum traffic assignment results naturally from the overall travel times' minimization as part of the objective function.

The assumptions of the problem are:

- A constant trip matrix exists for AV drivers and another one for CV drivers;
- No external trips to the city considered;
- Each trip is assigned to an AV or a CV;
- AVs circulate everywhere, whereas CVs circulation is prohibited within AV dedicated roads;
- AVs are assumed to be Level 4 (SAE, 2018), meaning they can be driven manually outside dedicated roads and will assume autopilot mode inside AV zones;
- Public authorities invest in each dedicated road to make it fit for AVs;
- A dedicated road comprises both directions dedicated to automated traffic;
- Every road link has sidewalks for pedestrians.

To formulate the MIQP model, the following notation is introduced:

Sets

$\boldsymbol{I} = (1, \ldots, i, \ldots, I)$:	set of notes in the network, where I is the number of nodes.
$\boldsymbol{O} = (1, \ldots, o, \ldots, O)$:	vector of origin nodes for the trips within the network, where O is the number of nodes.
$\boldsymbol{D} = (1, \ldots, d, \ldots, D)$:	vector of destination nodes of the trips within the network, where D is the number of nodes.
$\boldsymbol{R} = \{\ldots, (i, j), \ldots\}\ \forall i, j \in I \cap i{\neq}j$:	set of arcs of the road network where vehicles move.

$\boldsymbol{P} = \{\dots, (\boldsymbol{o}, \boldsymbol{d}), \dots\}\ \forall \boldsymbol{o} \in \boldsymbol{O} \cap \boldsymbol{d} \in \boldsymbol{D} \cap \boldsymbol{o} \neq \boldsymbol{d}$: set of origin-destination pairs that represent the trips demand in the network.

$\boldsymbol{V} = \{\boldsymbol{AV}, \boldsymbol{CV}\}$: set of vehicles present in the network: automated and conventional vehicles.

Parameters

ρ: penetration rate of AVs on the vehicle fleet, between 0 and 1.

α_{mixed}: coefficient that reflects the efficiency of automated traffic on the road capacity in mixed traffic conditions, i.e. the number of CVs to which an AV corresponds to. Defined between 0 (an AV has no effect on traffic) and 1 (an AV is like a CV).

$\alpha_{automated}$: coefficient that reflects the maximum efficiency of automated traffic on road capacity, e.g., in dedicated roads where only AVs are allowed, also between 0 and 1.

τ: walking speed, expressed in kilometers per hour.

VOT^{car}: value of travel time while travelling by car in monetary units per hour.

VOT^{walk}: value of travel time while walking in monetary units per hour.

VOI: value of investment for V2I communication, in each dedicated road, in monetary units per kilometer.

D_{od}^{v}: trips of mode $v \in \boldsymbol{V}$ from an origin, node o, towards a destination, node d, $\forall\ o \in \boldsymbol{O} \cap d \in \boldsymbol{D}$.

t_{ij}^{min}: minimum travel time in each road link $(i, j) \in \boldsymbol{R}$, expressed in hours.

t_{ij}^{max}: maximum travel time in each road link $(i, j) \in \boldsymbol{R}$, expressed in hours.

L_{ij}: length of each road link $(i, j) \in \boldsymbol{R}$, expressed in kilometres.

C_{ij}: capacity of each road link $(i, j) \in \boldsymbol{R}$, in vehicles for the period of analysis.

M: big number.

Decision variables

x_{ij} : binary variable equal to 1 if road link $(i, j) \in \boldsymbol{R}$ is assigned for AV only driving.

f_{ijod}^{v} : continuous variable that corresponds to the flow of vehicle $v \in \boldsymbol{V}$ in each link $(i, j) \in \boldsymbol{R}$ and each pair $(o, d) \in \boldsymbol{P} \cap D_{od}^{m} > 0$.

w_{ijod} : discrete variable that indicates the flow of CV trips which are not allowed in dedicated roads, and therefore, represent the people that are walking towards their destination, in each link $(i, j) \in \boldsymbol{R}$ and each pair $(o, d) \in \boldsymbol{P}$.

z_{ijod} : continuous variable that represents the flow of AVs when a link $(i, j) \in \boldsymbol{R}$ is dedicated for AVs only ($x_{ij} = 1$), regarding each O-D pair $(o, d) \in \boldsymbol{P}$.

