

Modeling the resilience of road networks in the presence of connected automated vehicles

Modeling the resilience of road networks in the presence of connected automated vehicles

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of Doctorat en sciences de l'ingénieur et technologie by

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Abstract

The modern road transport system is facing challenges that can affect its resilience. These challenges include the growth and greater diffusion of traffic flow linked to urbanization, infrastructure aging, the emergence of new technologies like navigation apps or Connected Automated Vehicles (CAVs), and environmental requirements. Due to such challenges, road user behavior is being profoundly transformed. In the past, road users relied on their own experience to select a path on the road network. However, with the increase in demand on the network, many users now use navigation apps to reduce their travel time and find the route with the shortest travel time. When CAVs enter the network of roads in the near future, they will have different driving and route choice behaviors compared to ordinary users.

The development of CAVs can affect the capacity of signalized intersections, weather condition data collection and prediction, driving behavior (e.g., headway, route choice behavior, etc.), adaptive cruise control performance, advanced traveler information systems, and the performance of traffic management systems. CAV users can differ in their route choice and driving behavior compared to Human Driven Vehicles (HDVs). The process of automation will probably lead to the massive use of CAVs in the medium term, which will have a significant impact on road network performance. Therefore, it is crucial to evaluate the road network performance when new types of users co-exist on the road network.

The performance of a transportation network is multifaceted, encompassing several key concepts, including reliability, vulnerability,

robustness, and resilience. Scholars have previously classified reliability, vulnerability, and robustness as integral components of resilience, underscoring the interrelated nature of these four concepts. Notably, the notion of resilience has garnered significant attention in recent scholarship, signifying its salience in contemporary discussions surrounding transportation network performance.

Several factors affect the network's resilience, including the capacity of the road network, vehicle routing, availability of alternative routes, and availability of information for road users. Given that CAVs improve road capacity, and traffic management centers can dynamically route them, it is crucial to study their potential benefits on the road network's resilience. Therefore, the aim of this study is to investigate the resilience of the Belgium road network in the presence of CAVs.

This study uses simulation-based methods to investigate the resilience of road networks in the presence of CAVs. To capture the effects of different road users on road network performance and test different traffic strategies, researchers implement traffic simulation. To examine the resilience of the network using simulation-based methods, the supply and demand data must be provided. The supply data refers to the data related to the roads, while the demand data refers to the number of trips taken on the road network in Belgium.

To meet the demand for travel data in Belgium, a travel demand model has been developed using only vehicle kilometer travelled, population, and distance data. This model has been validated with real data. Then, the relationship between supply and demand data is formulized by determining how travelers choose their routes through the network. This is known as the traffic assignment problem, which involves allocating traffic demand to the transportation network's links while computing traffic flows. However, this study assumes that CAVs and HDVs have different driving and route choice behaviors, requiring a solution to the multiclass traffic assignment problem of mixed traffic flow of CAVs and HDVs.

The multiclass traffic assignment problem refers to allocating traffic flows from multiple vehicle classes to a transportation network's links while minimizing total travel time and congestion. CAVs and HDVs are considered as different vehicle classes with distinct characteristics, such as speed, headway, driving behavior, and route choice behavior. This study proposes a solution framework for the multiclass traffic assignment problem of mixed traffic flow of CAVs and HDVs.

After providing the material for evaluating the resilience of Belgium road network, this study investigates how to assess the network resilience, taking into account the presence of CAVs. The resilience of road networks is crucial in light of increasing disruptions and uncertainties, and one popular approach to measuring road network resilience is the resilience triangle framework, which considers four main dimensions of resilience: robustness, redundancy, resourcefulness, and rapidity (recovery). However, as CAVs become more prevalent, it is important to consider how these technologies affect road network resilience. Therefore, a new measure (accumulation) is proposed in this study to incorporate the impact of CAVs on road network resilience.

The simulation results demonstrate that as the percentage of CAVs increases, travel time and network resilience improves in all scenarios. The enhancement of network resilience is attributed to the route selection behavior of CAVs and their different driving behaviors, which are safer and faster compared to HDVs. The route selection behavior of CAVs is based on the system optimal, and they have the ability to reroute when an incident occurs on the network. The results of the study offer a broader insight into the resilience of road networks, contributing valuable information for transportation planning and decision-making.

Keywords: Resilience; Connected Automated Vehicle; Simulation; Traffic Assignment

Résumé

Le système moderne de transport routier est confronté à des défis qui peuvent affecter sa résilience. Ces défis comprennent la croissance et la diffusion accrues du flux de circulation liées à l'urbanisation, le vieillissement des infrastructures, l'émergence de nouvelles technologies telles que les applications de navigation ou les véhicules automatisés connectés (CAV), et les exigences environnementales. En raison de ces défis, le comportement des utilisateurs de la route est profondément transformé. Dans le passé, les utilisateurs de la route se fiaient à leur propre expérience pour choisir un itinéraire sur le réseau routier. Cependant, avec l'augmentation de la demande sur le réseau, de nombreux utilisateurs utilisent désormais des applications de navigation pour réduire leur temps de trajet et trouver l'itinéraire le plus court. Lorsque les CAV entreront dans le réseau routier dans un avenir proche, ils auront des comportements de conduite et de choix d'itinéraire différents par rapport aux utilisateurs ordinaires.

Le développement des CAV peut affecter la capacité des intersections signalisées, la collecte et la prédiction des données météorologiques, le comportement de conduite (par exemple, l'intervalle de sécurité, le choix d'itinéraire, etc.), les performances du régulateur de vitesse adaptatif, les systèmes avancés d'information pour les voyageurs et les performances des systèmes de gestion du trafic. Les utilisateurs de CAV peuvent différer dans leur choix d'itinéraire et leur comportement de conduite par rapport aux véhicules conduits par des humains (HDV). Le processus d'automatisation conduira probablement à une utilisation massive des CAV à moyen terme, ce qui aura un impact significatif sur la performance du

réseau routier. Il est donc crucial d'évaluer la performance du réseau routier lorsque de nouveaux types d'utilisateurs coexistent sur le réseau routier.

La performance d'un réseau de transport est multifacette, englobant plusieurs concepts clés, dont la fiabilité, la vulnérabilité, la robustesse et la résilience. Les chercheurs ont précédemment classé la fiabilité, la vulnérabilité et la robustesse comme des composantes intégrales de la résilience, soulignant la nature interdépendante de ces quatre concepts. Notamment, la notion de résilience a suscité une attention significative dans les récentes recherches, soulignant son importance dans les discussions contemporaines sur la performance des réseaux de transport.

Plusieurs facteurs influent sur la résilience du réseau, notamment la capacité du réseau routier, l'acheminement des véhicules, la disponibilité d'itinéraires alternatifs et la disponibilité d'informations pour les utilisateurs de la route. Étant donné que les CAV améliorent la capacité routière et que les centres de gestion du trafic peuvent les acheminer dynamiquement, il est crucial d'étudier leurs avantages potentiels sur la résilience du réseau routier. Par conséquent, l'objectif de cette étude est d'investiguer la résilience du réseau routier belge en présence de CAV.

Cette étude utilise des méthodes basées sur la simulation pour examiner la résilience des réseaux routiers en présence de CAV. Pour capturer les effets des différents utilisateurs de la route sur la performance du réseau routier et tester différentes stratégies de circulation, les chercheurs mettent en œuvre une simulation de trafic. Pour examiner la résilience du réseau à l'aide de méthodes basées sur la simulation, les données d'offre et de demande doivent être fournies. Les données d'offre se réfèrent aux données liées aux routes, tandis que les données de demande se réfèrent au nombre de trajets effectués sur le réseau routier en Belgique.

Pour répondre à la demande de données de déplacement en Belgique, un modèle de demande de déplacement a été développé en utilisant uniquement les kilomètres parcourus en véhicule, la population et les données de distance. Ce modèle a été validé avec des données réelles. Ensuite, la relation entre les données d'offre et de demande est formulée en

déterminant comment les voyageurs choisissent leurs itinéraires à travers le réseau. Cela est connu sous le nom de problème d'assignation de trafic, qui consiste à allouer la demande de trafic aux liens du réseau de transport tout en calculant les flux de trafic. Cependant, cette étude suppose que les CAV et les HDV ont des comportements de conduite et de choix d'itinéraire différents, nécessitant une solution au problème d'assignation de trafic multiclasse du flux mixte de CAV et HDV.

Le problème d'assignation de trafic multiclasse consiste à allouer les flux de trafic de plusieurs classes de véhicules aux liens d'un réseau de transport tout en minimisant le temps de trajet total et la congestion. Les CAV et les HDV sont considérés comme différentes classes de véhicules avec des caractéristiques distinctes, telles que la vitesse, l'intervalle de sécurité, le comportement de conduite et le choix d'itinéraire. Cette étude propose un cadre de solution pour le problème d'assignation de trafic multiclasse du flux mixte de CAV et HDV.

Après avoir fourni le matériel pour évaluer la résilience du réseau routier belge, cette étude examine comment évaluer la résilience du réseau, en tenant compte de la présence de CAV. La résilience des réseaux routiers est cruciale face aux perturbations et aux incertitudes croissantes, et une approche populaire pour mesurer la résilience du réseau routier est le cadre du triangle de la résilience, qui prend en compte quatre dimensions principales de la résilience : la robustesse, la redondance, la débrouillardise et la rapidité (récupération). Cependant, à mesure que les CAV deviennent plus courants, il est important de considérer comment ces technologies affectent la résilience du réseau routier. Par conséquent, une nouvelle mesure (accumulation) est proposée dans cette étude pour incorporer l'impact des CAV sur la résilience du réseau routier.

Les résultats de la simulation démontrent qu'à mesure que le pourcentage de CAV augmente, le temps de trajet et la résilience du réseau s'améliorent dans tous les scénarios. L'amélioration de la résilience du réseau est attribuée au comportement de sélection d'itinéraire des CAV et à leurs comportements de conduite différents, qui sont plus sûrs et plus rapides par rapport aux HDV. Le comportement de sélection d'itinéraire des CAV est

basé sur l'optimum du système, et ils ont la capacité de changer d'itinéraire lorsqu'un incident se produit sur le réseau. Les résultats de l'étude offrent un aperçu plus large de la résilience des réseaux routiers, fournissant des informations précieuses pour la planification et la prise de décision en matière de transport.

Mots-clés : Résilience ; Véhicule Automatisé Connecté ; Simulation ;
Assignation de Trafic

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List of Abbreviations

AS: Average Speed

ATL: Average Time Loss

CAVs: Connected Automated Vehicles

DNL: Dynamic Network Loading

DSO: Dynamic System Optimal

DTA: Dynamic Traffic Assignment

DUE: Dynamic User Equilibrium

FD: Fundamental Diagram

HDV: Human Driven Vehicles

ITSs: Intelligent Transportation Systems

MSA: Method of Successive Average

MSAR: Method of Successive Average Ranking

MS-TAP-M: Multiclass Simulation-based Traffic Assignment Problem
for the Mixed traffic flow of CAVs and HDVs

MSWA: Method of Successive Weighted Average

MTT: Marginal Travel Time

O-D Matrix: Origin-Destination Matrix

OSM: Open Street Map

PSP: Path Selection Procedure

RMS: Road Maintenance Site

SB-DSO: Simulation-Based Dynamic System Optimal

SB-DUE: Simulation-Based Dynamic User Equilibrium

SO: System Optimal
STA: Static Traffic Assignment
TAP: Traffic Assignment Problem
TTT: Total Travel Time
UE: User Equilibrium
V2I: Vehicle to Infrastructure
V2P: Vehicle to Pedestrian
V2V: Vehicle to Vehicle
VBS: Vehicle-Based Simulation

1. Introduction

This chapter commences by outlining the impetus behind the study, followed by an exposition of the study's objectives. Subsequently, the study approach and its contribution to the field are discussed. Finally, this chapter provides an overview of the thesis overall framework.

1.1. Research Motivation

During the last decades, there has been an upward trend in the number of people who live in urban areas. In 1950, only 30% of the population lived in cities, while, in 2018, 55% of the world's population lived in urban areas. It is expected that this proportion will increase to 68% by 2050 (Nations 2019). While this urbanization process has many benefits for residents (e.g., health, education, mobility, etc.), disadvantages cannot be ignored (e.g., overcrowding, pollution, etc.). One of the main disadvantages of urbanization is traffic congestion (overcrowding) that occurs on urban transportation road networks. Traffic congestions have lots of direct and indirect costs. These costs include (Hayes 2017):

- 1- Travel Time Delay
- 2- Cost of Emissions
- 3- Vehicle Operating Costs
- 4- Schedule Delay
- 5- Reliability Costs
- 6- Wider Economic Impacts (such as agglomeration)
- 7- Environmental Costs
- 8- Safety Impacts

Transport accounts for a quarter of greenhouse gas emissions, a figure that continues to rise as demand grows (Commission 2019). Demand for mobility will continue to grow over the next three decades. By 2030, annual passenger traffic will surpass 80 trillion passenger kilometers (50% increase); global freight volumes will grow by 70%; and an additional 1.2 billion cars will be on the road by 2050 (double today's total) (Kristalina et al. 2017). Higher demand means higher levels of pollution and an increased need for infrastructure maintenance. As a result, modern societies are seeking to develop a sustainable transport sector in which less pollution is caused. Under current trends, road transport and private cars remain dominant and have an ever-greater role to play in meeting this additional demand. One way to develop a sustainable transport sector is to reduce road

transport pollutants since road transport is responsible for more than 70% of emissions (Alonso Raposo et al. 2019).

Also, urbanization generates demand for infrastructure management. By properly managing the traffic flow and evaluating its performance in different scenarios, it is possible to reduce the costs related to traffic congestions. Policymakers and infrastructure managers measure the performance of infrastructures in terms of efficiency, sustainability, and resilience and try to improve the urban infrastructures' performance in these three terms. Efficiency refers to the ability to achieve maximum productivity with minimum wasted effort or expenses (e.g., energy, money, time, etc.). Sustainable (development) is "development that meets the needs of the present without compromising the ability of future generations to meet their own needs" (Brundtland 1985), and resilience refers to the "ability to reduce the magnitude and/or duration of disruptive events" (Berkeley 2010).

At the same time, the modern road transport system is facing challenges that can affect its resilience. These challenges include:

- 1- The growth and greater diffusion of traffic flow linked to urbanization (increasement in traffic volume, which are loading on the road network) (Hanin 2004)
- 2- The infrastructure aging (Garavaglia and Sgambi 2016)
- 3- The emergence of new technologies like navigation apps or Connected Automated Vehicles (CAVs)
- 4- Environmental requirement (Decoster et al. 2020)

Due to such challenges, road user behavior is being profoundly transformed, which influences road network performance (resilience). For example, when there is an increase in demand on a network, it causes many users to use navigation apps in order to reduce their travel time and look for the route with the shortest travel time. In other words, in the past, road users used their own experience to select a path on the road network while today, many users employ navigations apps. Or when CAVs enter the network of roads in the near future, they will have different driving and

route choice behaviors compared to ordinary users. For example, self-driving cars can have information about accidents based on their connectivity capabilities and adjust their routes accordingly. CAVs offer two types of communication. The first one is vehicle-to-vehicle (V2V) communications (shown in Figure 1-1), used when CAVs communicate among themselves. The second one is vehicle-to-infrastructure (V2I) communications, used when a CAV sends or requests some information to a traffic management center, or it needs to access some content on the Internet. CAVs can collect traffic-related data and send such data to other CAVs using V2V communication. They can also use V2I communications to send such data to road network infrastructure or traffic management centers. By exploiting such data, traffic management centers can provide services that may potentially improve road network resilience. One of such services is route strategies services which will be studied through this study. The choice of the path between the point of departure and the point of arrival is being increasingly made based on the use of calculation algorithms to check the level of traffic, accidents, or the presence of work sites on the road (updated real time information). These algorithms attempt to provide a more efficient path compared to the one chosen based on driver experience.

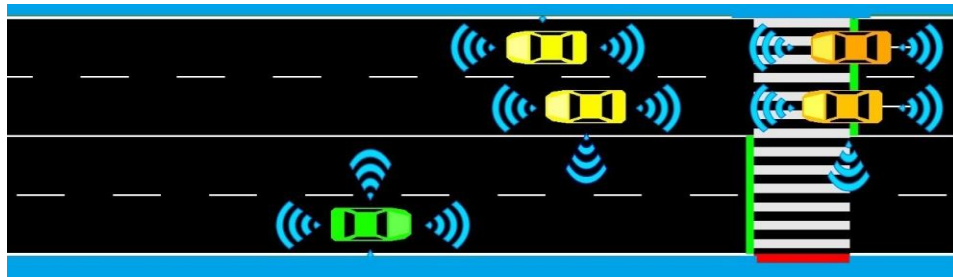


Figure 1-1: Vehicle to Vehicle Communication (source: Author)

In the medium term, the process of automation will probably lead to the massive use of CAVs. According to the literature, the development of CAVs can affect (Ahmed, Dey, and Fries 2019):

- 1- The capacity of signalized intersections
- 2- Weather condition data collection and prediction
- 3- Driving behavior (e.g., headway)
- 4- Route choice behavior
- 5- Adaptive cruise control performance
- 6- Advanced traveler information systems
- 7- The performance of traffic management systems.

In particular, CAV users can differ in their route choice and driving behavior compared to Human Driven Vehicles (HDV). Therefore, it can be concluded that the evaluation of road network performance, when there is a disruption in the road network and new types of users co-exist on the road network, road network resilience, is a pressing topic for research. The impact of the above-mentioned behavioral changes on road network performance and the territory should be investigated. This study's motivation is to obtain a road network resilience framework that considers the presence of CAVs and their coexistence with HDVs in the road network. This evaluation can help us to understand better whether CAVs can reduce the traffic congestions related costs or not.

1.2. Research Objective and Questions

CAVs that employ modern CAVs navigation systems and share their routing information will be introduced in the near future. On the other hand, the use of navigation apps has dramatically increased in recent years. Consequently, the use of the road network is being transformed. To deal with such changes, new methods must be developed for assessing the performance of the road network. The transportation network's performance includes four concepts: reliability, vulnerability, robustness, and resilience (Calvert and Snelder 2018). Previous studies have classified reliability, vulnerability, and robustness as resilience characteristics (El Rashidy 2014), which indicates that the four concepts are close to each other. The concept of resilience has attracted widespread interests in recent years.

The resilience is essential for a road network because it governs how the network reacts to a possible disruption. The disturbance effect caused by abnormal conditions (e.g., accidents) may differ in the presence of CAVs. In other words, the presence of CAVs can lead to a new definition of road network resilience measures. Several factors affect the network's resilience, including:

- 1- Capacity of the road network.
- 2- Vehicle routing.
- 3- Availability of alternative routes.
- 4- Knowledge of road users, etc.