The main decision variables are $x_{ij},\ f_{ijod}^{m}$.The remaining variables depend on the first through the constraints.

Objective Function

$$\text{Min(Cost)} = VOT^{car} \times \sum_{i,j\in I}\left[f_{ij} \times \left(t_{ij}^{min} + \frac{(t_{ij}^{max} - t_{ij}^{min})}{C_{ij}} \times f_{ij}\right)\right] + VOT^{walk} \times \sum_{i,j\in I}\left[\sum_{o,d\in \boldsymbol{I}} w_{ijod} \times \frac{L_{ij}}{\tau}\right] + VOI \times \sum_{i,j\in I} x_{ij} \times L_{ij} \quad \text{(A.19)}$$

The objective function (A.19) minimizes the costs of travel times (driving and walking) and a road investment cost, expressed in monetary units. The first component of the objective function computes the cost of driving travel times of all travelers. The travel time function is linear (see Figure A.2) between $]t_{ij}^{min}, t_{ij}^{max}]\ \forall(i,j) \in \boldsymbol{R} \cap f_{ij} > 0$. To perform the minimization of all users' travel time costs, the model computes the product of the total flow and the travel time at each link, leading to a quadratic term in the objective function. The second component of the objective function computes the cost associated with the walking travel times of the CV drivers. The walking travel times are computed in each link through the product between the walking flow and the walking travel time of that link (quotient of link length and walking speed).The third component of the objective function computes the total cost of V2I communication investment through the number and length of the dedicated road links.

Remind the reader that the value of travel time of both AVs and CVs is implicitly calculated in the objective function. Since the total flow involves a discount factor for AVs regarding their efficiency (different in mixed and dedicated roads), the value of travel time spent inside CVs is the (VOT^{car}) whereas a reduction of the AV travel time cost occurs both in dedicated links ($VOT^{car} * \alpha_{automated}$) and mixed links ($VOT^{car} * \alpha_{mixed}$).

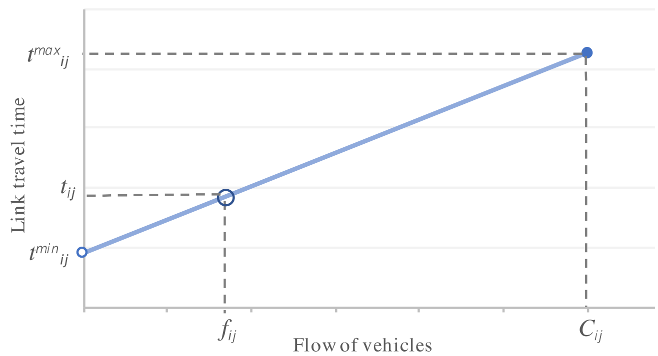


Figure A.2 – Driving travel time as a function of the flow of vehicles

Constraints

The objective function is subject to the following constraints (A.20)-(A.36).

$$\sum_{j\in \boldsymbol{I}} f_{ijid}^{v} = D_{id}^{v}, \forall\ i \in \boldsymbol{O}, d \in \boldsymbol{D}, v \in \boldsymbol{V} \quad \text{(A.20)}$$

$$\sum_{j\in \boldsymbol{I}} f_{jioi}^{v} = D_{oi}^{v}, \forall\ o \in \boldsymbol{O}, i \in \boldsymbol{D}, v \in \boldsymbol{V} \quad \text{(A.21)}$$

$$\sum_{i\in \boldsymbol{I}} f_{ijod}^{v} - \sum_{i\in \boldsymbol{I}} f_{jiod}^{v} = 0, \forall\ o \in \boldsymbol{O}, d \in \boldsymbol{D}, i \in \boldsymbol{I}, v \in \boldsymbol{V} \cap \mathrm{i} \neq o, d \quad \text{(A.22)}$$

$$\mathrm{f}_{ij} = \sum_{o,d\in \boldsymbol{I}} \left[\left(\alpha_{automated} * z_{ijod} + \alpha_{mixed} * (f_{ijod}^{AV} - z_{ijod})\right) + \left(f_{ijod}^{CV} - w_{ijod}\right)\right] \forall\ i,j \in \boldsymbol{I} \quad \text{(A.23)}$$

$$f_{ij} \leq C_{ij} \;\; \forall\, i,j \in \boldsymbol{I} \tag{A.24}$$

$$w_{ijod} \geq f_{ijod}^{CV} - M * (1 - x_{ij})\, , \forall\, \mathrm{i}, j \in \boldsymbol{I}, o \in \boldsymbol{O}, d \in \boldsymbol{D} \tag{A.25}$$

$$w_{ijod} \leq f_{ijod}^{CV}\, , \forall\, \mathrm{i}, j \in \boldsymbol{I}, o \in \boldsymbol{O}, d \in \boldsymbol{D} \tag{A.26}$$

$$w_{ijod} \leq w_{jiod} + C_{ij} * x_{ij}, \forall\, \mathrm{i}, j \in \boldsymbol{I}, o \in \boldsymbol{O}, d \in \boldsymbol{D}, i \neq o, d \tag{A.27}$$

$$\sum_{j \in \boldsymbol{I}} w_{jiod} \leq \sum_{j \in \boldsymbol{I}} w_{ijod}\, , \forall\, \mathrm{i}, j \in \boldsymbol{I}, o \in \boldsymbol{O}, d \in \boldsymbol{D}, i \neq o, d \tag{A.28}$$

$$w_{ojod} \leq D_{od}^{CV} * x_{oj}, \forall\, j \in \boldsymbol{I}, o \in \boldsymbol{O}, d \in \boldsymbol{D}, i \neq d \tag{A.29}$$

$$w_{idod} \leq \sum_{j \in \boldsymbol{I}} w_{jiod} + C_{id} * x_{id}, \forall\, i, j \in \boldsymbol{I}, o \in \boldsymbol{O}, d \in \boldsymbol{D}, i \neq d \tag{A.30}$$

$$z_{ijod} \leq Q_{ij} * x_{ji}\, , \forall\, i, j, o, d \in \boldsymbol{I} \tag{A.31}$$

$$z_{ijod} \leq f_{ijod}^{AV}\, , \forall\, i, j, o, d \in \boldsymbol{I} \tag{A.32}$$

$$z_{ijod} \geq f_{ijod}^{AV} - \mathrm{M} * (1 - x_{ij}), \forall\, i, j, o, d \in \boldsymbol{I} \tag{A.33}$$

$$x_{ij} = x_{ji}\, , \forall\, i, j \in \boldsymbol{I} \tag{A.34}$$

$$x_{ij} \in \{1,0\}\, , \forall\, (i,j) \in \boldsymbol{R} \tag{A.35}$$

$$f_{ij}, f_{ijod}^{v}, w_{ijod}, z_{ijod} \in \mathbb{N}\, , \forall\, (i,j) \in \boldsymbol{R}, o, d \in \boldsymbol{I} \tag{A.36}$$

Constraints (A.20)-(A.22) assure the traffic flow distribution. For each O-D pair, both AVs and CVs flows ($v \in \boldsymbol{V}$) are generated (A.20) in the origin node $o \in \boldsymbol{O}$, absorbed (A.21) in the destination node $d \in \boldsymbol{D}$ and there is a flow equilibrium (A.22) in the intermediate nodes, between the origin and destination, where the balance between the flow that arrives and departs must be null. Constraints (A.23) compute the total flow in each link $(i,j) \in \boldsymbol{R}$. The total flow includes the AVs flow (discounted by the efficiency benefit) and the flow of CVs (discounted by the walking flow). Constraints (A.24) limit the flow to the capacity of each link $(i,j) \in \boldsymbol{R}$. Constraints (A.25) to (A.30) define the walking flows. In detail, constraints (A.25) and (A.26) assure for each O-D pair that, in dedicated roads $(i,j) \in \boldsymbol{R} \cap x_{ij} = 1$, the walking flow is identical to the CV flow. In non-dedicated roads $(i,j) \in \boldsymbol{R} \cap x_{ij} = 0$, the range of walking flow is $\left[0;\, f_{ijod}^{CV}\right] \forall i, j, o, d \;\in\; \boldsymbol{I}$, yet the lower limit of that interval is naturally chosen since the nature of the model is the minimization. Constraints (A.27) assure that the walking flow of link $(i,j) \in \boldsymbol{R}$ is limited to the preceding flow of link $(j,i) \in \boldsymbol{R}$ and extra walking flow might be added if that link is dedicated. Constraints (A.28)guarantee the continuity of the walking flow through the network: walking flow departing node $i \in \boldsymbol{I}$ shall be higher than the walking flow arriving to that node, except in the origin and destination of each O-D pair. Constraints (A.29) assure that travelers shall start their trips in CVs and they can only start their trips by walking if their path starts inside a AV subnetwork. Constraints (A.30) give a valid inequality of the walking flow concerning the links around the destination node of each O-D pair. Constraints (A.31)-(A.33) compute variables z_{ijod} to distinguish efficiency between dedicated and non-dedicated roads (automated and mixed traffic, respectively). In a non-dedicated road, this variable is null by constraints (A.31) whereas, in a dedicated road, the variable assumes AV flow through constraints (A.32) and (A.33). Constraints (A.34) assure that a dedicated road for AVs comprises both directions of the road. Constraints (A.35) and (A.36) set the domain of the decision variables.