Given that CAVs improve road capacity and traffic management centers can dynamically route them, it is of high importance to study their potential benefits on the road network resilience. Therefore, the aim of this study is to investigate resilience of Belgium road network in the presence of CAVs, and it attempts to answer the following questions in order:

1. **How to model travel demand for Belgium road network?** Obtaining accurate travel demand data is a critical aspect in transportation planning and management. However, the process of collecting such data can be both time-consuming and costly. As a result, it is essential to explore alternative methods of developing travel demand models that do not rely on expensive survey data. The emergence of probabilistic travel demand models has opened up new opportunities to achieve this goal.
2. **How to model CAVs and HDVs in road networks?** Proper modeling of the mixed traffic consisting of CAVs and HDVs is of utmost importance. This requires a two-fold approach. Firstly, the mixed traffic flow of CAVs and HDVs should be modeled in a manner that distinguishes between their driving behaviors. Most existing studies adopt microscopic models of traffic flow, such as car-following and lane-changing, to model CAVs' traffic flow. However, since this study aims to model a large-scale network in Belgium, it is necessary to calibrate the parameters of queuing

models in order to model CAVs' traffic flow at a mesoscale level. The use of mesoscale queuing models provides higher accuracy and relatively faster computation time. Secondly, the multiclass traffic assignment problem needs to be modeled in a way that distinguishes between the route choice behavior of CAVs and HDVs. This multiclass traffic assignment problem can be solved by developing a model that considers the different travel behaviors of CAVs and HDVs. This will allow for proper modeling of the route choice behavior of each vehicle type, leading to more accurate predictions of traffic patterns and congestion levels.

3. **How to assess the resilience of road networks in the presence of CAVs?** In the context of CAVs, the development of a road network resilience measure is of paramount importance, as the unique driving and route choice behaviors of CAVs necessitate a measurement that can accurately account for their presence and impact on network resilience.
4. **How the resilience value of the Belgian road network is altered concerning CAVs?** It is crucial to comprehend the extent to which the presence of CAVs can affect the resilience value of the Belgian road network. Understanding the magnitude of this impact is imperative in assessing the network's overall resilience in the context of CAVs.

In the next section, the research approach is explained that helps us systematically find the answer to the above-mentioned questions.

1.3. Research Approach

In the study of transportation network resilience, various methods can be used, such as graph theory, big data analysis, and simulation-based methods. Each method has its advantages and disadvantages, which will be discussed on section 4. The purpose of this study is to investigate the resilience of road networks in the presence of CAVs using simulation-based methods. To capture the effects of different road users on road network performance and test different traffic strategies, researchers

implement traffic simulation. Researchers have long employed simulation as a powerful tool for simplifying reality. May (May 1990) defines simulation as a “numerical technique for conducting experiments on a digital computer.” Simulations employ mathematical models and might include microscopic or macroscopic stochastic characteristics. Simulation is a viable alternative to analytical models since such models have the highest degree of simplification in model representation.

Traffic simulation assumes that travelers follow different behavioral models (car-following models, lane changing models, route choice models, etc.) that determine their movements and travel choices. These choices are then considered altogether during a period of time to produce the traffic patterns in the networks. Traffic simulation allows us to forecast a road network's states in both normal and hypothetical scenarios. Simulation-based methods provide a more accurate assessment of network resilience compared to other methods. There are several reasons for this. First, simulation-based methods allow for different traffic modes and vehicle classes (HDVs and CAVs) to be simulated based on their behavior and characteristics. This means that the impact of CAVs on network resilience can be evaluated accurately. Second, simulation-based methods take into account the interaction between vehicles. This means that the behavior of one vehicle affects the behavior of others, and this can be modeled accurately. Third, simulation-based methods allow the geometric and topological features of roads to be considered simultaneously. This means that the impact of road characteristics on network resilience can be evaluated accurately. Fourth, simulation-based methods allow for the comparison of various failure types, demand strategies, recovery strategies, and resource allocations. This means that the most effective strategy for improving network resilience can be identified. Finally, simulation-based methods allow for the calculation of various traffic-related measures (e.g., average speed) and pollutant emissions. This means that the impact of network resilience on the environment can be evaluated accurately.

To examine the resilience of the network using simulation-based methods, the supply and demand data must be provided. The supply data refers to

the data related to the roads, while the demand data refers to the number of trips taken on the road network in Belgium. Therefore, in this study, a travel demand model for Belgium has been developed. The only input data for this model is the population of cities and the distance between them. This model has been calibrated and validated using real data. The next step is to formalize the relationship between supply and demand data, which can be done by determining how travelers choose their routes through the network (traffic assignment problem). Traffic assignment is the process of determining how traffic demand is loaded onto the network. It also provides the means for computing traffic flows on the network links.

However, since the assumption of this study is that CAVs and HDVs have different driving and route choice behaviors, the multiclass traffic assignment problem of mixed traffic flow of CAVs and HDVs must be solved. The multiclass traffic assignment problem of mixed traffic flow of CAVs and HDVs refers to the problem of allocating traffic flows from multiple classes of vehicles to a transportation network consisting of links (e.g., roads, highways, etc.) in a way that minimizes total travel time and congestion. In this problem, CAVs and HDVs are considered as different vehicle classes with distinct characteristics, such as speed, driving behavior, and route choice behavior. The mixed traffic flow implies that both types of vehicles share the same infrastructure, and the interactions between them affect the overall traffic performance. The goal of the multiclass traffic assignment problem is to determine the optimal assignment of vehicles to links in the network, taking into account the demand for travel, the capacity of the links, the travel time, and the impact of traffic congestion on the overall system performance.

The next step is to investigate how to assess the network resilience, taking into account the presence of CAVs. Road network resilience has become a crucial area of study as transportation systems face increasing disruptions and uncertainties. One popular approach to measuring road network resilience is the use of the resilience triangle framework, which considers the four main dimensions of resilience: robustness, redundancy, resourcefulness, rapidity (recovery). However, as the transportation

industry evolves with the emergence CAVs, it is important to consider how these technologies impact road network resilience. Given that connectivity and consequently, the rerouting of CAVs can have a significant impact on network resilience, we are looking for a resilience criterion that can consider this feature. Therefore, in this study, a new measure is proposed to form the resilience triangle that takes into account the impact of CAVs on the road network. By incorporating this new measure, we aim to provide a more comprehensive understanding of road network resilience and inform future transportation planning and decision-making.

1.4. Contributions

The objective of this study is to investigate the impact of CAVs on the resilience of road networks. The study addresses the practical problem of understanding how the presence of CAVs affects the resilience of road networks. To achieve this objective, the researcher has implemented a traffic simulation model capable of simulating a real road network in a dense region such as Belgium. The simulation model not only provides traditional network resilience metrics, such as travel time and emissions, but also introduces a new road network resilience measure.

The research makes four main contributions to the field of transportation engineering (academic level). Firstly, it develops a probabilistic travel demand model that enhances the accuracy of travel demand forecasting. Secondly, it proposes a new solution framework for the multiclass traffic assignment problem that accommodates both CAVs and HDVs. This solution framework can be implemented on any big-scale road network as is freely available to all. Thirdly, it introduces a new road network resilience measure that captures the effects of CAVs. This new measure can be suitable for both operational and academic goals, as it provides a new perspective on network resilience. Finally, it investigates the impact of CAVs on road network resilience, providing valuable insights for policy makers and decision makers. An innovative practical aspect of this research is the development of a Belgium road network traffic simulation model that is calibrated and validated using real-world data. This model can be used

by policy makers and decision makers to test various management scenarios and to make informed decisions. However, in the development process of this model, numerous assumptions have been made. Thus, the probabilistic travel demand model should be further examined in future studies.

The research presented in this study has both academic and practical contributions, as shown in Figure 1-2.

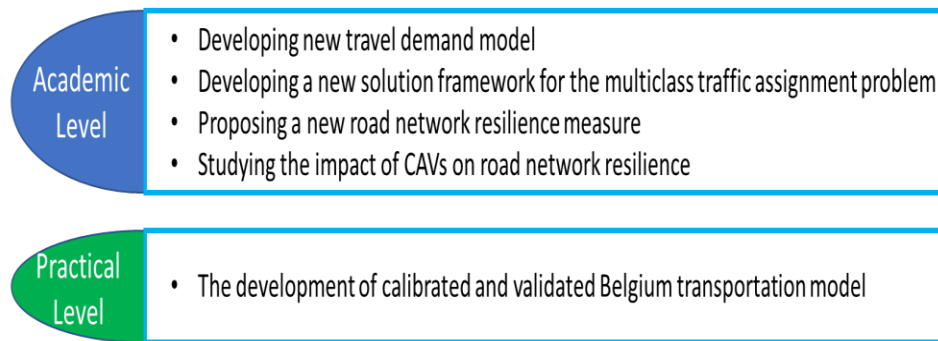


Figure 1-2: Research Contributions (source: Author)

1.5. Outline

The thesis consists of six chapters, with the outline illustrated in Figure 1-3. Chapter One provides an introduction to the study, which aims to investigate the resilience of Belgium's road network to disruptions in the presence of CAVs. Chapter Two presents a probabilistic model for travel demand, calibrated and validated using traffic count data and Google API data. This model is based on an examination of Belgium's roadways and population information. In Chapter Three, the focus shifts to the simulation of CAVs in a mesoscale simulation platform, with a discussion on the problem of multi-class traffic assignment. Chapter Four introduces a new resilience measure, which serves as a measure of network resilience in the presence of CAVs. This chapter explains how the criterion was developed and how it can be used to quantify the resilience of road networks. Chapter Five combines the simulation framework, traffic assignment problem-

solving tool, and the new resilience measure to examine the resilience of Belgium's road network. The quantitative results of the study are presented in this chapter, providing insights into how the network performs under different levels of CAV disruptions. The findings of the study offer valuable information to policymakers and stakeholders in the transportation industry, enabling them to make informed decisions regarding the development and deployment of CAVs. Finally, Chapter Six presents the conclusions of the study, highlighting the key findings and their implications for the resilience of Belgium's road network. The chapter also discusses the limitations of the study and provides recommendations for future research. Overall, this thesis provides a comprehensive analysis of the resilience of Belgium's road network in the presence of CAVs, using a novel approach that combines probabilistic modeling, simulation, and a new resilience criterion.

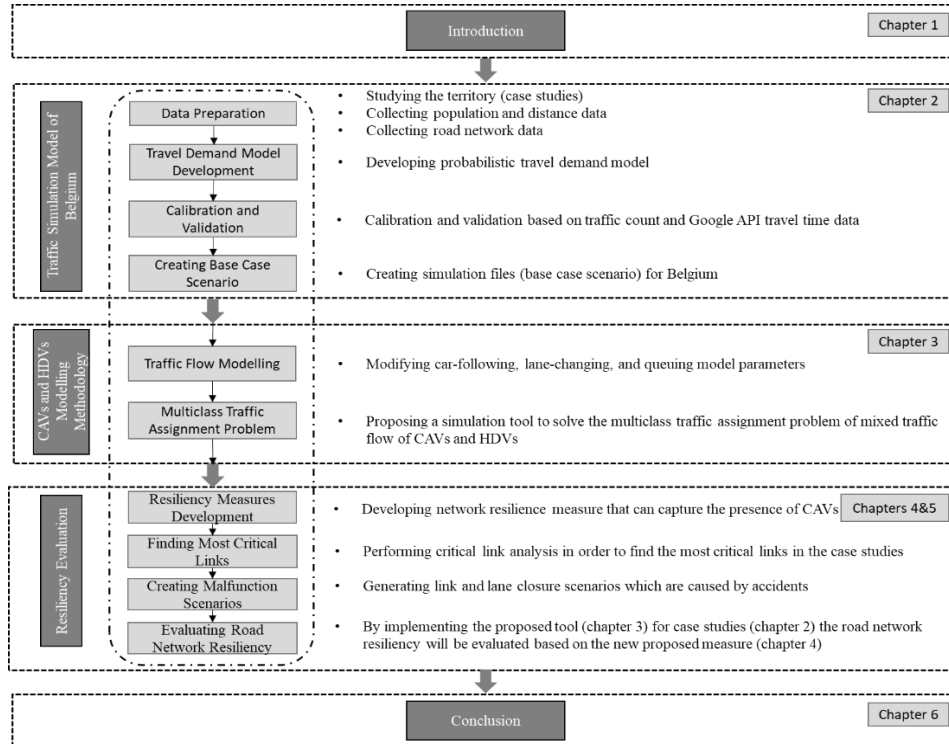


Figure 1-3: Research Outline (source: Author)

2. Traffic Simulation Model of Belgium

In this chapter, the process of developing, calibrating, and validating the traffic simulation model of Belgium is discussed. The developed base-case model, which is described in this chapter, is used to evaluate the road network resilience in the presence of CAVs. The contents of this chapter are drawn from the listed publications:

- Bamdad Mehrabani, B., Sgambi, L., Maerivoet, S. and Snelder, M. Development, calibration, and validation of a large-scale traffic simulation model: Belgium road network. SUMO User Conference (Berlin, from 02/05/2023 to 04/05/2023). <https://doi.org/10.52825/scp.v4i.199> (Mehrabani et al. 2023)
 - Bamdad Mehrabani, B., Sgambi, L., Garavaglia, E. and Madani, N. (2021), Modeling Methods for the Assessment of the Ecological Impacts of Road Maintenance Sites. Environmental Sustainability and Economy (ESEcon), Chapter 10, Elsevier, USA, <https://doi.org/10.1016/B978-0-12-822188-4.00009-9>. (Mehrabani et al. 2021)
-

2.1. Introduction

Several transportation researchers use traffic simulation models to test different scenarios in different network scales (e.g., evaluating road network resilience in different CAVs penetration rate). Based on the intended application, there are three distinct approaches to simulation: microscopic, macroscopic, and mesoscopic. The main differences between these approaches are the level of aggregation and the tradeoff between optimizing simulation speeds and estimating traffic states (or traffic phenomena) as accurately as possible. These approaches are briefly described in what follows.

1. **Microscopic Traffic Simulation Modeling:** This approach considers the dynamics of individual vehicles (or the response of individual drivers). Microscopic traffic simulation modeling is based on the description of the motion of individual vehicles in the traffic stream. In other words, microscopic models consider the interactions of individual vehicles. Information considered by these models include acceleration, deceleration, speed, and the lane-changing behavior of individual vehicles. Microscopic models describe vehicles (as well as their drivers) individually in the form of varying characteristics and multiple classes. This type of simulation takes highly detailed information from road sections into consideration and is usually used for modeling on the street or intersection level. Microscopic parameters for describing traffic flow are headway, gap, and occupancy.
2. **Macroscopic Traffic Simulation Modeling:** These models are the aggregated versions of microscopic models. Macroscopic models are based on the aggregate behavior of the traffic flow and do not consider individual vehicles. Instead of tracking vehicles on an individual level, macroscopic simulations take place on a section-by-section basis, which is why they are employed by studies that address the behavior of the entire transport network. The variables employed by macroscopic models are general descriptors representing traffic conditions as flows at a high level of

aggregation without distinguishing their parts. Macroscopic parameters, which characterize the traffic stream as a whole, are volume (rate of flow), speed, and density.

3. Mesoscopic Traffic Simulation Modeling: These models combine some of the characteristics of macroscopic and microscopic models. Mesoscopic models consider most parameters at a high level of detail but describe the activities and the interactions between vehicles at a much lower level of detail compared to microscopic models. Mesoscopic models assume that vehicles move together as packets or platoons.

As this study covers the entire Belgian road network, using microscopic models for the analysis would incur high computational costs. Therefore, mesoscopic transportation models have been utilized, which allow for accurate modeling of the presence of commercial vehicles in the simulation while also providing speedy calculations.

The first step in traffic simulation is providing two types of information: the supply data and demand data. Supply data includes all the information related to the transportation network and services, such as the geometric and functional specification of the road network, traffic control; public transport services; and other data, such as fleet vehicles. Also, the travel demand data are typically extracted from travel demand models. The travel demand model is a set of mathematical relationships which describes when, why, and how people and goods move within a particular geographic area. These models estimate travel behavior and demand for a specific (future) time frame, based on several assumptions about the population, land use, household, etc. Travel demand models incorporate economic aspects, technical aspects, lifestyle aspects of society, a specific individual, psychological elements, and factor of time to provide the most accurate representation of a specific travel demand problem (e.g., number of passengers traveling between Brussels to Antwerp by car at P.M. peak hour). Demand data contain the mobility needs of people and goods, which questionnaires, mobile data, etc., can collect. Several travel demand models have been developed, like (Miller 2020):

1. Classical four-step model,
2. Tour-based model,
3. Activity-scheduling model.

The most well-known travel demand model is the classical four-step model:

1. Trip generation: determines the number of passengers traveling from a specific city or region.
2. Trip distribution: estimates the number of trips between particular cities or regions. The output of this step is an Origin-Destination (O-D) matrix. The O-D matrix determines the number of trips between each origin and destination.
3. Modal split: determines which transportation mode passengers will use when traveling from their origin to their destination.
4. Traffic assignment: determines the routes passengers choose to reach their destination.

For a classical transportation model, the output of the first three steps, an O-D matrix for each transport mode, is fed into a traffic assignment model (either simulation-based or analytical traffic assignment models) to calculate links loads. Several methods are available for estimating the O-D matrix, including traffic counts/surveys, travel surveys, GPS data, public transportation data, social media and web data, model-based approaches, and mobile phone data. However, most of these methods require a large volume of data (Afandizadeh Zargari, Memarnejad, and Mirzahosseini 2021). In this study, due to the unavailability of access to such data (such as traffic count data), model-based approaches have been utilized. These approaches demand less extensive datasets.

The four-step travel demand model has been used by many researchers and showed its excellent performance. However, the most critical disadvantage of this model is that it relies heavily upon household surveys and census data that are very costly and time-consuming to collect. Thus, the availability of household data is very challenging in implementing a four-step model, especially for large-scale road networks (e.g., Belgium). In this

study, an alternative approach to four-step modeling is proposed to develop a traffic simulation model for Belgium road network. First, a travel demand model named as probabilistic travel demand model is proposed. This travel demand model only considers the population, distances, passenger-kilometer traveled, and the number of yearly truck trips as the input data to provide hourly O-D matrices on a country level (Belgium). The reason for developing such a travel demand model is that it needs less data than classical four-step modeling. Then, the extracted O-D matrices are inputted into the traffic simulation model to solve the traffic assignment problem. This traffic simulation model is calibrated and validated by traffic count and travel time data.

The following section (section 2.3) gives information about the Belgium road network (available supply and demand data). Section 2.3 explains the Base-case model development methodology. Then, the process of calibration and validation of the model is provided in section 2.4. Finally, sections 5 and 6 describe the results and the conclusion of this chapter.

2.2. Case Study (Belgium)

Belgium is a European country with a land area of 30,688 km² and a population of 11.5 million (OECD 2022). Belgium is divided into three regions: the Flanders in the north, the Wallonia in the south, and the Brussels-Capital Region. The transport network in Belgium, including road, rail, sea, and air, is well-developed and well-connected to other parts of Europe. This transport network includes 13.2 thousand kilometers of main/national roads; 5 international airports; 3,602 kilometers of usable rail network; and five seaports (Statista 2009, 2020). Belgium plays a crucial role in road travel in Europe and ranks 7 in terms of passenger-kilometer among European Union countries. Also, Belgium's motorway network is the third dense after the Netherlands and Luxembourg in Europe (Decoster et al. 2020). There are more than eight international E-roads in Belgium which connect the east of Europe to the west and south of Europe to the north.

In Belgium, three mobility surveys have been carried out by SPF Mobilité et Transports to examine mobility and road safety patterns in detail, using both household and individual data. These surveys, named MOBEL (1999), BELDAM (2012), and MONITOR (2018), provide a comprehensive understanding of the subject (SPF Mobilité et Transport 2018). As far as the authors are aware, the origin-destination matrix from these studies is not accessible to the public.

2.2.1 Supply Data

The Open Street Map (OSM) file was extracted to build the network. The OSM is a free editable map of the world that users make. The road network file is directly imported into traffic simulation software (SUMO). SUMO is a robust, open-source microscopic traffic simulation package capable of handling large networks and can also simulate traffic at the mesoscopic level (DLR 2023).

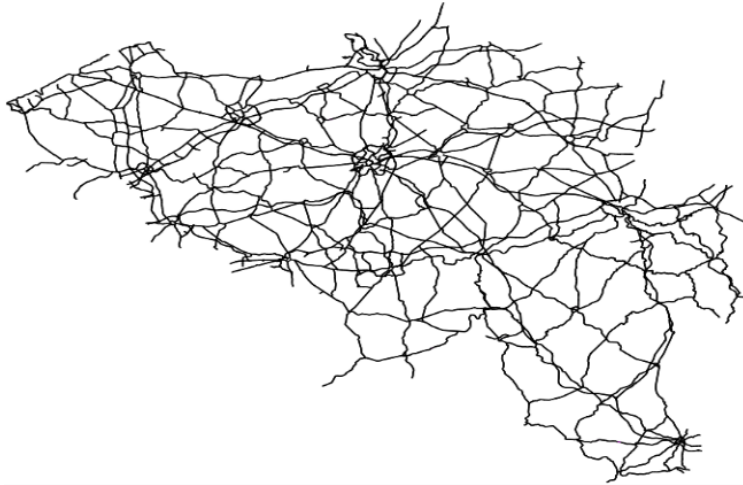


Figure 2-1: Belgium road network in SUMO (source: Author)

The OSM file contains all categories of roads (named Motorway, Trunk, and Primary roads in OSM). Roads in Belgium are categorized into three types, which are 1- Highways ("Autoroute") (e.g., A2 (E314)); 2- Provincial and regional roads ("Routes provinciales et régionales") (e.g.,

A501); 3- Municipal roads ("Routes communales"). Since this study provides a travel demand model for outer-city trips, only highways and provincial and regional roads (classified as Motorway, Trunk, and Primary roads on OSM) are modeled, and inner-city traffic roads are not modeled. The network is checked and fixed manually for any error in the SUMO environment (using the SUMO network warning and error tool). Cities are considered as centroids that can generate and attract trips. In total, 60 cities are modeled. The criteria for selecting cities are described in the next section. The OSM file already included road network features like speed and capacity. However, they were double-checked with Google Maps data to ensure accuracy. Figure 2-1 shows the inserted network into SUMO.

Also, to ensure that the network's geometry and the highways' length are imported to SUMO correctly, the shortest distance between the cities in the simulation is compared with reality. The real shortest distances are taken from Google API. A comparison between the shortest distances in reality and the simulated network is given in Figure 2-2. The shortest distances between 3600 O-D pairs in reality and simulation are compared. This figure shows that the length of highways and the geometry of the network is simulated with a high accuracy rate.

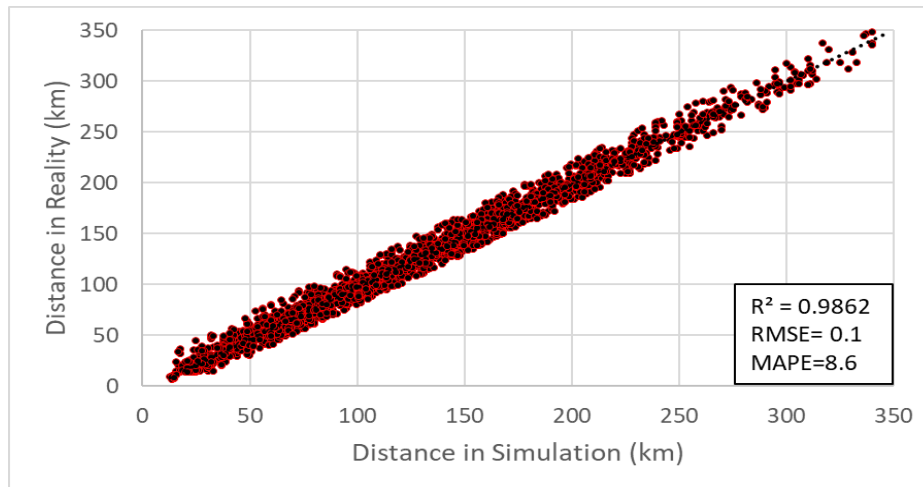


*Figure 2-2: Comparison of distances between cities in simulation and reality
(source: Author)*

2.2.2 Demand Data

The data considered as inputs to the probabilistic travel demand model for passenger car trips include the population of each city, the distance between cities, and the passenger-kilometer traveled by the Belgium population each year. Population data for all Belgian municipalities are extracted from STATBEL (STATBEL 2022b). STATBEL is the Belgian statistical office that collects, produces, and disseminates reliable and relevant figures on the Belgian economy, society, and territory.

Belgium has three regions and 11 provinces. The provinces are subdivided into 43 administrative arrondissements and 581 municipalities, 83 of which have a population of more than 30,000. A list of Belgium's arrondissements with their municipalities was provided. Then, 60 municipalities (cities) were chosen as centroids in the travel demand model based on the following criteria. The list of the selected 60 cities are provided in Table 2-1.

- All municipalities with over 30,000 population were first selected as centroid (to address the effects of most populated cities).
- If the distance between two municipalities (within the same arrondissement) is less than 15 km, two municipalities are combined and considered one centroid.
- If an arrondissement consists of less than four municipalities, the first populous municipality is selected (even if the population is less than 30,000).
- If the arrondissement consists of more than five cities, at least three are included.

The geographic distance between cities is also calculated based on the longitude and latitude of cities. The passenger-kilometer travel data for passenger cars is extracted from Federal Planning Bureau (FPB) website (FPB 2017). This independent public agency draws up studies and projections on economic, social, and environmental policy issues.

Table 2-1: List of cities considered in travel demand modelling

No.	City	No.	City
1	Ypres	31	Maasmechelen
2	Lapanne	32	Tongeren
3	Ostend	33	Namur
4	Knokke-Heist	34	Philippeville
5	Bruges	35	Chimay
6	Roeselare	36	Beauring
7	Courtrai	37	Neufchâteau
8	Gand	38	Arlon
9	Eeklo	39	Aubange
10	Anvers	40	Bastogne
11	Turnhout	41	Dinant
12	Tongerlo	42	Marche-En-Famene
13	Malines	43	Werbomont
14	Saint-Nicolas	44	Saint-Vith
15	Alost	45	Malmedy
16	Ronse	46	Liege
17	Tournai	47	Huy
18	Enghien	48	Hamont
19	Brussels	49	Ath
20	Nivelles	50	Beringen
21	La Louviere	51	Deinze
22	Mons	52	Diksmuide
23	Charleroi	53	Geraardsbergen
24	Sombrefe	54	Halle
25	Louvain-La-Neuve	55	Hannut
26	Tienen	56	Leuven
27	Saint-Trond	57	Ninove
28	Hasselt	58	Tielt
29	Lommel	59	Waregem
30	Genk	60	Virton

According to Table 2-2 (FPB 2017), the total passenger-kilometer traveled per year for all three regions of Belgium in highways, provincial and regional roads are equal to 85.762×10^9 .

Table 2-2: Passenger kilometers traveled per year in Belgium (million passenger-kilometer)

	Wallonia	Flanders	Brussels-Capital
Highways	16373.6	23676.5	520.7
Provincial and regional roads	18286.0	25058.0	1848.1
Municipal roads	9456.2	10662.2	1059.1

Also, for modeling the freight transport trips (trucks), the number of yearly trips by Belgian trucks (by country of loading and unloading) is extracted from STATBEL (STATBEL 2022a). The number of truck trips loaded in Belgium and unloaded in Belgium is given in Table 2-3.

Table 2-3: Number of yearly Trucks trips in Belgium

	Loaded in Belgium	Unloaded in Belgium	Total
Number of Yearly trucks trips	16173401	15829069	32002470

2.3. Probabilistic Travel Demand Model

The probabilistic travel demand model first determines the total number of daily trips based on the passenger-kilometer traveled data (Figure 2-3). Then, it indicates the origin and destination of each trip by applying a random selection on the weighted distribution function of population and distances between the cities (Jacquin 2019; Sgambi et al. 2021). The core assumption behind the model is that the larger a city's population, the greater its likelihood of being chosen as the origin city of a trip. Also, more population of a city and lower distance between cities increase its likelihood of being selected as the city of destination. This model's principles are similar to the gravity model (Ortúzar and Willumsen 2011). In this study, the attractiveness between two cities for travel has been

explored by considering a probabilistic choice based on population distribution and the combined population-distance distribution. However, it is important to note that in the context of the proposed probabilistic travel demand model, which is based on the gravity model, a decay function can be employed to determine the probability of travel between two points. The decay function, in this case, is commonly utilized to depict how the appeal of a location, typically the origin, diminishes as the distance increases. It is integrated into the denominator of the gravity model equation, influencing the impact of distance on trip distribution. Nevertheless, the challenge with this function lies in the necessity to calibrate and validate it for the specific network under investigation to obtain accurate results. This calibration process falls outside the scope of our study. Therefore, in this research, it is opted to rely on the probabilistic choice based on population distribution and the combined population-distance distribution.

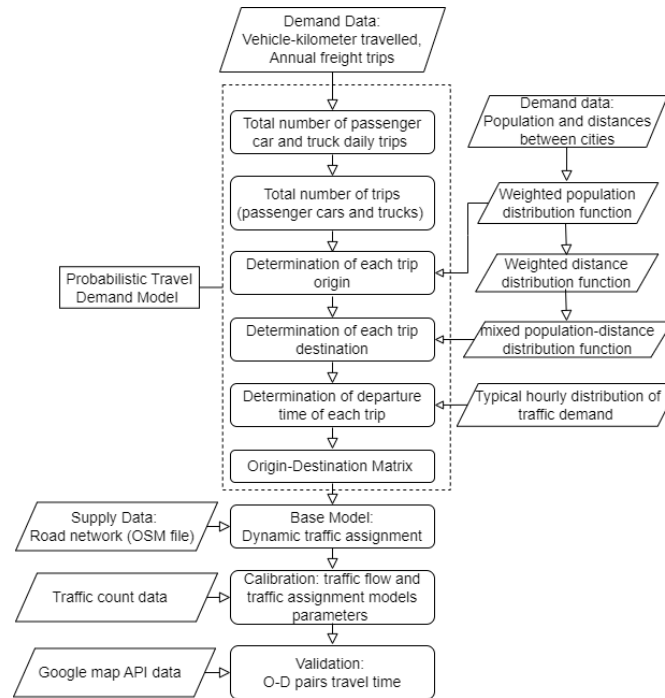


Figure 2-3: Overall process of the traffic simulation modeling for Belgium (source: Author)

The steps of the probabilistic travel demand model are as follows. Also, the Pseudocode of the model is given in Table 2-4.

Table 2-4: Pseudocode code of probabilistic travel demand model

Probabilistic Travel Demand Model

Input: road network, yearly passenger-kilometer traveled, yearly trucks trips

Output: hourly O-D matrix

Initialization: set the total number of daily trips $T_T = 3.3 \times 10^6$ and trip index $t = 1$

Main loop:

For trip t in the range $[1, T_T]$:

- i. Form the weighted population probability distribution function ($f_{PO}(x_i)$)
- ii. Apply a random selection on $f_{PO}(x_i)$ to determine the city of origin for trip t .
- iii. Form the weighted distance function ($f_D(x_{ij})$) for the origin city.
- iv. Form the mixed population-distance function ($f_M(x_{ij})$) for the origin city.
- v. Apply a random selection on $f_M(x_{ij})$ to determine the city of destination for the trip t .
- vi. Apply a random selection on the typical hourly traffic demand distribution (based on the type of vehicle) to determine the departure time of trip t .
- vii. $t = t + 1$

End of loop

I. Determination of the total number of passenger cars daily trips

As shown in Table 2-2, the total number of passenger-kilometer traveled on highways, and the provincial and regional road is equal to 85.762×10^9 . Assuming that each passenger travels 85 kilometers per day (round trip) and the weekend traffic is considered to be half as high, this gives approximately 3.2 million trips per day in the Belgium road network.

The equation for calculating the total number of passenger cars daily trips (T_{PC}) is as follows:

$$T_{PC} = \frac{\text{passenger kilometer travelled (yearly)}}{365 \times \text{day weight} \times \text{average length of trips}} \quad (2 - 1)$$

II. Determination of the total number of trucks daily trips

Table 2-3 shows the total number of Belgian trucks' yearly trips. To calculate the number of daily truck trips, equation 2 is used. Similar to passenger car trips, it is assumed that the number of weekend trips is half the weekday trips. Equation 2-2 gives 102572 trucks' trips per day.

$$T_{TR} = \frac{\text{number of trucks' trips (yearly)}}{\text{days in each year} \times \text{day weight}} \quad (2 - 2)$$

By summing up the passenger car trips and truck trips, the total number of all trips can be calculated.

$$T_T (t \in T_T) = 3.2 + 0.1 = 3.3 \text{ million trips} \quad (2 - 3)$$

III. Determination of trips Origins

After determining the total number of daily trips in Belgium (both passenger cars and trucks) ($T_T = 3.3$), the origin for each trip (t) should be specified. It is assumed that the probability of selecting a city as the origin city is proportional to its population. A random selection is applied to the weighted probability distribution of cities' populations. The weighted probability distribution function is given in equation 4. The logic behind this selection is that a city with a larger population is more likely to be chosen as the origin city.

$$f_{PO}(x_i) = p_i(X = x_i) = \frac{Po_i}{\sum_{i=1}^{60} Po_i} \quad (2 - 4)$$

$$0 < f_{PO}(x_i) < 1; \sum_{i=1}^{60} f_P(x_i) = 1$$

Where $f_{PO}(x_i)$ is the weighted population probability distribution function; $p_i(X = x_i)$ is the probability of city i to be chosen as the origin city for trip t ; and PO_i is the population of city i .

IV. Determination of trips Destinations

In this step, the destination for each trip is determined. The decision for selecting the city of destination is based on the assumption that the larger the population of a city and the closer it is to the city of origin, the higher the likelihood of it being chosen as the destination city. To put this assumption into mathematical form, the weighted distance distribution function is defined for each origin city i as follows:

$$f_D(x_{ij}) = p(X = x_j|x_i) = \frac{\frac{1}{(Dis_{ij})^3}}{\sum_{j=1}^{j=60} \frac{1}{(Dis_{ij})^3}} \quad (2-5)$$

$$0 < f_D(x_{ij}) < 1; \sum_{j=1}^{60} f_D(x_{ij}) = 1$$

Where $f_D(x_{ij})$ is the weighted distance distribution function; $p(X = x_j|x_i)$ is the probability of selecting city j as the destination if city i is chosen as origin city; and Dis_{ij} is the distance between cities i and j . Then, the population distribution and the distance distribution are mixed to generate the new distribution. The mixed population-distance probability distribution function is defined as:

$$f_M(x_{ij}) = p(X = x_j|x_i) = \lambda \times f_{PO}(x_i) + (1 - \lambda) \times f_D(x_{ij}) \quad (2-6)$$

Where $f_M(x_{ij})$ is the mixed population-distance distribution function; $p_{ij}(X_{ij} = x_{ij}|x_i)$ is the probability of selecting city j as destination if city i was selected as origin; $f_{PO}(x_i)$ is the weighted population probability distribution function; $f_D(x_{ij})$ is the weighted distance probability

distribution function; λ is a calibration parameter that indicates the importance of considering the population or distance between the cities in the probability of being selected as the destination city. The destination city of trip t is determined by applying a random selection on the mixed population-distance distribution function mentioned above.

It's worth noting that in this study, the behavior of both passenger cars and trucks trips are assumed to be the same in terms of origin and destination. However, the nature of truck trips may vary based on the locations of terminals, distribution centers, and companies within different sectors, and further research is necessary to investigate these differences.

V. Determination of departure times

Each trip t is assigned to each hour of the day by the typical hourly distribution of travel (based on the type of vehicles: passenger car or truck), which is presented by NCHRP (2004) (Figure 2-4). At this step, the hourly O-D matrix for each hour of the day is available. The O-D matrix of the morning peak hour is given in Table 2-5.

Table 2-5: Pick hour O-D matrix for Belgium road network

[illegible]

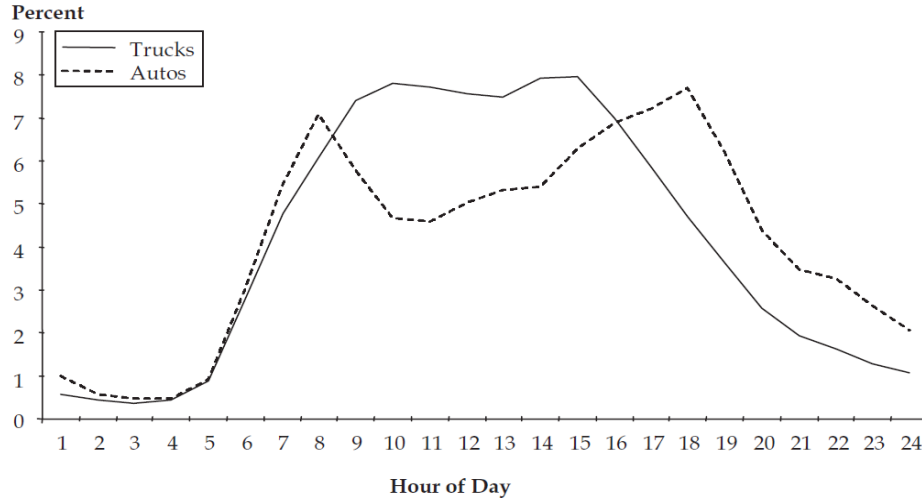


Figure 2-4: Typical hourly Distribution of Traffic Demand (Source: NCHRP 2004)

2.4. Base-Case Model

After obtaining the hourly O-D matrix, a base model was simulated. For the base-case model, Dynamic User Equilibrium (DUE) traffic assignment was used to assign travel demand to the network. The traffic assignment tool in SUMO, *dualIterate.py*, is used to perform DUE. Please refer to (Bamdad Mehrabani et al. 2022; DLR 2023) for more information on dynamic traffic assignment in SUMO. Dijkstra's algorithm is used to find the shortest path. The Logit model is used as the route choice model. The simulation is performed at the mesoscopic level, distinguishing between passenger cars and trucks.

The base-case model used in chapter represents the current traffic situation in Belgium, thus it only considers HDVs and trucks while neglecting other road users such as CAVs. However, as will be detailed in the third chapter, a multi-class traffic assignment model will be employed to investigate the effects of network resilience under various scenarios involving CAVs. It should be noted that in this basic model, all of the traffic flow model's parameters and the traffic assignment model's parameters are considered

the default values of SUMO. Then, they are modified based on the calibration process explained in the next section. The simulation period was 24 hours; however, this chapter reports on calibration and validation for the morning peak.