NUMERICAL EXPERIMENTS IN A TESTING NETWORK

A simple testing network is used for verification purposes of the MIQP formulation. The testing network (Figure A.3) has 7 arcs and 5 nodes (two ways circulation allowed). Three experiments are tested with 50% of AVs presence in the vehicle fleet:

- *Experiment A:* no road investment considered in the objective function to understand if the MIQP is working properly in producing the assignment within the network.
- *Experiment B:* road investment considered for dedicated roads: 2000 €/km. This experiment is important to validate the convergence of the model.
- *Experiment C:* does not consider a subnetwork at all. This experiment is useful to understand the congestion state without a subnetwork and evaluate how much this strategy can be beneficial for the system.

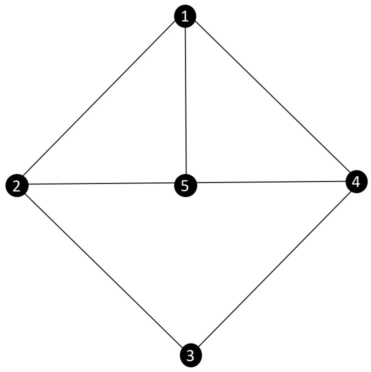


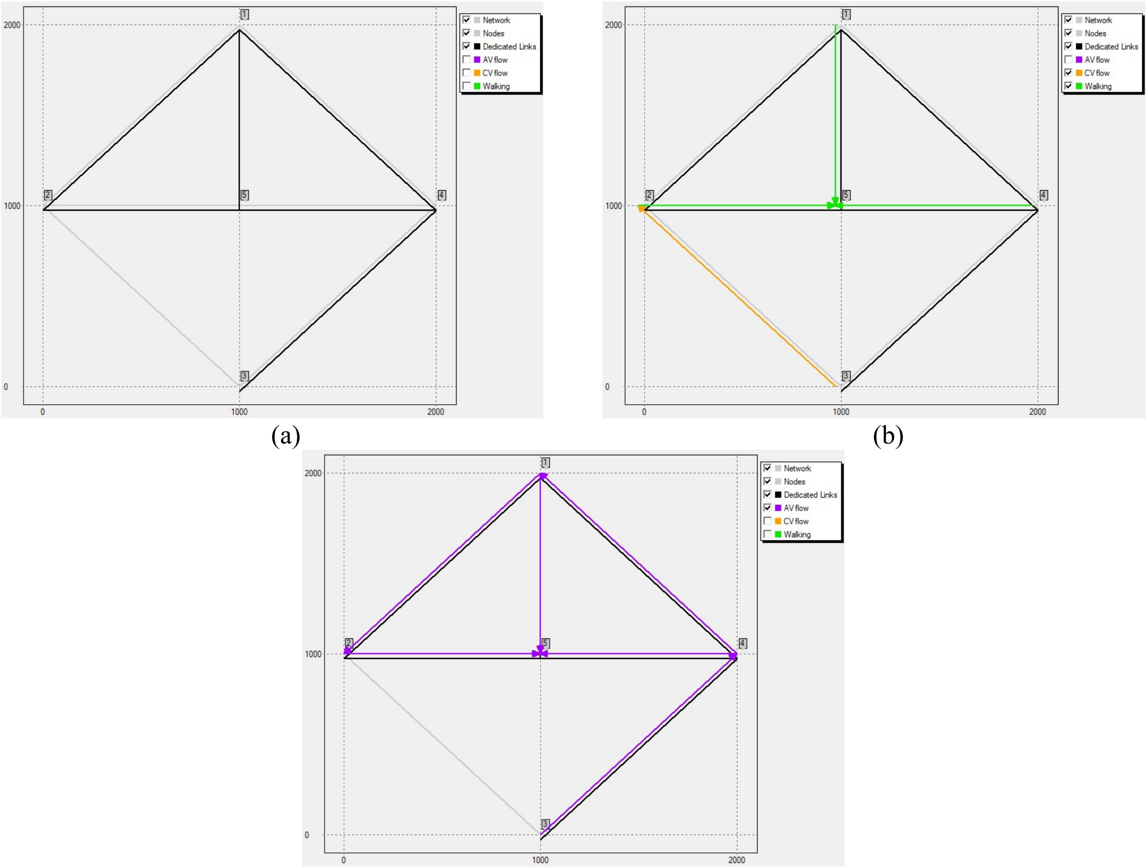
Figure A.3 – Testing network

The trips were equally distributed in four O-D pairs with 1000 trips each. The trip origins correspond to the external nodes (1,2,3,4) with a single destination, the central node (5). In order to give some realism to the problem, the internal links were given a free-flow speed of 30km/h and a capacity of 1000 veh/h, whereas the external links were given a free-flow speed of 50km/h and a capacity of 1500 veh/h. Furthermore, a value of travel time in the car of 10 €/h and walking of 12 €/h were used (Yap et al., 2016). The minimum travel time in each link was calculated under free-flow conditions, i.e., with maximum speed allowed, whereas the maximum travel time was calculated for a free-flow speed degradation of 90% when capacity is reached. The walking speed reflects the average pedestrian's speed on an empty sidewalk, 5.0 ft/s equivalent to 5.48 km/h (HCM, 2010). The efficiency coefficient in dedicated links was considered to be 1.68 in dedicated links and 1.22 in mixed links, given a penetration rate of 50% (Calvert et al., 2011).

The model has been implemented in the Mosel language and solved using Xpress 7.7 (FICO, 2014). This optimization tool solves quadratic problems, quite similar to the mixed integer programming (MIP), the only difference is that the initial LP relaxation is solved by the Newton-Barrier algorithm, not with the Simplex method. Then it performs MIQP root cutting and heuristics in the initial phase of the search solution and then Branch-and-Bound search, like in MIP problems. When the search is completed, the optimality of the final solution is guaranteed. Each scenario was run in a computer with a processor of 2.9 GHz Intel Core i5 and 8GB RAM. The model runs each experiment in just one second. The outputs obtained by FICO Xpress software are shown from Figure A.4 to Figure A.7.

The main results of the three experiments are summarized in Table A.5. Experiment A obtained an optimal solution where most of the network should be dedicated for AVs (six out of eight road links). In contrast, the optimal solution of experiment B only includes two out of the eight possible road links in the network. This was already expected since a subnetwork is not cost free in experiment B.

With respect to experiment A, Figure A.4-(a) depicts the subnetwork solution, Figure A.4-(b) illustrates the distribution of both CV and walking flows, and, lastly, Figure A.4-(c) shows the assignment of AV flows. For a penetration rate of 50%, an AVs subnetwork covers most of the network which means that this is a cost-efficient solution. Figure A.5 illustrates the convergence of the model through the MIP objective and gap charts obtained from Xpress.



(a) (b) (c)

Figure A.4 – Experiment A optimal solution: dedicated links, figure (a), and flow distribution of CV, walking and AV flor, figures (b) and (c) respectively.

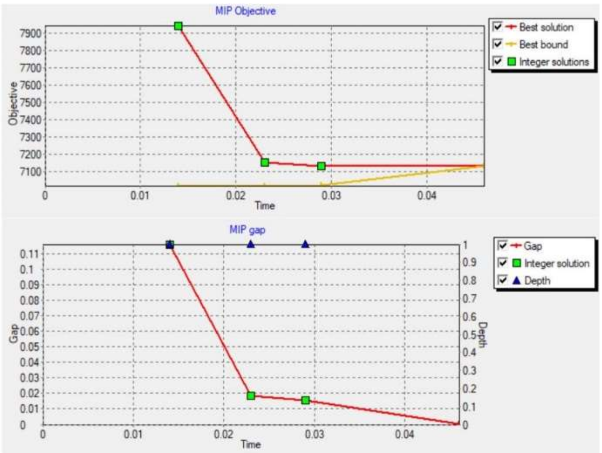


Figure A.5 – Experiment A: MIP objective and MIP gap.