2.5. Calibration and Validation of the Base case Model

Model calibration is the process of varying model parameters in a way that the system performance of the model meets real data output. This is the most critical and complex step of traffic simulation. Previous studies have suggested that two types of parameters should be calibrated in traffic simulation (Aghababaei, Costello, and Ranjitkar 2019; Barceló 2010; Casas et al. 2010):

1. Calibration of traffic flow model parameters (capacity calibration): This type of calibration consists of local and global parameter modifications and tries to reproduce observed traffic capacities in the field by modifying traffic flow model parameters (reaction time, headway, etc.).
2. Calibration of dynamic traffic assignment (global or local parameters) model parameter: This calibration is intended to make the path selection of vehicles in simulation close to reality. Usually, it is done by comparing the real and simulated traffic counts on specific links. To make the simulated traffic count closer to reality, either the inserted O-D matrix is modified, or the traffic assignment model is modified (by changing the assignment method, route choice model parameters, number of iterations, etc.).

2.5.1 Calibration of traffic flow model parameters

The traffic flow modeling is performed on the mesoscopic scale in SUMO. The mesoscopic model of SUMO is based on the work of Eissfeldt (Eissfeldt 2004). This model is a queue base model which computes the time at which a vehicle travels from a queue based on the traffic state in the current and subsequent queue, the minimum travel time, and the stage of

intersection (e.g., red, green, yellow). Some examples of queuing model parameters are minimum headway, queue length, etc. This model's parameters are calibrated for large-scale networks in the work of Presinger (Presinger 2021). This study uses the same parameters of the queuing model as the work of Presinger. Please refer to chapter 3 for more information about queuing model parameters.

2.5.2 Calibration of dynamic traffic assignment model parameters

The dynamic traffic assignment model was calibrated based on a comparison of real count data and the model-assigned count data for 50 detectors on the network. The segments are selected in a way that covers the entire Belgian network. The traffic count data was extracted from the website of the Flanders government (Vlaanderen 2022). This calibration consists of two parts. First, the O-D matrix is adjusted by testing the different values of λ (section 2.3). As mentioned in previous sections, λ is a calibration parameter in the travel demand model. It determines the importance of a city's population and its distance from the city of origin in determining each trip's destination. After testing several values of λ , it was finally concluded that $\lambda = 0.25$ leads to an O-D matrix with the closest simulated traffic count to the real traffic count. In the context of the gravity model (which is the base of the proposed travel demand model), the calibration factor λ is a crucial parameter that influences the way the model represents the travel demand between different origin-destination pairs. The specific calibration factor λ is affecting the balance between the influence of population and distance in the gravity model. A lower value of λ would reduce the significance of population, while a higher value would increase its importance. By setting $\lambda=0.25$, it suggests that the population factor have less impact in comparison to distance in terms of the destination city selection. The second part is to modify parameters of DUE. The models and parameters considered in the calibration process are warm-up time, routing algorithm, route choice model (e.g., deterministic, or stochastic), route choice model parameters, number of available

alternatives, swapping algorithm, and number of iterations. By altering these parameters, it was found that the Dijkstra routing algorithm with the Logit route choice model and ten iterations gives the best results.

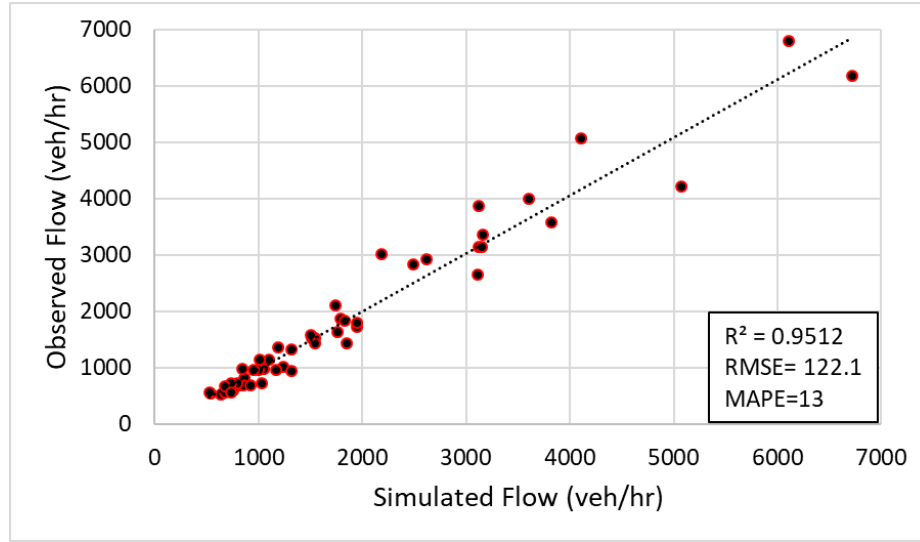


Figure 2-5: Observed and simulated hourly traffic volumes (source: Author)

Figure 2-5 shows the hourly simulation flows versus the observed flows. In addition to the scatter plot, the GEH criterion is calculated to compare the simulated and real traffic volumes. GEH determines the tolerance of relative and absolute errors on the network's traffic count. GEH formula is as follows:

$$GEH = \sqrt{\frac{2(M - C)^2}{M + C}} (2 - 7)$$

M is the simulation's hourly traffic volume, and C is the real-world hourly traffic count. The average GEH is equal to 4.9. In this study, 78% of observations have GEH criteria less than 7.5, which is in the acceptable threshold (Aghababaei et al. 2019).

2.5.3 Validation

Various methods exist to validate traffic simulation models, including traffic count and travel time comparison between reality and simulation. One of the new methods of large-scale traffic simulation models' validation, which has been used in previous studies (Shafiei, Gu, and Saberi 2018), is the comparison of real and simulated travel times at the origin-destination pair level. This method extracts the simulated travel time between each origin and destination (cities) from DUE (for a specific time interval). The real travel times are exported from Google Maps' Distance Matrix API. The Distance Matrix API provides travel distance and time for a matrix of origins and destinations (Google LLC 2017). In this study, this method is implemented for validation.

To validate the traffic simulation model, the O-D pairs' travel times are compared in reality and simulation in A.M. peak hour conditions. The real travel times for a typical peak hour is extracted from Google API Distance Matrix. The Google API Distance Matrix is a powerful tool that provides valuable information about the distance and travel time between two or more locations. This API can provide data on various transportation modes, such as driving, walking, and cycling, which makes it ideal for use in transportation planning and logistics management. The Distance Matrix API can also offer information on traffic conditions, route optimization, and estimated arrival times, allowing businesses and individuals to make informed decisions about their travel plans. By leveraging this API, developers can easily integrate accurate distance and travel time data into their applications and create more efficient and effective transportation solutions. Figure 2-6 compares simulated and real travel times in A.M. peak hours. Figure 2-6 consists of 3600 (60×60) O-D pair travel times throughout the network and shows that the simulation model is a good representation of reality with a high level of accuracy ($R^2 = 0.93$) in congested conditions. The closeness of the travel times in reality and the simulation in a congested state can indicate that the traffic counts in the simulation are near the real traffic count. Since the travel time between O-D pairs depends on the number of vehicles on the path.

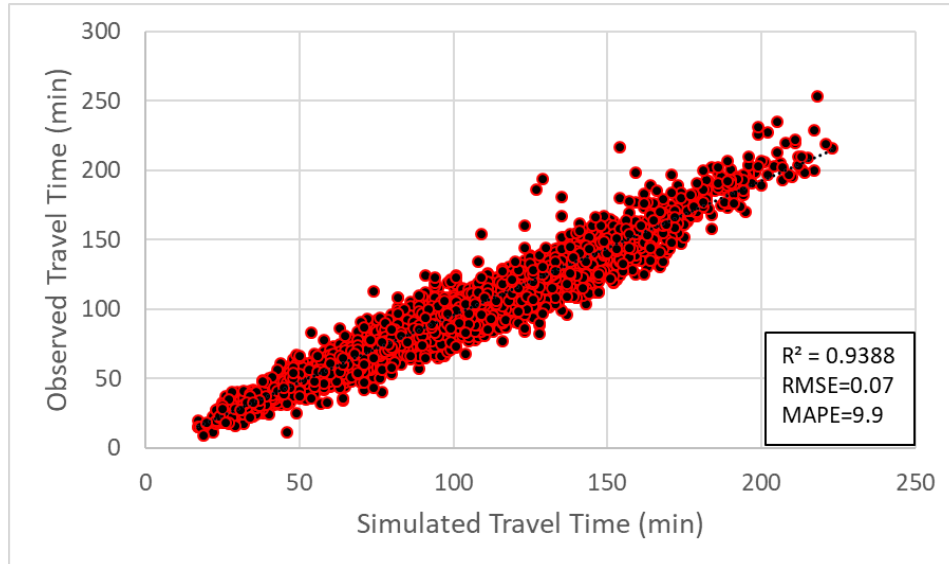


Figure 2-6: Observed vs. simulated travel times (source: Author)

Moreover, to assess the efficacy of the proposed model in O-D pairs characterized as high congestion, figures 2-7 have been presented.

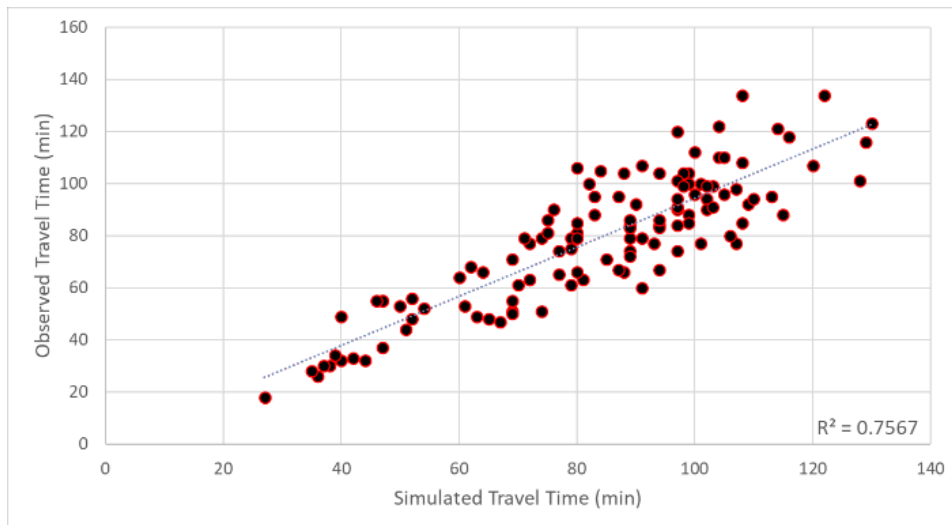


Figure 2-7: Observed vs. simulated path travel for congested O-D pairs (source: Author)

Figure 2-7 illustrates the simulated travel time versus actual travel time in instances where the peak hour travel time to free-flow travel time ratio exceeds 1.5. As depicted in this figure, the R-square value for these o-d pairs is 0.75, indicating that the model performs well for congested O-D pairs. This emphasizes the model's robustness in handling highly congested scenarios.

2.6. Calibrated and Validated Base-Case Model Results

The findings of the calibrated and validated traffic simulation model for Belgium during a A.M. peak hour are displayed in Table 2-6.

Table 2-6: Calibrated and Validated traffic simulation model results

Traffic assignment	Total travel time (hr)	Average speed (km/hr)	Average travel time (min)
DUE	338896	61	79.2

This table reveals that the overall travel time was 338896 hours and the average speed for all vehicles was 61 km/hr. In addition, this table indicates that the average travel time in Belgium for intercity trips is 79.2 minutes. To ensure that this model accurately represents reality, it is necessary to compare this average travel time with actual data. However, a notable point is that, to the best of the knowledge of the author of this doctoral thesis, precise information on the average intercity travel time during peak hours in Belgium is not available, despite the existence of a considerable number of statistics on the average travel time of commuters. For this reason, Google Maps data was used to examine the accuracy of this model. Therefore, the travel time data between origin-destination pairs in this study, extracted from Google Maps, was weighted according to the demand between each origin-destination pair. The weighted average intercity travel time based on real data is 71.5 minutes. Hence, it can be stated that the average travel time in the model is close to the actual average travel time. Additionally, Figure 2-8 presents a comparison between the simulated and actual speeds on the roads in Belgium. As seen in this figure, in many

instances, the speed of vehicles in simulations is similar to the speed of vehicles in reality. This indicates that in the simulation model, not only the travel time of vehicles is realistic but also the simulation model has been able to form traffic congestion in the right locations. Thus, it is possible once again to confirm the accuracy of the travel demand model and the traffic assignment model.

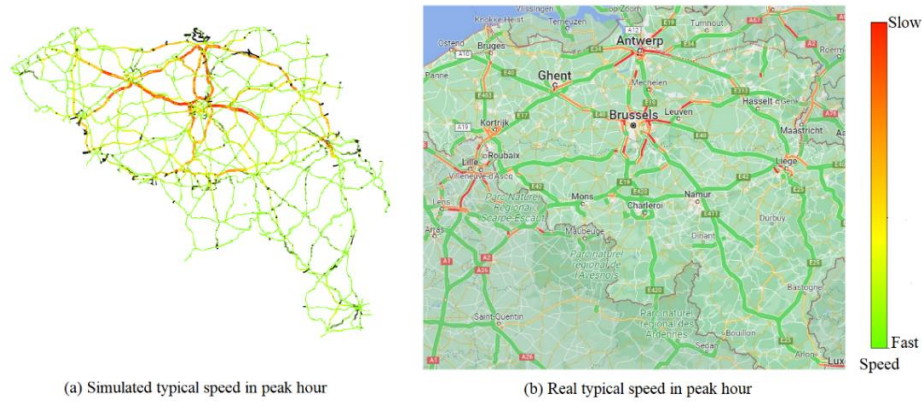


Figure 2-8: Simulated vs real speeds of the Belgium road network (source: Google Map)

2.7. Base-Case Model Limitation

While efforts have been made in the development process of this model to ensure that, based on the available data, the proposed base case model bears the closest resemblance to reality, certain limitations of the model are outlined below. It is important to note that the primary objective of this doctoral dissertation is not to achieve an extremely accurate model for the Belgian network; rather, the study aims to access a base case model that has some degree of similarity to reality. This base case model is intended to be used for the main objectives of this thesis, which include solving the multiclass traffic assignment model algorithm and exploring novel methods for network resilience assessment.

- Given that this study focuses on investigating network resilience on interurban routes, local and intra-urban traffic is not simulated in

this research. However, it is important to highlight that modeling intra-urban networks requires extensive data on intra-urban travel demand and traffic count data, which falls beyond the scope of this study. Additionally, as mentioned in previous sections, when centroids are close to each other, they have been merged. Therefore, it is crucial to acknowledge the limitation that some interurban traffic in cases where centroids are within a distance less than 15 kilometers has not been modeled.

- The transit traffic from other countries is not considered in the model (both passenger cars and trucks). The reason for this is that to consider the passing traffic through Belgium, access to traffic data from neighboring countries of Belgium was required, which are beyond the scope of this study. It is important to acknowledge this limitation in the interpretation of the results.
- The behavior of both passenger cars and trucks trips are assumed to be the same in terms of origin and destination. However, the nature of truck trips may vary based on the locations of terminals, distribution centers, and companies within different sectors, and further research is necessary to investigate these differences.

2.8. Summary

This chapter reports the development, calibration, and validation of the traffic simulation model of Belgium. First, a probabilistic travel demand model is developed using population, distances between the cities, yearly vehicle-kilometer travelled by passenger cars, and annual truck trips. The probabilistic travel demand model calculates the number of all trips based on the yearly vehicle-kilometer travelled and the trucks' trips. The origin and destination of each trip are determined by applying random selection on the population distribution and the mixed distribution of population and the distance between the cities, respectively. The departure time of each trip is based on the typical distribution of travel demand. Then the probabilistic travel demand model's outputs (hourly O-D matrices) are imported to SUMO's traffic simulation software. After that, a base model is simulated using the mesoscopic feature of the SUMO traffic simulator

and the DUE traffic assignment to assign travel demand to the network. This basic model is calibrated by real traffic count data. The calibration process includes the calibration of traffic flow model parameters (queuing model) and the parameters of dynamic traffic assignment. Finally, the model is validated using real travel times between cities in congested conditions. The real travel times are extracted from Google map Distance Matrix API. In this study, for modeling the freight demand, only trucks with Belgian license plates were taken into consideration. However, for achieving highly precise outcomes, it's imperative to factor in the transit traffic of cargo vehicles from other nations as well. This task, though, requires access to cargo data from those other countries.

The calibrated and validated base-case model presented in this chapter will be utilized in the upcoming chapters to evaluate the resilience of the Belgian road network under various scenarios involving the use of CAVs. Therefore, in the next chapter, information on how to consider CAVs in traffic simulation is presented.

3. Modelling HDVs and CAVs

Following the development of the base-case model for Belgium, it is necessary to determine how CAVs would be modeled in accordance with the objectives of this study. This chapter focuses on determining how the presence of CAVs is incorporated into traffic flow modeling and traffic assignment modeling. The content of this chapter is based on the following papers.

- Bamdad Mehrabani, B., Erdmann, J., Sgambi, L., Seyedabrishami, S., & Snelder, M. (2023). A multiclass simulation-based dynamic traffic assignment model for mixed traffic flow of connected and autonomous vehicles and human-driven vehicles. *Transportmetrica A: Transport Science*, 1-32. <https://doi.org/10.1080/23249935.2023.2257805>. (Bamdad Mehrabani et al. 2023)
 - Bamdad Mehrabani, B., Erdmann, J., Sgambi, L., and Snelder, M. Proposing a Simulation-Based Dynamic System Optimal Traffic Assignment Algorithm for SUMO: An Approximation of Marginal Travel Time. SUMO User conference 2022, Berlin, Germany <https://doi.org/10.52825/scp.v3i>. (Bamdad Mehrabani et al. 2022).
 - Karbasi, A. H., Bamdad Mehrabani, B., Cools, M., Sgambi, L., Saffarzadeh, M. (2022). Comparison of Speed-Density Models in the Age of Connected and Automated Vehicles, *Transportation Research Record*, <https://doi.org/10.1177/0361198122111853>. (Karbasi et al. 2022).
-

3.1. Road Network Users

Currently, Belgium's road network only has HDVs in operation. However, it is expected that CAVs will be introduced to the transportation system in the near future. This means that both types of vehicles will coexist on the roads. As a result, this thesis includes simulations for both HDVs and CAVs. The difference between these users can be considered in simulation in two ways. First, their driving behavior and second, their route choice behavior. In the following subsections, each of these two types of users will be introduced, and the assumptions made for modelling them will be expressed.

3.1.1 HDVs

HDVs refer to vehicles that are operated by human drivers. These vehicles rely on the manual operation of pedals, steering wheels, and other controls by human drivers to control their movement and direction. HDVs are the most common mode of transportation worldwide and have been in use for over a century.

HDVs, exhibit normal driving behavior and can be categorized into two groups based on their route choice behavior. The first group consists of users who always opt for the route that minimizes their own travel time, achieving a user equilibrium (assumed to be 50% of HDVs). The second group of HDVs use navigation apps such as Google and Waze to choose their route based on real-time travel times (assumed to be 50% of HDVs). The capability of rerouting is only applicable to performing routing before entering the network, and it is assumed that this category of vehicles does not have the ability to reroute during travel. Both groups of route choice behavior are considered as HDVs in this study. The reason for assuming that 50% of HDVs use navigation apps is that previous studies using surveys have shown that more than 49.6% of users utilize mobile navigation applications (Yang et al. 2021).