The traffic assignment is confirmed through the following Table A.3 and Table A.4, detailing the decision variables of the optimal solution per arc $(i, j) \in \boldsymbol{R}$ and O-D pair $(o, d) \in \boldsymbol{P}$.

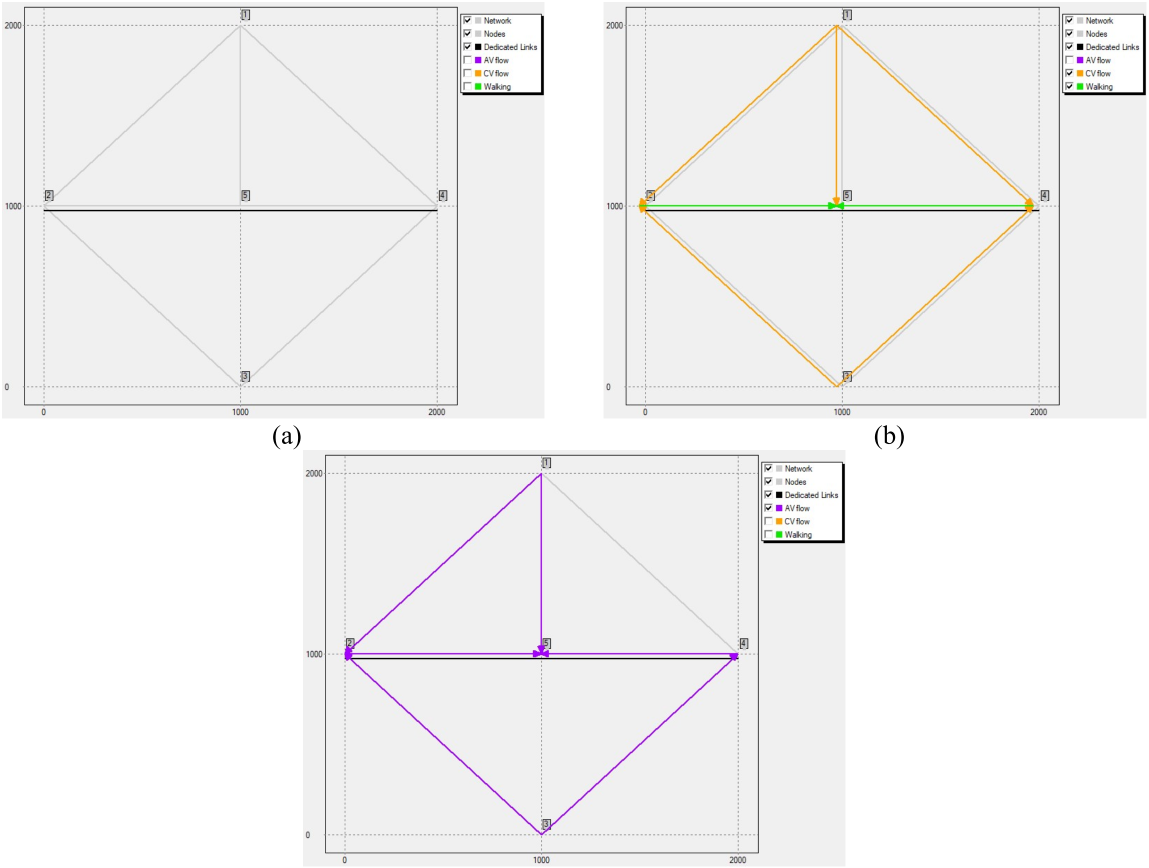
Table A.3 – Experiment A results per arc $(i, j) \in \boldsymbol{R}$.

Roadway link		Decision variables					
Node i	Node j	f_{ij}	$\sum_{(o,d)\in \boldsymbol{P}} f_{ijod}^{AV}$	$\sum_{(o,d)\in \boldsymbol{P}} z_{ijod}$	$\sum_{(o,d)\in \boldsymbol{P}} f_{ijod}^{CV}$	$\sum_{(o,d)\in \boldsymbol{P}} w_{ijod}$	x_{ij}
1	2	18	30	30	0	0	1
1	4	0	0	0	0	0	1
1	5	381	640	640	500	500	1
2	1	0	0	0	0	0	1
2	3	0	0	0	0	0	0
2	5	316	530	530	1000	1000	1
3	2	500	0	0	500	500	0
3	4	298	500	500	0	0	1
4	1	102	171	171	0	0	1
4	3	0	0	0	0	0	1
4	5	493	829	829	500	500	1
5	1	0	0	0	0	0	1
5	2	0	0	0	0	0	1
5	4	0	0	0	0	0	1

Table A.4 – Experiment A results per O-D pair, $(o, d) \in \boldsymbol{T}$.