3.1.2 CAVs

CAVs are vehicles that are equipped with advanced technologies that enable them to communicate with each other and with their surrounding environment, and to operate autonomously without direct human input. The technology that powers CAVs comprises of two key components: automation and connectivity. Automation involves the integration of decision-making and control systems between humans and machines to operate the vehicle, which can range from level 0 (completely manual) to level 5 (full autonomy) (presented in table 3-1).

This hierarchy represents the level of collaboration between humans and machines in controlling the vehicle. The second feature, connectivity, allows the vehicle to communicate with various other elements, including infrastructure (V2I), other vehicles (V2V), and pedestrians (V2P). Even though these vehicles are yet to be widely adopted in transportation systems, a significant amount of research has been conducted on their impact on the performance of transportation networks. While there are conflicting opinions on the effects of CAVs on road networks, they are anticipated to bring several benefits: 1- Due to their automation, CAVs' driving behavior will improve road capacity. This improved road capacity will lead to changes in link travel times, impacting the route choice of both CAVs and HDVs. 2- As a traffic management center may control CAVs, they may have full information about the status of the road network; hence they can follow different route choice principles compared to HDVs. For instance, they can follow the route which minimize the whole system travel time (System Optimal (SO)) instead of selfish routing (User Equilibrium (UE)). 3- Thanks to the connectivity feature of CAVs, they can respond to traffic congestion or disruption sooner than other types of vehicles by adjusting their routes (rerouting capability).

Table 3-1: Levels of Automation (SAE 2018)

Level of Automation	Definition
Level 0: No automation	The full-time performance by the human driver of all aspects of the dynamic driving task, even when enhanced by warning or intervention systems.
Level 1: Driver Assistance	The driving mode-specific execution by a driver assistance system of either steering or acceleration/deceleration using information about the driving environment and the expectation that the human driver performs all remaining aspects of the dynamic driving task.
Level 2: Partial Automation	The driving mode-specific execution by one or more driver assistance systems of both steering and acceleration/deceleration using information about the driving environment and the expectation that the human driver performs all remaining aspects of the dynamic driving task.
Level 3: Conditional Automation	The driving mode-specific performance by an autonomous driving system of all aspects of the dynamic driving task with the expectation that the human drivers respond appropriately to a request to intervene.
Level 4: High Automation	The driving mode-specific performance by an autonomous driving system of all aspects of the dynamic driving task, even if a human driver does not respond appropriately to a request to intervene.
Level 5: Full Automation	The full-time performance by an autonomous driving system of all aspects of the dynamic driving task under all roadway and environmental conditions that can be managed by a human driver.

This study makes certain assumptions about CAVs. Firstly, it assumes that CAVs exhibit safer and faster driving behavior. Secondly, it assumes that these vehicles will choose a route that minimizes the total travel time (known as SO). Finally, the study assumes that a portion of these vehicles (50%) are equipped to reroute based on real-time updated information such as an accident. The process of rerouting can be utilized by CAVs both prior

to entering the network and during driving based on real-time information of traffic congestion. This can help in optimizing the route and enhancing the overall efficiency of the transportation system.

While acquiring real-time information from the entire network poses some challenges in reality, it is imperative to consider that leveraging the deployment of routing software and accessing both historical and real-time data through such applications can bring the network closer to system optimal. Notably, routing software (e.g., google map), given the high penetration rates in road networks, constrains routes based on the real-time shortest path. Consequently, integrating data from connected vehicles with the real-time and historical data from routing software allows for the substitution of the shortest path with a marginal path, approaching a route that aligns with the system optimal.

While this study has made above assumptions about how CAVs influence driving behavior and route selection, it is important to acknowledge that some studies have made differing and at times contradictory assumptions. For example, some researchers assume CAVs will follow the SO routines (Aziz 2019; Bagloee et al. 2017; Chen et al. 2020; Guo, Ban, and Aziz 2021; Li, Liu, and Nie 2018; Mansourianfar et al. 2021; Ngoduy et al. 2021; Sorani and Bekhor 2018; Wang et al. 2020; Zhang and Nie 2018), while others think CAVs will follow UE principles (Bahrami and Roorda 2020; Samimi Abianeh et al. 2020; Wang et al. 2021; Wang, Peeta, and He 2019; Xie and Liu 2022; Zhang, Lu, and Hu 2020). Also, some studies model the deterministic route choice behavior of CAVs (Wang et al. 2020, 2021, 2022, 2019), and some others assume the stochastic route choice behavior for CAVs (Xie and Liu 2022; Zhang et al. 2020). On the other hand, numerous studies have suggested that CAVs can boost route capacity and improve safety (Atkins 2016; Karbasi and O'Hern 2022; Liu and Fan 2020; Mehrabani et al. 2021; Viridi et al. 2019), while others argue that they may reduce it. Since CAVs are not yet available on the market, it is impossible to verify or reject any of these claims with certainty. The only way to examine the potential effects of CAVs is to explore various hypotheses related to their impact.

Section 3.2 discusses how to account for the dissimilarities between the typical driving behavior of HDVs and the safer and quicker driving of CAVs. Section 3.3 deals with how to model the variations in route selection between CAVs and HDVs. It is important to note that all simulations that will be discussed in the following chapters will consider trucks in addition to the two types of vehicles (HDVs and CAVs) mentioned earlier. It is assumed that trucks always choose their routes based on the user equilibrium principle. Furthermore, their driving behavior is characterized by lower speeds and greater time gaps compared to regular cars. Additionally, their size is larger than that of regular cars.

3.2. Traffic Flow Modeling

In this section, it is specified how the traffic flow propagation for HDVs and CAVs has been modeled in the SUMO. Additionally, it is explained how the distinction between the driving behavior of HDVs and CAVs has been considered in the simulation. First, the modeling of CAVs and HDVs in the microscopic scale is explained. Then, it is described how microscopic-scale simulations have been utilized to simulate CAVs and HDVs in mesoscopic-scale.

3.2.1 Microsimulation

The movement of vehicles is modelled using car-following and lane-changing models on the microscale. A car following model is a mathematical model that describes the behavior of a vehicle as it follows another vehicle on a roadway. The model aims to capture the dynamics of the vehicles' interactions, including factors such as acceleration, speed, and distance between two vehicles. There are various car following models that have been developed, such as the Gipps model, the Intelligent Driver Model (IDM), and the Krauss model. These models differ in their assumptions and mathematical formulations, but they all aim to describe the behavior of vehicles as they follow one another on a roadway. For analyzing the longitudinal movement of vehicles, the Krauss car-following model is employed, which describes the safe speed (Krauss, Wagner, and

Gawron 1997; Song et al. 2014). This car-following model is the default car-following model in the SUMO simulator. In contrast to Wiedemann car-following model available in VISSIM software, which includes an acceleration function tailored to different traffic regimes, the Krauss model is a continuous-space car-following model that places significant importance on ensuring safe driving speeds (Wiedemann 1974).

A lane-changing model is a component of a traffic simulation model that describes the lateral movement of vehicles and their behavior as they change lanes on a roadway. Lane-changing models are designed to capture the decision-making process of drivers when changing lanes, such as when to initiate a lane change, which lane to switch to, and how to adjust their speed and position to merge into the new lane safely. This study uses LC2013 lane changing, a lane-changing model in the SUMO simulator (DLR 2023). The SUMO software incorporates three distinct motivations for lane changing. The first of these is referred to as strategic lane-changing, which occurs when a driver changes lane due to the lack of a direct connection between their current lane and the next route edge. Another motivation is cooperative lane-changing, which involves a driver changing lanes solely to assist another vehicle with their own lane change. In this model, vehicles are notified when they are blocked by other vehicles and may change lanes in either direction, provided there is no strategic impediment to doing so. The third motivation is tactical lane-changing, which allows a vehicle to switch lanes when following a slower-moving vehicle (Erdmann 2015). The LC2013 lane-changing model is utilized to demonstrate how both connected and human-driven vehicles behave in this context, with the most important parameter modified accordingly (DLR 2023). The sketch of car-following and lane-changing model is illustrated in Figure 3-1.

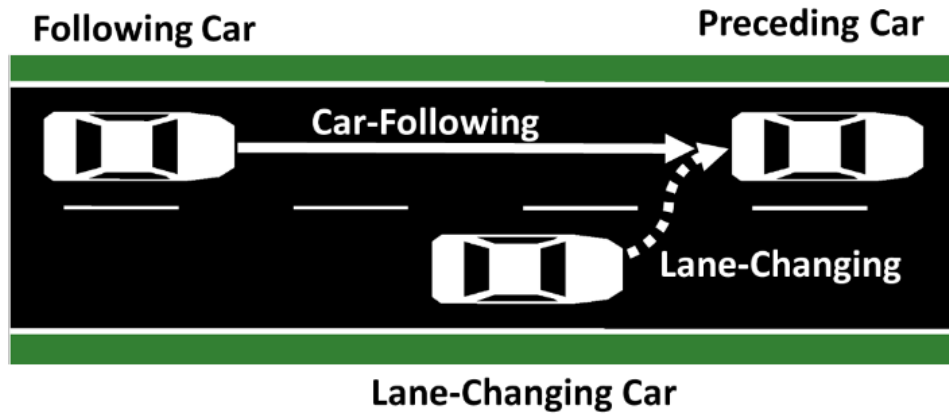


Figure 3-1: Illustration of car-following and lane-changing model (source: Author)

The method for modelling CAVs in this study is in line with the work of Lu et al. (Lu et al. 2020) and Karbasi et al. (Karbasi et al. 2022). The fundamental idea behind modelling the longitudinal movement of CAVs is that they have the same car-following model as HDVs, with some modifications to simulate the full automation feature of CAVs. Thanks to automation technologies, CAVs have a shorter reaction time, allowing them to follow the leading vehicle with a smaller headway distance compared to HDVs. It is assumed that CAVs have a shorter time headway (reaction time), a smaller minimum gap, and a faster acceleration than HDVs, and they can avoid collisions if the leading vehicle begins braking within their acceleration bounds (Karbasi et al., 2022; Lu et al., 2020). The parameters modified for CAVs in the Krauss car-following model (Krauss et al. 1997) are listed in Table 3-2. Time headway, acceleration, and minimum gap for HDVs are based on the default value in the SUMO simulator, CAV parameters are taken from Atkins Ltd, and driver imperfection values (σ) for HDVs and CAVs are taken from Lu et al (Atkins 2016; DLR 2023; Lu et al. 2020). The reason for choosing CAV driving behavior from Atkins' study (Atkins 2016) is that this study suggests car-following values for urban and high-speed networks. Since

this study investigates the impact of CAVs on the freeway networks, car-following values based on Atkins's study are reasonable (Atkins 2016).

Table 3-2: Parameters of the car-following model in SUMO

	Mingap (m)	Accel (m/s ²)	Decel (m/s ²)	Emergency Decel (m/s ²)	Sigma	Tau (s)
HDV	2.5	2.6	4.5	8	0.5	1.0
CAV	1.5	3.5	4.5	8	0	0.9

Mingap: the offset to the leading vehicle when standing in a jam (m).

Accel: the acceleration ability of vehicles (m/s²).

Decel: the deceleration ability of vehicles (m/s²).

Emergency Decel: the maximum deceleration ability of vehicles in case of emergency (m/s²).

Sigma: the driver imperfection (between 0 and 1).

Tau: the driver's desired (minimum) time headway (reaction time) (s).

The studies conducted by Mintsis et al. and Lücken et al. (Lücken et al. 2019; Mintsis et al. 2018) were used to identify the differences in lane-changing behavior between CAVs and HDVs. These studies were based on SUMO simulator lane-changing concepts, and the most important parameter of the lane-changing model for both CAVs and HDVs was derived from them. Mintsis et al. determined that the *lcAssertive* parameter, which describes the willingness of a vehicle to accept lower front and rear gaps on the target lane, had the strongest influence on driving behavior from a lane-changing perspective. A higher value of *lcAssertive* indicates a more aggressive attitude towards shorter gaps, meaning that the vehicle is more willing to change lanes with smaller gaps. Lücken et al. showed that this value for CAVs could range from 0.6 to 0.8. In this study, the value of *lcAssertive* is set to 0.7 for CAVs and 1.3 for HDVs. All other parameters were set to SUMO's default values. This reflects the differences in the lane-changing behavior between the two vehicle types.

3.2.2 Mesosimulation

The mesoscopic model in SUMO is based on the research conducted by Eissfeldt (Eissfeldt 2004). This model involves organizing vehicles in traffic queues, which is similar to the cell transmission model (Daganzo 1995). The vehicles are generally released from the queues in the same order they entered, following the first-in-first-out principle (Amini, Tilg, and Busch 2019). The model calculates the time it takes for a vehicle to travel from the queue by considering the traffic state in the current and subsequent queues, the minimum travel time, and the stage of the intersection (e.g., red, green, yellow). There are four possible combinations of traffic states between consecutive segments (DLR 2023). The amount of the minimum headway between vehicles varies for each of the four cases:

1. when a vehicle travels from a free segment to another free segment (default minimum headway 1.13),
2. when a vehicle travels from a free segment to a congested segment (default minimum headway 1.13),
3. when a vehicle travels from a congested segment to a free segment (default minimum headway 1.73),
4. when a vehicle travels from a congested segment to another congested segment (default minimum headway 1.4)

The parameter τ is employed to establish the minimum headways between vehicles, acting as a multiplier for each of the four potential combinations. Each of these values is multiplied by the τ configured in the vehicle type of the relevant vehicle (with the default τ set to 1). A sketch outlining the queuing model in SUMO is depicted in Figure 3-2.

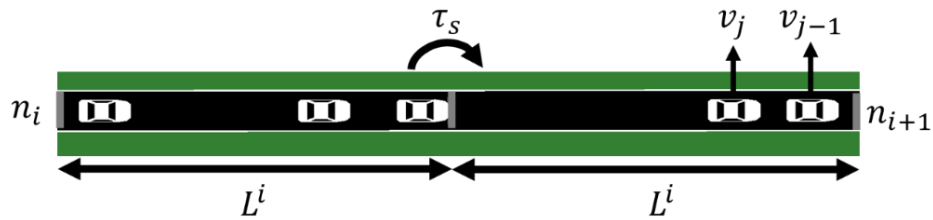


Figure 3-2: Sketch of queuing model in SUMO (source: Author)

It should be noted that although the SUMO software is first developed for simulation at microscopic level, the use of its mesoscopic capability is valid due to the following reasons:

- The mesoscopic SUMO model is a queue-based model with a very high speed, validated by numerous previous studies such as the study of (Presinger 2021).
- Mesoscopic simulations operate at a higher level of abstraction than microscopic simulations, providing a good balance between detail and computational efficiency. SUMO's mesoscopic features make it well-suited for simulating large urban areas and longtime durations.
- Mesoscopic simulations are generally faster than microscopic simulations, as they abstract away many of the detailed vehicle-level interactions. Mesoscopic simulation runs up to 100 times faster than the microscopic model of SUMO. This speed advantage is beneficial for quickly assessing different traffic scenarios and running simulations for extended time periods.
- SUMO is an open-source software, allowing users to customize and extend its functionality. This is advantageous for modelling CAVs using customized traffic flow modelling parameters.

Although some research has explored using cell transmission models or simplified car-following models to model CAVs in mesoscale networks (Mansourianfar et al. 2021; Melson et al. 2018), to the best of the author's knowledge, there has been no previous investigation of modeling CAVs using an Eissfeldt queuing model in the SUMO software.

Thus, in this study, the author adopts the same approach used to model CAVs on the microscale to model CAVs in mesoscale networks. Specifically, CAVs and HDVs are distinguished based on their queuing model parameters, with different queue (τ) values applied to each vehicle class. The assumption is that CAVs can follow more efficiently between consecutive segments compared to HDVs, leading to a lower τ parameter value for CAVs (Yu et al. 2021).

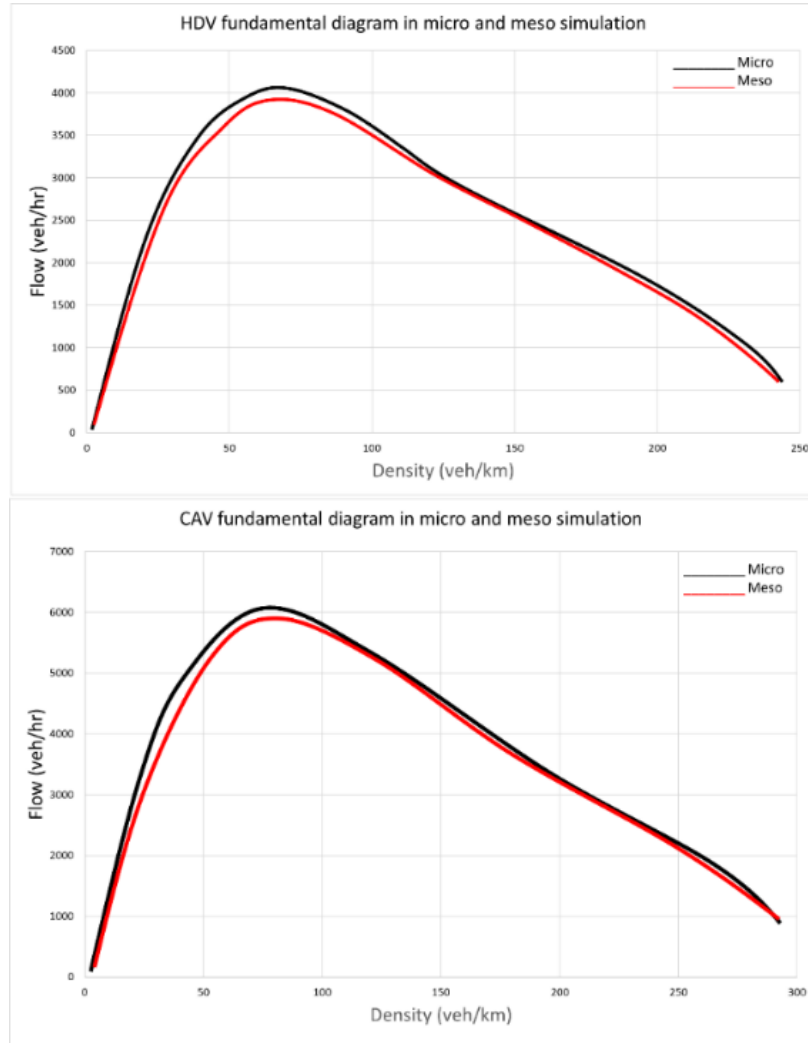


Figure 3-3: Fundamental diagrams in micro & meso simulations (source: Author)

To ensure consistency between the mesoscopic and microsimulation results, the τ parameter is calibrated for both CAVs and HDVs to obtain a Fundamental Diagram (FD) that is consistent between the two scales. To begin the calibration process, the microsimulation parameters are set according to Table 3-2, and the mesosimulation parameters are based on

Presinger's work (Presinger 2021). The comparison between the meso and micro scales was performed by conducting a micro simulation for each class of vehicles on a typical highway using the parameters in Table 3-2 and extracting its FD. Then, for each class of vehicles, the τ parameter was adjusted in the meso scale in such a way that it had the closest FD to the micro scale. This type of calibration of mesoscopic parameters is recommended by previous studies (Tympakianaki et al. 2022).