Roadway link		Trip O-D pair		Decision variables				
Node i	Node j	Origin	Destination	f_{ijod}^{AV}	z_{ijod}	f_{ijod}^{CV}	w_{ijod}	x_{ij}
1	5	1	5	500	500	500	500	1
2	5	2	5	500	500	500	500	1
3	2	3	5	0	0	500	0	0
3	4	3	5	500	500	0	0	1
4	1	3	5	30	30	0	0	1
1	2	3	5	30	30	0	0	1
2	5	3	5	30	30	500	500	1
4	5	3	5	470	470	0	0	1
4	1	4	5	141	141	0	0	1
1	5	4	5	141	141	0	0	1
4	5	4	5	329	329	500	500	1

From experiment B, Figure A.6-(a) shows two roads selected to be dedicated for AVs in the center of the urban testing network (destination node). Figure A.6-(b) depicts CV and walking flows, whereas Figure A.6-(c) shows the AV flows distribution. In this small example, regular roads (such as link 3-2) have both AV and CV co-existing within mixed traffic, and dedicated roads (such as link 2-5) where CV traffic is transformed in walking flow and AV flow circulates autonomously.



(a) (b)

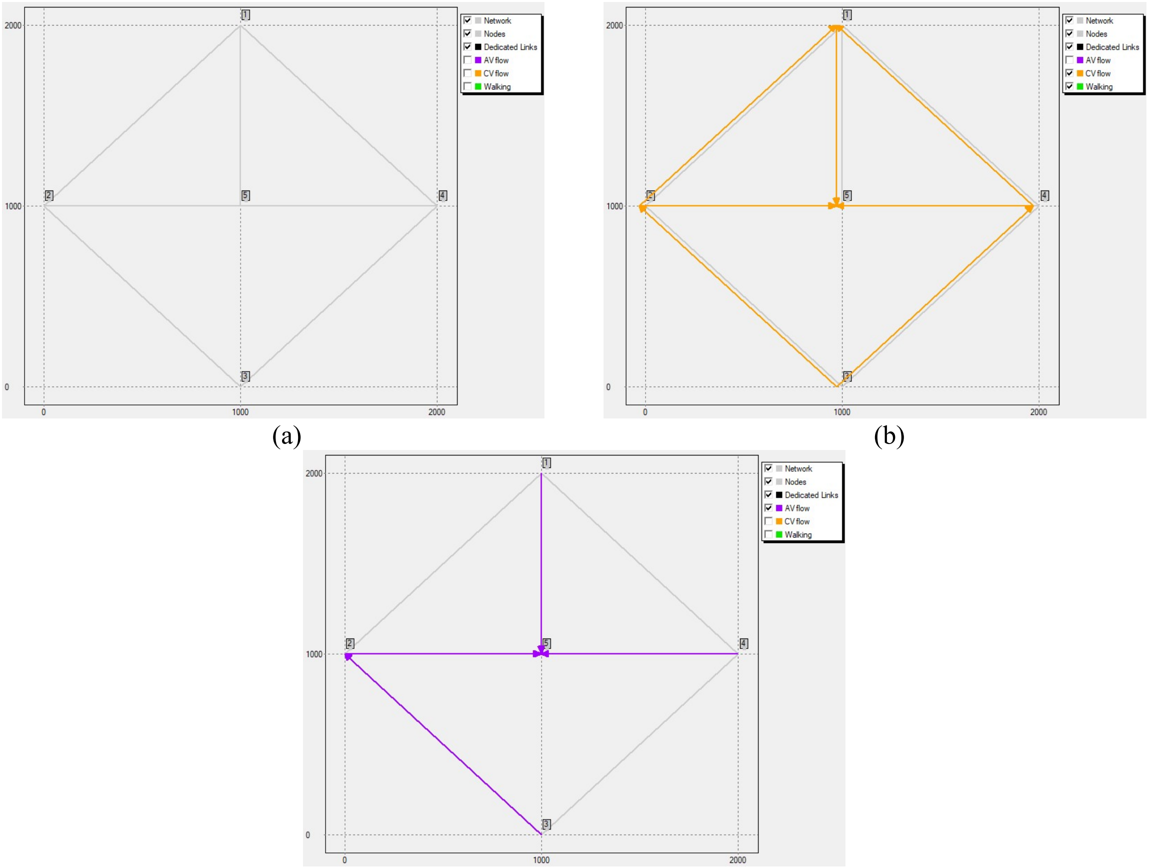
(c)

Figure A.6 – Experiment B optimal solution: dedicated links, figure (a), and distribution of CV, walking and AV flor, figures (b) and (c) respectively. Output from Xpress-MP.