After calibration and comparison of FDs between the micro and mesoscales, the authors find that the value of τ is 1.06 for HDVs and 0.79 for CAVs. These values indicate that CAVs exhibit a faster behavior when travelling from one segment to another. It should be noted that the difference between CAVs and HDVs in terms of headway is more pronounced in the meso scale compared to the micro scale. This is because the considered headway in the micro scale encompasses the spacing between vehicles in all conditions, not just when they are moving from one queue to another. The FDs generated at the meso and micro scales for CAVs and HDVs are shown in Figure 3-3 using the calibrated parameters.

3.3.Multiclass traffic assignment model for mixed traffic flow

This section explores how the different route choice behavior of CAVs affects the road network, building on the findings of the previous section, which analyzed how CAVs driving behavior impacts traffic flow. In this study, it is assumed that HDVs choose a route that minimizes their own travel time, while CAVs select a route that minimizes the total travel time of the network. CAVs, on the other hand, have the ability to en-route rerouting based on updated information. This variation in route choice behavior has a significant impact on the traffic assignment problem, which is used to assess network resilience. After determining travel demand, the traffic assignment problem must be solved to determine the number of vehicles on each link, allowing for the measurement of network resilience metrics.

Traffic assignment determines the routes that are used by vehicles based on certain behavioral principles, such as, for example, each vehicle seeks to minimize its own travel time. Many of the current traffic assignment algorithms are based on the two behavioral principles of Wardrop (Wardrop 1952): (1) Wardrop's first principle: under user equilibrium (UE) conditions, no vehicle can unilaterally reduce its travel time by shifting to another route; (2) Wardrop's second principle: under system optimal (SO) conditions, traffic should be arranged in congested networks such that the average (or total) travel time is minimized. The first principle (UE) assumes that each vehicle attempts to minimize its own travel time (selfish routing). In contrast, in the second principle (SO), it is considered that each vehicle selects a route that minimizes not only its own travel time but also the entire network's travel time.

Traffic assignment models can be broadly classified into two categories: 1) static traffic assignment (STA) and 2) dynamic traffic assignment (DTA) (Saw, Katti, and Joshi 2015; Tsanakas 2019). In STA, the traffic demand is static with respect to time and is typically used for strategic transportation planning. In DTA, the traffic demand is not static and varies over time, and the arrival time at a link is different from the departure time. Although the computational expenses of DTA are higher than those of STA, DTA attracts researchers owing to the several limitations of STA, for example, 1) limitations of static models because of the use of volume delay functions (such as no overtaking effects and no representation of the phenomenon of congestion spillback), 2) limitations in modeling of signal synchronization, 3) limitations in modeling of lane-based effects (such as high-occupancy vehicle lanes), and 4) limitations in modeling intelligent transportation system-related applications, such as traveler information systems (Y.-C. Chiu et al. 2011). This study works on the dynamic models of traffic assignment.

When there is only one type of user in a network (for example, only HDV or only CAV), the dynamic traffic assignment problem can be solved based on one of the principles of Wardrop. However, when both HDVs and CAVs users co-exist in the network, the traffic assignment problem needs to be

solved for mixed traffic flow. To solve the TAP in mixed traffic, multiclass traffic assignment models are developed. These models investigate the route choices of heterogeneous users. This heterogeneity can be in terms of value of time, travel mode, travel disutility function, information quality, network topology, and different routing behavioral principles (Xie and Liu 2022). The last group of heterogeneity causes (following other routing behavioral principles) can be formulated as a multiclass traffic equilibrium first addressed by Harker (Harker 1988). Therefore, in this section, we are looking to solve multiclass traffic assignment problem of mixed traffic flow of CAVs and HDVs. Multiclass refers to the fact that two types of users (HDVs and CAVs) follow different path selection principles, while mixed traffic refers to the fact that these two types of users have different driving behaviors.

However, the multiclass traffic equilibrium of CAVs and HDVs, following different routing behavioral principles, is a relatively new problem and needs more investigation. Table 3-3 provides the list of previous studies which implement or propose a framework for solving the multiclass TAP of mixed traffic of CAVs and HDVs. The literature review reveals that the majority of existing studies on multiclass TAP of mixed traffic flow and CAVs have focused on either the impact of CAVs on road capacity, specifically their driving behavior (Aziz 2019; Bahrami and Roorda 2020; Ngoduy et al. 2021; Zhang et al. 2020), or on the difference in routing principles between CAVs and HDVs, either SO or UE (Bagloee et al. 2017; Chen et al. 2020; Hu et al. 2018; Li et al. 2018; Medina-Tapia and Robusté 2019; Olia et al. 2016; Samimi Abianeh et al. 2020; Sorani and Bekhor 2018; Wang et al. 2019; Xie and Liu 2022; Zhang and Nie 2018). While a few studies, such as Fakhrmoosavi et al. (Fakhrmoosavi et al. 2020), Liu et al. (Liu et al. 2019), and J. Wang et al. (Wang et al. 2021, 2022), have considered both the distinct route choice behavior of CAVs and their impact on road capacity, they do not solve the multiclass equilibrium problem. They assumed that CAVs and HDVs follow the same routing behavioral principle (e.g., both classes follow UE principles). Few studies solve the multiclass equilibrium TAP (mixture of SO users and UE users) considering CAVs' impacts on road capacity (Guo et al. 2021;

Mansourianfar et al. 2021; Wang et al. 2020). Also, less attention is paid to the effects of CAVs' rerouting capability in the multiclass equilibrium problem (Hu et al. 2018). For instance, Mansourianfar et al. 2021 (Mansourianfar et al. 2021) solved the multiclass equilibrium TAP by the simulation-based method. CAVs' impact on road capacity is modeled by applying modified parameters of a simplified car-following model in meso simulation. However, in Mansourianfar et al.'s work, CAVs' rerouting capability is not considered. Also, in these studies, different solution methods have been considered for solving the multiclass equilibrium TAP. There are two main categories of solutions: simulation-based models and analytical-based models. Simulation-based methods and analytical-based methods differ in their approaches to solving the traffic assignment problem. Simulation-based methods involve the creation of detailed simulation models that replicate the dynamic and stochastic nature of traffic, considering factors such as individual driver behavior. On the other hand, analytical-based methods rely on mathematical formulations and algorithms to represent traffic flow. However, they often involve simplifying assumptions, sacrificing some level of realism.

Looking at Table 3-3, the number of studies using analytical-based methods is higher than those using simulation-based techniques. Analytical models of DTA use analytical formulations to predict the propagation of traffic in a network (network loading). Traffic propagation models, which are used in analytical models, are typically based on extensions of the Lighthill–Whitham–Richards (LWR) model (Lighthill and Whitham 1955; Richards 1956). LWR is a macroscopic one-dimensional traffic model that uses traffic density and speed for traffic flow propagation (Li 2016). The traffic flow propagation during dynamic network modeling can be based on the cell transmission model (Ziliaskopoulos 2000) or link transmission model (Yperman 2007). Although the mathematical closed form is available for the analytical solution algorithm (thus, they are highly accurate), in practice, they cannot model certain phenomena (such as individual vehicles and vehicle interaction) in detail due to their macro-scale nature. Also, applying analytical assignment problems to large-scale networks may be highly time consuming and complex to solve (Gawron

1999). On the other hand, simulation-based traffic assignment models use a traffic simulator to replicate the traffic flow dynamics (propagation) and spatio-temporal interactions (e.g., vehicle movements), which are based on micro/meso traffic flow simulation models (Saw et al. 2015). In addition, a traffic simulator is used as part of the search process to determine the optimal solution (Peeta and Ziliaskopoulos 2001). They typically conduct several iterations to obtain optimum values (no closed form is available). These models allow for greater detail in capturing the effects of CAVs on road capacity (Saw et al. 2015). These models often assume distinct driving behaviors for CAVs, such as faster reaction times (Mansourianfar et al. 2021) or deterministic acceleration models (Fakhrmoosavi et al. 2020). Compared to analytical models, simulation-based models are considered more accurate because they can depict traffic flow propagation with greater detail, especially regarding CAVs.

To summarize, by reviewing previous articles on the solution framework of multiclass equilibrium TAP in mixed traffic flow, the following gaps can be expressed:

1. Most of the studies have used analytical solutions, which can be challenging in large dynamic real cases.
2. The solution frameworks capable of considering the impacts of CAVs on road capacity and the impacts of CAVs on route choice (multiclass equilibrium with the rerouting capability) are very rare.
3. There are no commonly accepted assumptions about the future route choice and driving behavior of CAVs.

Table 3-3: Review of Previous Studies on Multiclass Traffic Assignment

Author	Goal of the Study	TA Method	TA Approach	Software	CAVs impacts on capacity
Olia et al. 2016	Assessing the impacts of CAVs	Simulation-Based (Micro)	DTA with rerouting capability (frequently rerouting for CAVs and infrequently rerouting for non-CAVs)		No
Samimi Abianeh et al. 2020	Evaluation of the impacts of CAVs on incidents		SUMO		
Liu et al. 2019	Evaluate the effect of route guidance under the CAV environment		Parameters		Yes
Hu et al. 2018	Presenting DTA for Mixed Traffic	Simulation-Based (Meso)	Multiclass equilibrium (DSO and DUE) with rerouting capability		No
Fakhmoosavi et al. 2020	Observing the impacts of CAVs by adaptive fundamental diagrams		DTA with rerouting capability for CAVs		
Mansourianfar et al. 2021	Proposing a joint routing and pricing control scheme		DYNAS MART-P Aimsun		Yes
Bamdad Mehrabani et al., 2023 (Current study)	Proposing an open-source solution framework for multiclass TAP in mixed traffic flow	Simulation-based	Multiclass equilibrium: DSO for CAVs (with rerouting) and DUE for HDVs (without rerouting)		Yes
J. Wang, Peeta, and He 2019	Providing a solution algorithm for multiclass traffic assignment	Variational Inequality-Based	Mixed static traffic assignment: cross-nested logit for HDVs and UE for CAVs		N.A.
Li, Liu, and Nie 2018	Providing a control Day-To-Day dynamical system to guide AVs		Multiclass equilibrium: UE for HDVs and SO for CAVs		Matlab
K. Zhang and Nie 2018	Proposing a route control scheme		Multiclass equilibrium with multiclass users: UE for HDVs and SO for CAVs		Matlab

Table 3-3: Review of Previous Studies on Multiclass Traffic Assignment

Author	Goal of the Study	TA Method	TA Approach	Software	CAVs impacts on capacity
Jiang et al. 2016	Capture multiple vehicle classes in a DTA model	Variational Inequality-Based	Dynamic User Optimal for cars and trucks		
F. Zhang, Lu, and Hu 2020	Examining equilibrium for mixed traffic flows		SUE with different cost functions for CAVs and Non-CAVs		
J. Wang et al. 2021	Control the HDV using the CAV/toll lanes		Gross nested logit with elastic demand for HDVs; UE with elastic demand for CAVs	N.A	Yes
J. Wang et al. 2022	proposing a worst-case mixed traffic assignment model		SUE for HDVs and UE for CAVs		
Bagloee et al. 2017	To highlight the benefit of the cooperative routing	Mathematical Programming	Multiclass equilibrium: UE for HDVs and SO for CAVs	GAMS	
Sorani and Bekhor 2018	Evaluation in the presence of autonomous vehicles		Multiclass equilibrium: UE for HDVs and SO for CAVs	N.A.	No
Medina-Tapia and Robusté 2019	Evaluating the effects of CAVs on a city road network		Static assignment with a modified cost function for CAVs and HDVs		
Chen et al. 2020	Develop a path-control scheme		Multiclass equilibrium: SO for CAVs and UE for HDVs	CPLEX	No
Aziz 2019	Develop a mathematical SO-DTA model for mixed traffic flow	Mathematical Programming	SO for both CAVs and HDVs		
Bahrami and Roorda 2020	Providing management policies for CAVs		UE for CAVs and HDVs	N.A.	Yes
Guo, Ban, and Aziz 2021	Explore a system-level control mechanism of CAVs consisting of CAV and HDV		Multiclass equilibrium: DSO for CAVs and DUE for HDVs		

Thus, this study fills these gaps by proposing a new open-source solution framework of the Multiclass Simulation-based Traffic Assignment Problem for the Mixed traffic flow of CAVs and HDVs (MS-TAP-M). This simulation-based solution framework considers the impact of CAVs on road capacity and the different route choice behavior of CAVs compared to HDVs (in micro and meso simulation scales). To address CAVs' impact on road capacity, modified parameters of car-following/lane-changing models (in microscale) and queuing model (in mesoscale) are utilized (described in the previous section). Also, to distinguish between CAVs and HDVs in terms of route choice, it is assumed that HDVs follow UE with pre-trip rerouting capability while CAVs follow SO with both en-route and pre-trip rerouting capability. Since the solution framework is open source, it is possible to model a variety of other assumptions on the driving behavior and route choice behavior of CAVs.

The proposed solution framework of the MS-TAP-M in this study use SUMO traffic simulator. To have a better view of the available simulation-based solution methods of the traffic assignment problem in the most widely used and well-known micro/meso traffic simulator packages, Table 3-4 is presented. In this table, the most prominent simulation software for traffic simulation (Saidallah, El Fergougui, and Elalaoui 2016), whether commercial or open source, utilized in the literature for solving traffic assignment problems, is presented. This list encompasses the most well-known software tools in the field of traffic simulation, extensively employed in various research endeavors.

The rationale behind employing the SUMO software in this study is rooted in its open-source nature, allowing for the incorporation of any necessary modifications related to vehicle modeling. Additionally, the flexibility exists to develop extensions for this software and integrate them, such as the traffic assignment problem-solving algorithm proposed in this study. In other words, our pursuit in this research was to identify software that could accommodate the connection of a traffic assignment algorithm. Specifically, we aimed to find software where the developed traffic assignment algorithm by the researcher could be seamlessly integrated.

Table 3-4: Micro/Meso traffic simulation packages and their available DTA solution methods

Simulator	Developer	Scale	Available DTA Methods
Aimsun	(J Barceló & Ferrer, 1997)	Micro/Meso	Stochastic Route Choice
CONTRAM	(Taylor, 2003)	Meso	DUE
CORSIM	(US-DOT 1995)	Micro	
DRACULA	(Liu 2010)	Micro	
DTALite	(Zhou and Taylor 2014)	Agent-based	
Dynameq	(Mahut 2001)	Micro	
DynaMIT	(Ben-Akiva et al. 1997)	Meso	Converge to observe flow
DynaSMART	(Jayakrishnan, Mahmassani, and Hu 1994)	Meso	Instantaneous information
			Predictive information
			DSO
DynusT	(Chiu et al., 2011)	Meso	DUE
INTEGRATION	(Van Aerde et al. 1996)	Micro/Meso	
MATSIM	(Dobler and Nagel 2016)	Agent-based	
PARAMICS	(Smith, Duncan, and Druitt 1995)	Micro	
PTV Vissim	(Fellendorf 1996)	Micro/Meso	
SUMO	(Lopez et al. 2018)	Micro/Meso	Stochastic Assignment
			DUE/DSO

Considering the investigations conducted by the researcher and the inquiries posed to developers of well-known software such as Aimsun and PTV, at the time of this thesis, the examined software did not provide the

capability to employ the researcher's developed traffic assignment algorithm within them. The sole software that facilitated this capability, allowing the utilization of the researcher's developed traffic assignment algorithm, was the SUMO software. In section 3.3.1, the notations and abbreviations are presented. Then section 3.3.2 outlines the methodology used to solve the multiclass TAP of mixed traffic flow.

3.3.1 Notation

The used notations are listed in Table 3-5. These notations are grouped in indices, sets, Variables, parameters, and elements.

Table 3-5: Notations

Indices	
f	index for traffic flow
i	index for iteration steps
k	index for path
j	index for vehicle
Sets	
$G(V, A)$	traffic network
$D_H(R, S)$	set of all HDVs ($J_H \in D_H$)
$D_C(R, S)$	set of all CAVs ($J_C \in D_H$)
$J_H(r, s)$	set of HDVs, travel from r to s ($j_h^{r-s} \in J_H$)
$J_C(r, s)$	set of CAVs, travel from r to s ($j_c^{r-s} \in J_C$)
A	set of links ($a \in A$)
V	set of nodes ($v \in V$)
R	set of origin nodes ($r \in R$)
S	set of all destination nodes ($s \in S$)
I	set of simulation iterations ($i \in I$)
δ_H	cardinality of set $D_H(R, S)$: number of HDVs O-D pairs
δ_C	cardinality of set $D_C(R, S)$: number of CAVs O-D pairs
π_H	cardinality of set $J_H(r, s)$: number of HDVs travel from r to s
π_C	cardinality of set $J_C(r, s)$: number of CAVs travel from r to s
$P_{j_h, i}^{r-s}$	set of alternative paths for HDV j_h^{r-s} in iteration i , travel from r to s
$P_{j_c, i}^{r-s}$	set of alternative paths for CAV j_c^{r-s} in iteration i , travel from r to s

Table 3-5: Notations

Variables, parameters, and elements	
c_a^i	travel time of link a in iteration i
c_a^0	free flow travel time of link a
$\bar{c}_a^i$	marginal travel time of link a in iteration i
C_k^i	travel time of path k in iteration i
$tt_{j_h,i}^{r-s}$	experienced travel time of HDV j_h in iteration i , travel from r to s
$\bar{t}t_{j_c,i}^{r-s}$	experienced marginal travel time of CAV j_c in iteration i , travel from r to s
$tt_{H,i}^{*,r-s}$	least experienced travel time by HDVs in iteration i , travel from r to s
$\bar{t}t_{C,i}^{*,r-s}$	least experienced marginal travel time by CAVs in iteration i , travel from r to s
$p_{j_h,i}^{r-s}$	selected path for HDV j_h^{r-s} in iteration i , travel from r to s
$p_{j_c,i}^{r-s}$	selected path for CAV j_c^{r-s} in iteration i , travel from r to s
$p_{j_h,i}^{*,r-s}$	final selected path for HDV j_h^{r-s} in iteration i , travel from r to s
$p_{j_c,i}^{*,r-s}$	final selected path for CAV j_c^{r-s} in iteration i , travel from r to s
pr_{k,j_h}^i	probability of selecting path k by HDV j_h in iteration i
pr_{k,j_c}^i	probability of selecting path k by CAV j_c in iteration i
$r_{j_c}^i$	probability of rerouting by CAV j_c during simulation in iteration i
ζ	updating travel times of each link interval

3.3.2 Methodology of solving traffic assignment model for mixed traffic

In this section, the solution algorithm of MS-TAP-M is presented. The MS-TAP-M is defined as a dynamic TAP in which two vehicle classes exist. The first class of vehicles is CAV which follows the SO principle; the second class is HDV, which follows the UE principles.

This framework can consider the rerouting behavior of CAVs while solving the MS-TAP-M. Also, it is possible to consider CAVs' impact on road capacity by setting some modified parameters of driving behavior on micro and meso scales.

The simulation-based approach for traffic assignment problem (TAP) was first proposed by Mahmassani and Peeta in 1993 (Mahmassani and Peeta 1993), followed by Peeta and Mahmassani in 1995 (Peeta and Mahmassani 1995). Unlike analytical models that rely on mathematical closed-form solutions, this method employs an iterative procedure to find the equilibrium solution. In a single-class setting, such as when all users seek user UE or SO, the path flow distribution is updated at each iteration based on a path-swapping algorithm. This reassignment process helps determine if the algorithm is progressing in the correct direction and leads to a more efficient path selection. After each iteration, a convergence criterion is calculated to determine if the algorithm has reached termination (Bamdad Mehrabani et al. 2022). In this study, the framework provided by (Mahmassani and Peeta 1993; Peeta and Mahmassani 1995) has been developed to consider two classes of vehicles (CAVs and HDVs).

Figure 3-4 depicts the solution framework for the MS-TAP-M, referred to as "*dualIterateMix*". The framework comprises two components, namely the Path Selection Procedure (PSP) and Dynamic Network Loading (DNL). The PSP employs Dijkstra's algorithm, while the DNL utilizes the Simulation of Urban Mobility (SUMO) (Lopez et al. 2018). SUMO is a robust, open-source microscopic traffic simulation package capable of handling large networks and can also simulate traffic at the mesoscopic level (DLR 2023).

Let $G(V, A)$ be the directed traffic network, consisting of a set of links A (with elements $a \in A$) and a set of nodes V (with elements $v \in V$). The set of all HDVs and CAVs between all origin and destination pairs (travel demand) is represented by $D_H(R, S)$ and $D_C(R, S)$ respectively. The set of all origin nodes is denoted by R (with elements $r \in R$) and the set of all destination nodes is denoted by S (with elements $s \in S$). $J_H(r, s)$ (with $J_H \in D_H$) is the set of HDVs traveling from origin r to destination s . Similarly, $J_C(r, s)$ (with $J_C \in D_H$) is the set of CAVs traveling from origin r to destination s . Thus, j_h^{r-s} represents an HDV traveling from origin r to destination s , and j_c^{r-s} represents a CAV traveling from origin r to destination s .

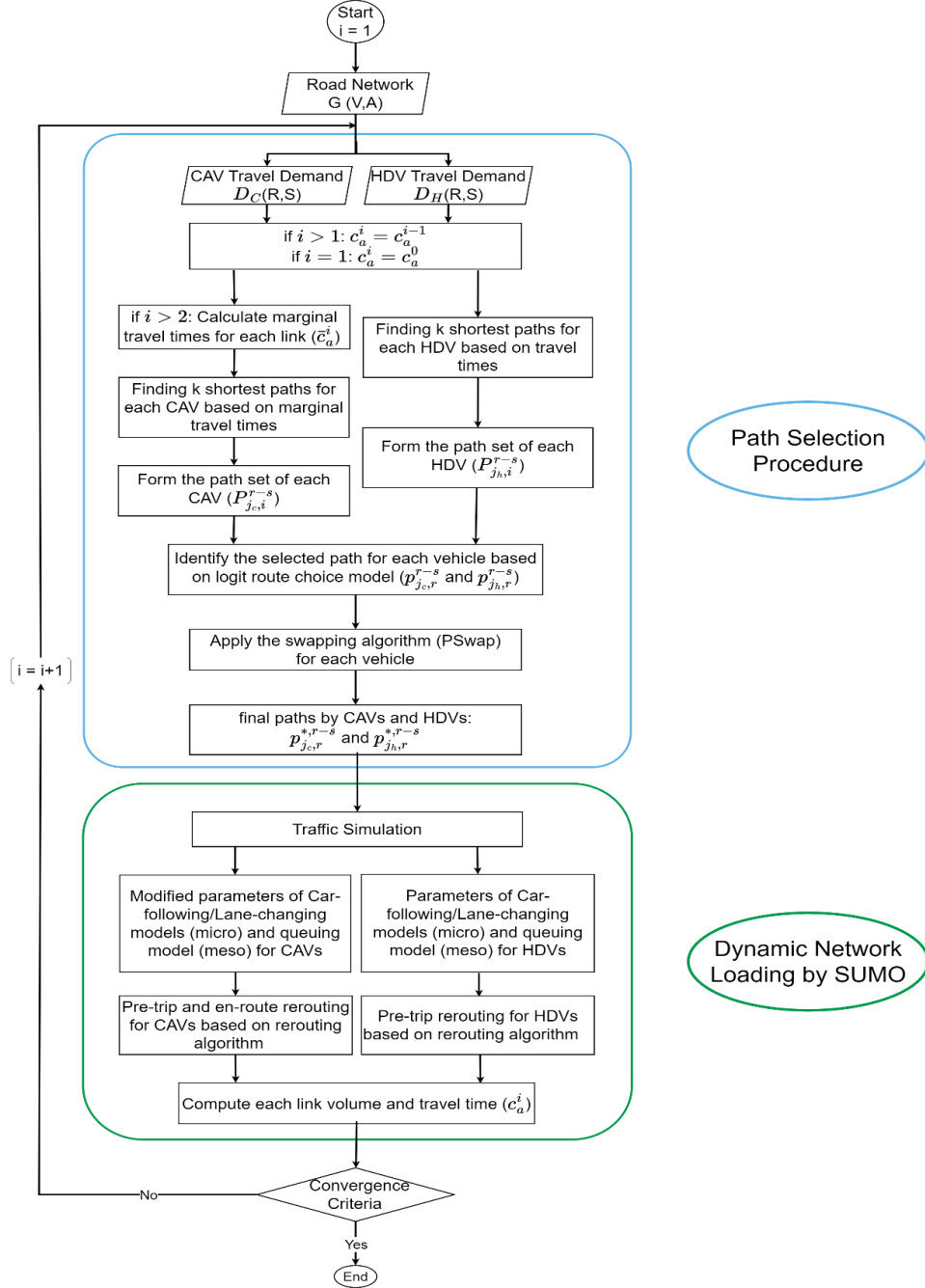


Figure 3-4: Framework of the MS-TAP-M (source: Author)

The assignment of $D_H(R, S)$ and $D_C(R, S)$ to $G(V, A)$ is the defined problem. The computation of the multiclass equilibrium condition involves calculating the shortest routes and travel times through iterative simulations. In each iteration i ($i \in I$), a routing algorithm (Dijkstra) is first applied to the road network to determine alternative paths, $P_{j_c, i}^{r-s}$ and $P_{j_h, i}^{r-s}$, for each vehicle, j_c^{r-s} and j_h^{r-s} . For each CAV (j_c^{r-s}), the k-shortest paths are computed based on the previous iteration's Marginal Travel Time (MTT), $\bar{c}_a^{i-1}$. For each HDV (j_h^{r-s}), the k-shortest paths are calculated based on the previous iteration's travel time, c_a^{i-1} . Then, a network loading model (Logit) is applied to the sets of alternative paths, $P_{j_c, i}^{r-s}$ and $P_{j_h, i}^{r-s}$, to select a path for each vehicle type $p_{j_c, i}^{r-s}$ ($p_{j_c, i}^{r-s} \in P_{j_c, i}^{r-s}$); $p_{j_h, i}^{r-s}$ ($p_{j_h, i}^{r-s} \in P_{j_h, i}^{r-s}$). Finally, a swapping algorithm is used to reassign a portion of vehicles in each class from their current paths to alternative paths to improve the selected path over iterations. The adjusted selected path (final path) of each vehicle type, $p_{j_c, i}^{*, r-s}$ and $p_{j_h, i}^{*, r-s}$, is then determined and sent to SUMO for traffic simulation. The traffic simulation can be performed either on microscopic or mesoscopic scales. On a microscale, the modified parameters of car-following and lane-changing models are implemented to consider the distinctions between CAVs' and HDVs' driving behaviour. While on the mesoscale, the modified parameters of queuing model are used to distinguish between CAVs and HDVs. Besides, a predefined percentage of CAVs ($r_{j_c}^i$) reroute during simulation based on the current state of the traffic. At the end of the simulation, SUMO calculates the current travel time of each link, c_a^i . This is done by aggregating and averaging the travel times of all vehicles on each link during a defined interval (ζ : 900 s). The resulting travel times, c_a^i , are used as input for the next iteration. The process is repeated iteratively with the aim of minimizing total travel time (TTT).

In this algorithm for solving the traffic assignment problem, the Dijkstra and k-shortest path algorithms are employed to find the shortest path. However, it should be noted that these methods of finding the shortest path have limitations, for instance: the k-shortest path algorithm often treats

each path independently and does not consider spatial or temporal dependencies between paths. In dynamic traffic situations, there may be correlations between different paths or time-dependent patterns that impact the overall performance of the algorithm. These limitations should be investigated in future studies using alternative methods.

3.3.2.1 Path Selection Procedure

The subsequent sections will provide a detailed discussion of the steps involved in the path selection procedure.

A. Calculation of Marginal Travel Times

In this framework, HDVs determine their path selections by utilizing the link travel times from the previous iteration, adhering to the UE principle. Conversely, CAVs make their decisions based on the link MTT, following the SO principle. Previous studies have proven that the SO condition can be achieved by replacing the path travel time with the path MTT (Hu et al. 2018; Mansourianfar et al. 2021; Patriksson 2015; Rahman, Siddique, and Shahid Mamun 2015). There are two ways to calculate the path MTT (Ameli, J.-P. Lebacque, and Leclercq 2020; Mansourianfar et al. 2021): 1) global approximation, which represents the changes in the total system travel time caused by an additional vehicle that is added to the path at a certain time interval, and 2) local approximation (Ghali and Smith 1995; Peeta and Mahmassani 1995), which represents the changes in the path travel time caused by an additional vehicle that is added to the route at a certain time interval. This approach considers the path MTT as a summation of the corresponding link MTTs. Although it has been proven that such a local approximation may lead to overestimation of the path MTT (Qian, Shen, and Zhang 2012; Shen, Nie, and Zhang 2007) it is a practical approximation in large-scale networks (Mansourianfar et al. 2021). Because the global approximation of MTT is computationally expensive and is not practical for large-scale DTA, this study implements the local approximation of MTT. Nevertheless, it is recommended that in future studies, the global approximation be employed, and the results be compared with the local approximation algorithm for robust findings.

To achieve the local approximation of path MTT, first, the MTT of each link should be calculated; then, the MTTs of the corresponding links in each path are summed up. Numerous formulations exist in the literature to approximate the MTT of the links; however, it may be inappropriate to compare these formulations numerically as they use their own traffic flow propagation method and assumptions (Doan and Ukkusuri 2015; Qian et al. 2012; Zhang and Qian 2020). In addition, the traffic simulators (as the DNL model) used in each study are different. Sheffi (Sheffi 1985) formulated the link MTT as follows and defined it as the “marginal contribution of an additional traveler on the a^{th} link to the TTT on this link.” In other words, MTT is the derivative of the travel time with respect to flow:

$$\bar{c}_a(f_a) = c_a(f_a) + f_a \frac{dc_a(f_a)}{df_a} (3 - 1)$$

This formulation is the sum of the two components. The first component, $c_a(f_a)$, is the travel time experienced by the additional traveler when the total link flow is f_a . This component can be explained as the average travel time on link a . The second component is the multiplication of $\frac{dc_a(f_a)}{df_a}$, the additional travel time burden that the additional traveler inflicts on each of the other travelers, by the number of travelers that already exist on the link (f_a). Therefore, the effect of one additional user on all the other travelers is considered by the second component.

An alternative approach to compute the link MTT is to calculate the average travel time in successive iterations (with a different number of vehicles assigned to each link in each iteration) and compute the difference in link average travel time. Using this method, the average inflicted additional travel time on the link can be calculated. Therefore, in this study, we developed a surrogate model of MTT to achieve SO as follows:

$$\bar{c}_a^i = c_a^{i-1} + f_a^{i-1} \frac{c_a^{i-1} - c_a^{i-2}}{f_a^{i-1} - f_a^{i-2}} (3 - 2)$$

The variable $\bar{c}_a^i$ represents the surrogate MTT of link a at simulation step i . The variables c_a^{i-1} and c_a^{i-2} represent the travel time, or cost, of link a at simulation steps $i - 1$ and $i - 2$, respectively. The variables f_a^{i-1} and f_a^{i-2} represent the traffic flow of link a at simulation steps $i - 1$ and $i - 2$, respectively. The first term of this equation represents the average travel time of link a and the second term represents the average inflicted additional travel time on the link. In other words, the second term of this model indicates the extent to which adding one vehicle to a link lead to an increase in the travel time of the vehicles that are already in the link. In this way, instead of feeding only the average travel time that each vehicle would experience along a route, the additional cost that it imposes on the total travel time by selecting the route is added. Hence, the additional travel time that other vehicles must “pay” (on average) is addressed if the subject vehicle selects that route.

B. Route Choice Model

The route choice can be represented through two different models, either deterministic or stochastic. In the deterministic approach, an "all-or-nothing" process is used, where all the traffic between each O-D pair is assigned to the path with the shortest travel time. On the other hand, in the stochastic approach, the routes are selected based on probabilities using discrete choice models. The researcher in this study chose the stochastic approach for practical reasons. Firstly, the deterministic approach is highly sensitive to even small changes in flow. For example, in a simple network consisting of two parallel routes of equal length, the all-or-nothing procedure results in oscillating route choices because drivers always choose the shortest route, which is the route with fewer cars. As a result, the solution is unstable, even in a clear equilibrium scenario where each route is used by 50% of the vehicles (Gawron 1999; Sheffi 1985). Secondly, when there are multiple alternative routes with slightly different travel times, it may be reasonable to select a route other than the strictly shortest route to avoid congestion on that route. The stochastic route choice models apply a scale parameter and converge to the optimum solution sooner than the deterministic approach.

The logit model is utilized to analyze the various route options available to individual vehicles, specifically $P_{c,i}^{r-s}$ and $P_{h,i}^{r-s}$. For each vehicle, the k -shortest paths are considered as potential alternatives. The formulation of the logit model is presented in equations 3-3, 3-4, and 3-5.

$$pr_{k,j_c}^i; pr_{k,j_h}^i = \frac{\exp(-\theta C_k^i)}{\sum_1^K \exp(-\theta C_k^i)} \quad (3-3)$$

$$C_k^i = \sum_{a \in A} \delta_{a,k}^i c_a^i \quad (3-4)$$

$$\delta_{a,p}^i = \begin{cases} 1 & \text{if link } a \text{ is on path } k \\ 0 & \text{otherwise} \end{cases} \quad (3-5)$$

The variables pr_{k,j_c}^i and pr_{k,j_h}^i represent the probabilities of CAV j_c and HDV j_h selecting path k in iteration i . C_k^i is the travel time, or cost, of path k in iteration i . A logit model scale parameter, θ , is used in the route choice procedure to prevent solution oscillations and instabilities. Although this study mainly focuses on a stochastic solution for the traffic assignment problem, it is possible to obtain a deterministic solution using the proposed algorithm by setting the scale parameter to approach infinity. It is suggested to consider employing the deterministic method in future studies, and its outcomes can be compared with the probabilistic algorithm outlined in this research for comparative purposes.

C. Swapping Algorithm

Most studies that implement simulation-based traffic assignment methods employ a swapping algorithm to reach the optimum value and avoid oscillating. The core idea of swapping algorithms is that not all vehicles should necessarily change their path in each iteration; instead, only a fraction of vehicles is in the reassignment process.

Thus, a proper direction for the next iteration is obtained. Most of the previous studies apply the Method of Successive Average (MSA) as their swapping algorithm. The conventional MSA is calculated as:

$$f^i = \left(\frac{i}{i+1}\right)f^{i-1} + \left(\frac{1}{i+1}\right)y^i \quad (3-6)$$

In which f^i is the path flow distribution of iteration i , y^i is the auxiliary path assignments obtained by all-or-nothing assignment, and i is the number of iterations. In the primary iterations, the value of step size is too large, thus the travel time of vehicles does not reduce after several iterations. While in the last iterations the value of step size is too small, which leads to slow convergence speed. Therefore, previous studies provided several heuristic algorithms (Ameli, J. Lebacque, and Leclercq 2020) or extensions of MSA (like Method of Successive Weighted Averages (MSWA) (Liu, He, and He 2009) or MSA Ranking (MSAR) (Sbayti, Lu, and Mahmassani 2007)) to address the disadvantages of MSA. However, most of the previous studies implement these extensions in combination with deterministic traffic assignment (all-or-nothing assignment which is highly sensitive to the small changes in traffic flow).

For the reassignment of a fraction of vehicles at each iteration, the Probabilistic Swapping (PSwap) algorithm is used instead of the traditional Method of Successive Average (MSA). The decision to use PSwap was made due to the limitations of MSA, which were highlighted in a previous study by Sbayti et al. in 2007 (Sbayti et al. 2007). In the authors' previous work, the PSwap algorithm was tested against MSA and demonstrated improved performance, as reported in Bamdad Mehrabani et al. in 2022 (Bamdad Mehrabani et al. 2022).

$$p_{j,i}^{*,r-s} = \begin{cases} p_{j,i}^{r-s} & \text{if } x \geq \rho_i \\ p_{j,i-1}^{*,r-s} & \text{if } x < \rho_i \end{cases} \quad (3-7)$$

The equation for $p_{j,i}^{*,r-s}$ includes several variables: $p_{j,i}^{r-s}$ represents the selected path by vehicle j in iteration i based on the current logit model, while $p_{j,i-1}^{*,r-s}$ refers to the final selected path by vehicle j in iteration $i-1$. Additionally, x is a random variable ranging from 0 to 1, and ρ_i is the sequence of step size in each iteration, which determines the probability of keeping the previous final selected path. The value of ρ_i is predetermined

and calculated using the equation $\rho_i = \frac{i}{\gamma}$, where i denotes the iteration number and γ is a scale parameter that controls the speed of convergence. Choosing a low value for γ results in faster convergence, but only a limited number of alternative paths will be explored by each vehicle. In contrast, a high value of γ slows down the convergence speed, but more alternative paths will be examined. For stochastic assignments, it is typically better to use higher values of γ . However, when dealing with large or medium-scale networks, waiting for a high number of iterations can be computationally expensive. In this study, the value of γ has been set to 10 for microscale networks and 50 for mesoscale networks.

3.3.2.2 Dynamic Network Loading

Dynamic network loading is the process of assigning travel demand, or O-D entries, to a network while considering the varying travel times on specific links. The loading is performed in a dynamic manner, considering real-time changes in traffic conditions. The SUMO software is utilized for this purpose, which is capable of handling both microscale and mesoscale networks. In other words, the dynamic network loading process involves importing vehicles into the simulator and calculating travel times for each link based on the number of vehicles in each link. In this study, simulation at the mesoscopic scale was used to obtain travel times and measure them in the Belgian road network. Details on how to model CAVs and HDVs in SUMO traffic simulator was provided in section 3.2 (traffic flow modelling).

During the dynamic network loading process, one crucial factor that impacts the travel time of vehicles is their capacity to be redirected. This study presumes that CAVs have the ability to undertake rerouting. The basis for this assumption lies in the fact that CAVs can link up with other CAVs or a traffic management center using Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication technology. Consequently, they can obtain real-time traffic data and adjust their route based on the updated information. The mechanism of rerouting in this study is that in

the dynamic network loading step, a predefined percentage of CAVs ($r_{j_c}^i$) receive updated travel times both before insertion and periodically during movement in the network. Also, a predefined percentage of HDVs (j_h^{r-s}) receive updated travel times before insertion into network. According to this updated travel time, if they find a path shorter than the pre-selected path's travel time, they will change their path to the newly found shortest path.