As mentioned before, the experiment C does not consider any subnetwork dedicated for AVs. Figure A.7 (a) confirms the non-existence of the subnetwork whereas Figure A.7-(b) and (c) depict the CV and AV flow assignment, respectively.

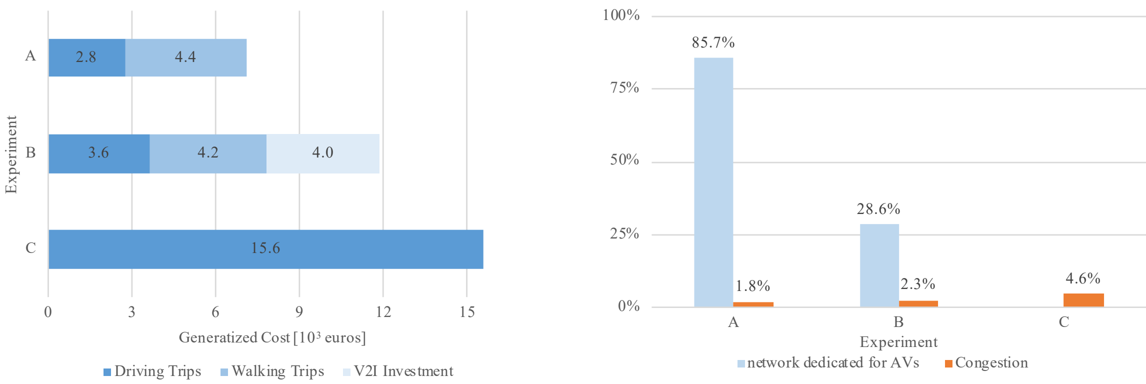
Figure A.8 summarizes the main results fromTable A.5. Figure A.8-(a) shows that a subnetwork reduces the generalized costs. Through Figure A.8-(b) it is possible to see that congestion is reduced to half by the presence of a subnetwork. Despite the road investment consideration, the congestion level of experiment B (2.3%) is comparable to experiment A (1.8%).

Regardless these statistics and results, this testing network was built on synthetic data, so no further conclusions can be taken. Both traffic assignment validation and formulation convergence have been accomplished.



(a) (b) (c)

Figure A.7 – Experiment C optimal solution: dedicated links, figure (a), and distribution of CV, walking and AV flor, figures (b) and (c) respectively. Output from Xpress-MP.



(a) Generalized costs of the three components from the objective function: driving, walking and V2I investment cost

(b) Overall percentage of AV subnetwork in the system and the corresponding percentage of congestion

Figure A.8 – Result analysis of the testing network experiments.

Table A.5 – Results from the testing network experiments

Experiment	Penetration Rate (ρ)	Generalized Costs: Objective Function [€]	Driving travel times costs [€]	Walking travel time costs [€]	Infrastructure V2I investment [€]	Network results: No. of Dedicated Links	Subnetwork [% of links]	Congestion[1] [%]	Delay [1] [h]	Delay reduction [2] [%]	Travel times: AV Driving [h veh]	CV Driving [h veh]	Walking (CV) [h veh]	Total [h veh]	Total Travel Time reduction [2] [%]	CV drivers who had to walk [%]	Model calculation time [s]
A	50%	7130.03	2750.47	4379.56	-	6	85.7%	1.8%	0.5	60.2%	364	58	365	787	117.66%	100.0%	1
B	50%	11860.84	3645.95	4214.89	4000.00	2	28.6%	2.3%	0.6	50.4%	395	97	351	844	103.17%	96.2%	1
C	50%	15595.80	15595.80	0.00	0	0	0.0%	4.6%	1.3	-	855	859	0	1714	-	0.0%	1

[1]Both congestion and delay are calculated based on the travel time driven above the free-flow speed.

[2] Comparison with experiment C where there is no subnetwork for AVs.