3.3.2.3 Convergence Criterion

Due to the absence of a closed-form solution for simulation-based methods, it is not possible to mathematically prove the convergence of the algorithm. All convergence criteria only act as a stopping point for the algorithm. In previous studies on UE solutions, a gap function is calculated to check for convergence. However, in multiclass traffic conditions where there are two types of vehicles, SO seeking CAVs and UE seeking HDVs, a different convergence criterion is necessary. In line with Mansourianfar et al.'s (Mansourianfar et al. 2021) research, this study proposes a hybrid gap function for algorithm convergence. The multiclass traffic assignment condition is deemed to be satisfied when the travel time experienced by HDVs (UE-seeking) and the marginal travel time experienced by CAVs (SO-seeking) for the same origin-destination (O-D) pair are both minimal and equal. A relative gap is calculated for each vehicle class, and the algorithm is considered converged if the average of these two gaps becomes constant and falls below ε .

$$Gap_1(i) = \frac{\sum_{H \in D_H} \left(\frac{\sum_{h \in H} tt_{j_h,i}^{r-s}}{\pi_H} - tt_{H,i}^{*,r-s} \right)}{\delta_H} \quad (3-8)$$

$$Gap_2(i) = \frac{\sum_{C \in D_C} \left(\frac{\sum_{c \in C} \bar{t}t_{j_c,i}^{r-s}}{\pi_C} - \bar{t}t_{C,i}^{*,r-s} \right)}{\delta_C} \quad (3-9)$$

$$\text{Hybrid Gap}(i) = \frac{\text{Gap}_1(i) + \text{Gap}_2(i)}{2} \quad (3 - 10)$$

Where $tt_{h,i}^{r-s}$ represents the travel time experienced by HDV j_h in iteration i , while traveling from origin r to destination s , and $\bar{t}t_{c,i}^{r-s}$ represents the experienced marginal travel time of CAV j_c in iteration i , while traveling from origin r to destination s . Similarly, $tt_{H,i}^{*,r-s}$ and $\bar{t}t_{C,i}^{*,r-s}$ represent the least experienced travel time by HDVs and least experienced marginal travel time by CAVs, respectively, in iteration i , while travel from origin r to destination s . In addition, π_H and π_C denote the number of HDVs and CAVs, respectively, traveling from origin r to destination s . Similarly, δ_H and δ_C denote the number of HDVs and CAVs O-D pairs.

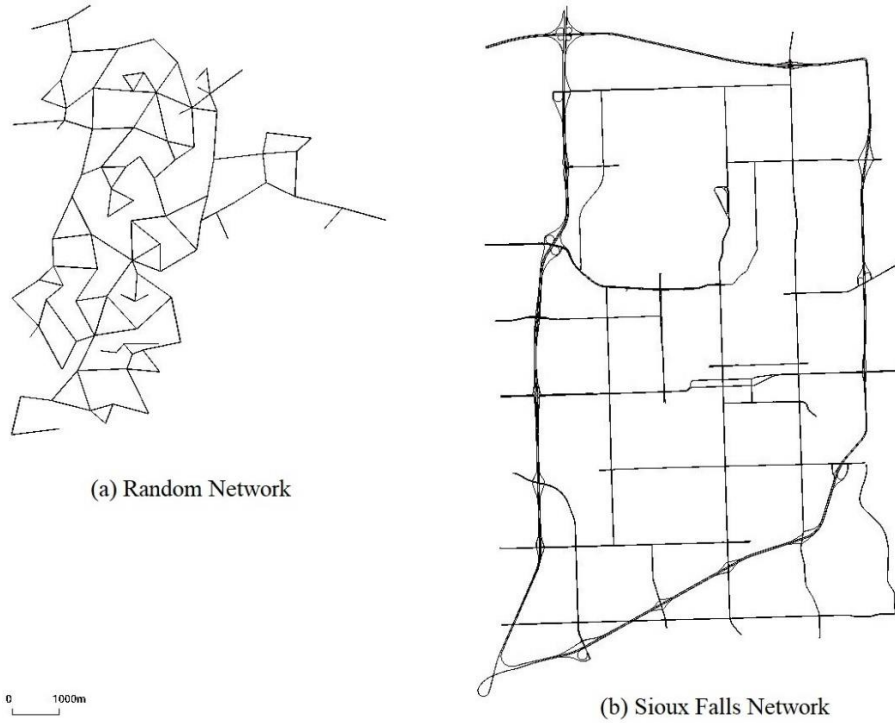


Figure 3-5: Test Networks (source: Author)

3.3.3 Testing the solution framework of multiclass traffic assignment

Before applying the proposed algorithm for solving the multi-class traffic assignment problem for Belgium road network, it is advisable to evaluate its performance on both classic and abstract networks to ensure its accuracy. The algorithm under consideration was tested on two distinct networks, which are illustrated in Figure 3-5: (a) Random network and (b) Sioux Falls network. The ensuing sections present the outcomes of the traffic simulations performed on the test networks. The scenarios that were modeled for each network are specified in Table 3-6.

Table 3-6: Test Networks Simulated Scenarios

Network	Scenario	CAV PR	HDV PR	CAVs rerouting	CAVs routing	HDVs routing
Random Network	1	0	100	0.5	SO	UE
	2	20	80			
	3	40	60			
	4	60	40			
	5	80	20			
	6	100	0			
Sioux Falls Network	1	0	100	0.5	SO	UE
	2	20	80			
	3	40	60			
	4	60	40			
	5	80	20			
	6	100	0			

3.3.3.1 Random Network

A random network was created, as illustrated in Figure 3-5 (a). The network consists of 278 edges and 100 intersections, with the length of each edge ranging from 200 to 1000 meters and featuring either one or two lanes. To simulate traffic for an hour, 7200 vehicles were randomly generated and dispersed throughout the network. Six different scenarios were simulated

for this network, as shown in Table 3-6, in order to investigate the potential capabilities of CAVs. In this case study, it is assumed that CAVs have different route choices and driving behaviors. The distinct route choice behavior is considered by assuming that CAVs follow SO and have the ability to reroute both pre-trip and en-route. On the other hand, the specific driving behavior is addressed by modifying the relevant car-following model's parameters, as explained in previous sections. A microsimulation was carried out, which converged after 10 iterations. The TTT for all vehicles in each iteration for each scenario is displayed in Figure 3-6.

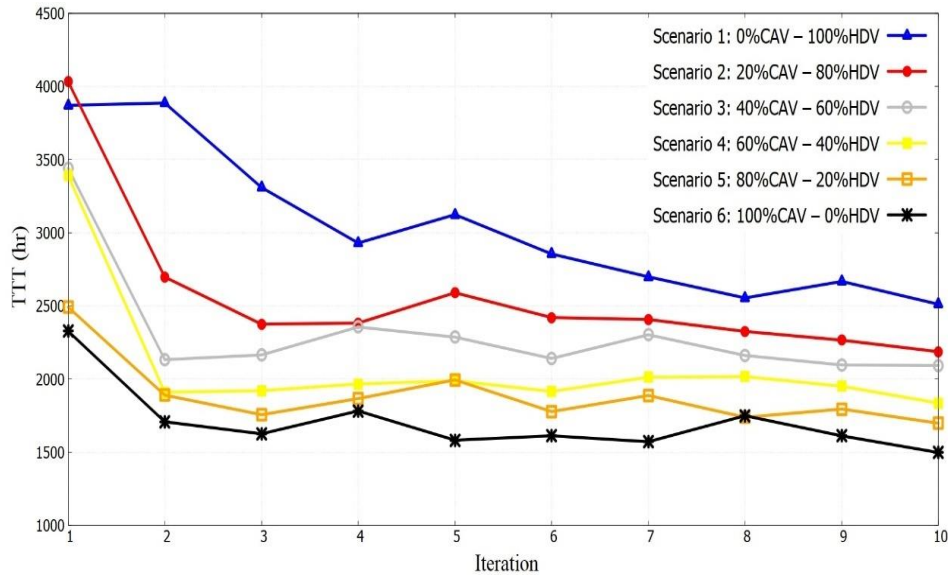


Figure 3-6: Convergence patterns for Random network (source: Author)

Table 3-7 displays the results of the simulations carried out on the Random network. A quick look at the table reveals that as the PR of CAVs increases, the TTT of vehicles decreases. The percentage of TTT reduction compared to scenario 1 (0% PR of CAVs) ranges from 12.9% (for 10% PR of CAVs) to 48.9% (for 100% PR of CAVs). This finding indicates that if all vehicles have the full automation driving mode (100% PR of CAVs) and follow SO routines with 50% probability of rerouting, the TTT can be reduced by 48.9% compared to the scenario where no CAVs are present. Moreover,

the simulations show an increasing trend of the average speed by vehicles as the PR of CAVs increases.

Table 3-7: Simulation Results for Random Network

Scenario	Hybrid Gap	Total Travel Time (hr.)	Average Speed (km/h)	TTT improvement (%)	Computational time (min)
1	12.49	2509.88	29.2	-	12
2	10.53	2185.54	31	12.9	09
3	9.86	2092.5	32	16.6	08
4	8.12	1834.36	34	26.9	08
5	7.44	1696.94	35.4	32.3	07
6	5.91	1496.72	37.5	48.9	06

Figure 3-7 illustrates the traffic volume (vehicles per hour) in the Random network at different PRs (penetration rates) of CAVs.

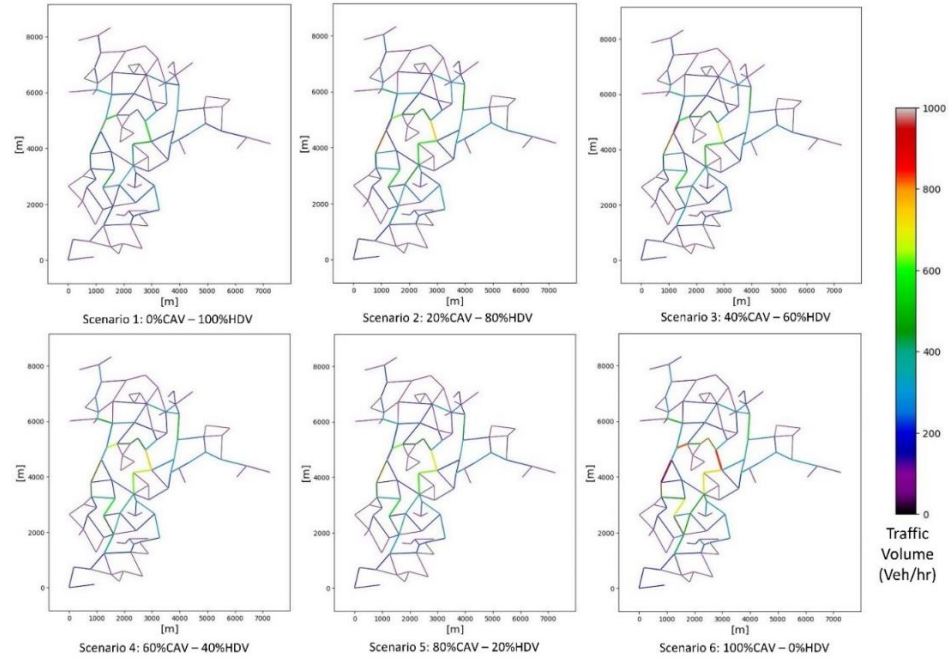


Figure 3-7: Traffic volume of Random network (source: Author)

Figure 3-7 shows that as the PRs of CAVs increase, the number of medium-volume and high-volume links also increases. This observation can be attributed to two reasons. Firstly, as the number of CAVs increases, the capacity of links also increases, enabling them to accommodate more vehicles. Consequently, the links that form part of the vehicles' shortest paths experience higher traffic volumes. The second reason is that as CAVs follow the SO, they are dispersed throughout the entire network and make use of any spare capacity available. As the PR of CAVs increases, the volume of alternative routes for each O-D pair also increases. This results in a greater number of blue links in 100% PR of CAVs as compared to 0% PR of CAVs.

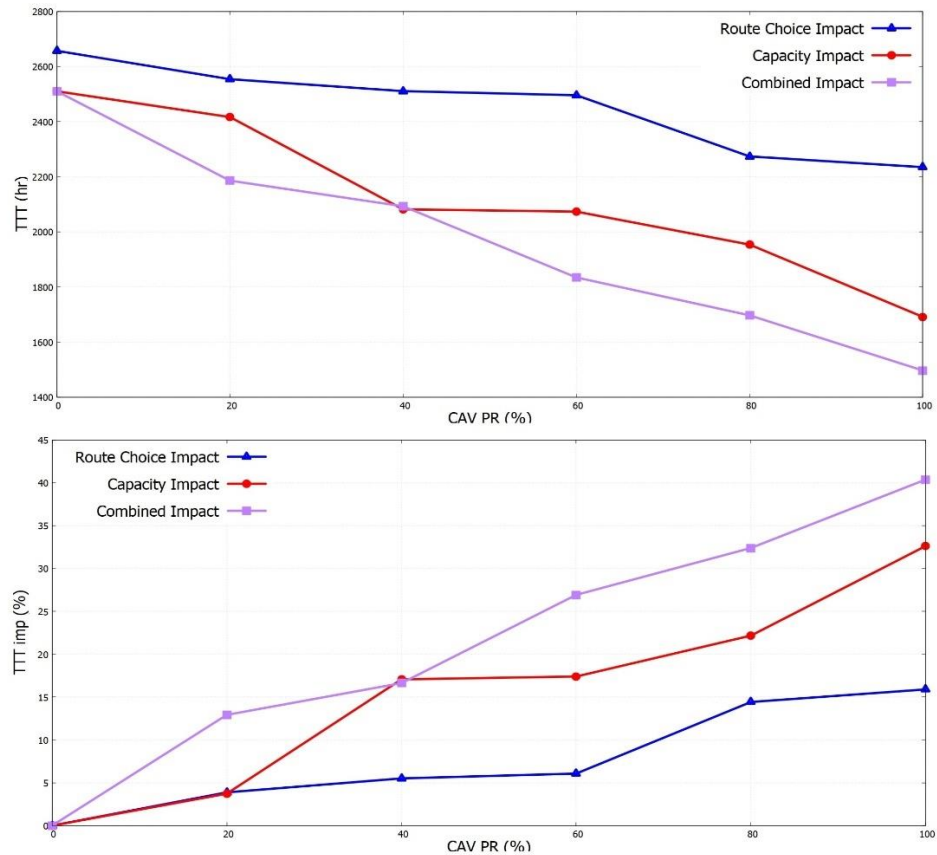


Figure 3-8: Impact of CAVs on TTT for different setting (Random network)
(source: Author)

The scenarios that have been studied so far for the random network are the scenarios in which we witness a reduction in TTT due to the combined impact of CAVs' different driving and route choice behavior. To have an in-depth view of the impacts of CAVs on TTT, several other scenarios have been investigated. Twelve new scenarios are simulated which either consider CAVs' different route choice behavior or CAVs different driving behavior (2*6 scenario). These new simulations have been compared with the results of the scenarios that have been done so far. The results of this comparison are illustrated in Figure 3-8.

In Figure 3-8, the TTT for three different categories of scenarios is shown. These categories include 1- scenarios in which only CAVs' different route choice behavior is modeled (Route choice impact) 2-scenarios in which only CAVs' different driving behavior is modeled (Capacity impact) 3-scenarios in which both CAVs' different route choice and driving behavior is considered (Combined impact). This figure also displays the amount of improvement in TTT for each of the scenarios mentioned above. By having a glance at Figure 3-8, it can be recognized that when CAVs have solely different route choice behavior in comparison to HDVs, they have the least improvement in TTT. However, when they have both different route choices and driving behavior, we observe the best improvement in TTT.

One of the factors that is important in examining the travel time difference between CAVs and HDVs for decision makers and policymakers is the concept of travel time heterogeneity. Investigating the extent to which CAVs experience a better travel time compared to when only HDVs are present is crucial in understanding the overall impact of CAVs on the transportation system. This study assumes that CAVs follow system optimal and have safer and faster driving behavior. Therefore, it is expected that a percentage of vehicles will experience longer travel times compared to when CAVs are not present.

To examine this issue, data related to travel time heterogeneity is presented in two figures: Figure 3-9 illustrates the percentage decrease in experienced travel time by vehicles compared to the percentage of vehicles experiencing this reduced travel time, considering different PRs of CAVs.

Additionally, Figure 3-10 shows the percentage of added travel time for the entire fleet of vehicles relative to the percentage of vehicles experiencing this additional travel time.

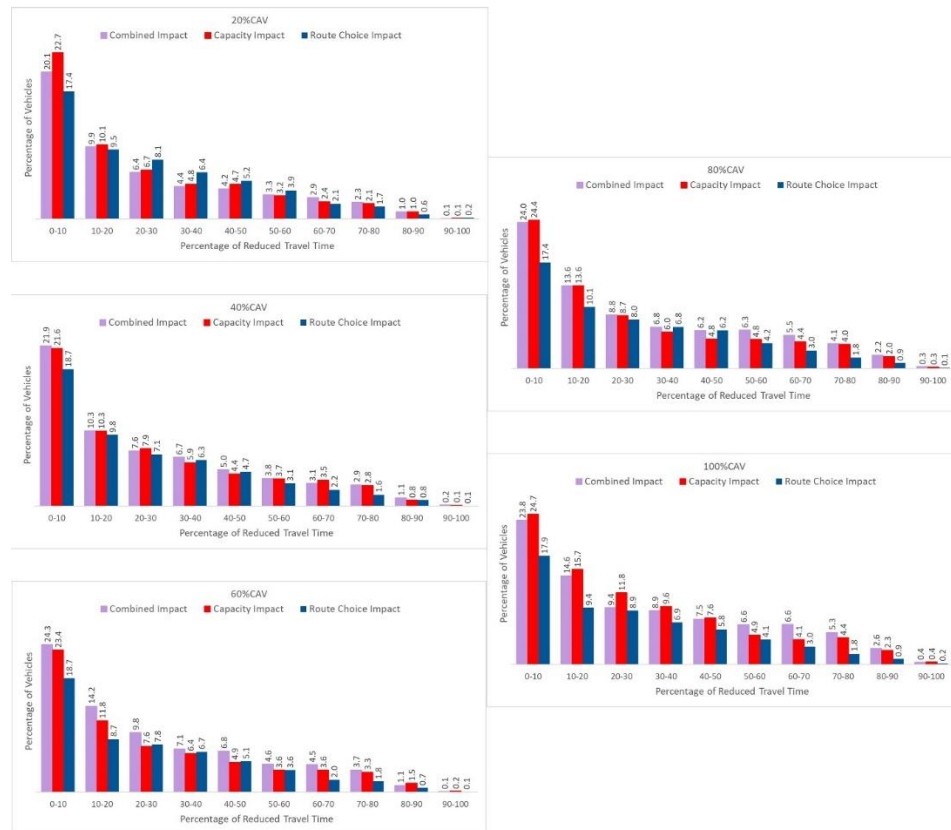


Figure 3-9: Travel Time Heterogeneity (Reduced) (Random Network) (source: Author)

Analyzing figures 3-9 reveals that when we have 20% CAV penetration, between 16% and 17.7% of vehicles experience a travel time that is 10% longer than when CAVs are not present. However, as the CAVs PR increases, this percentage decreases.

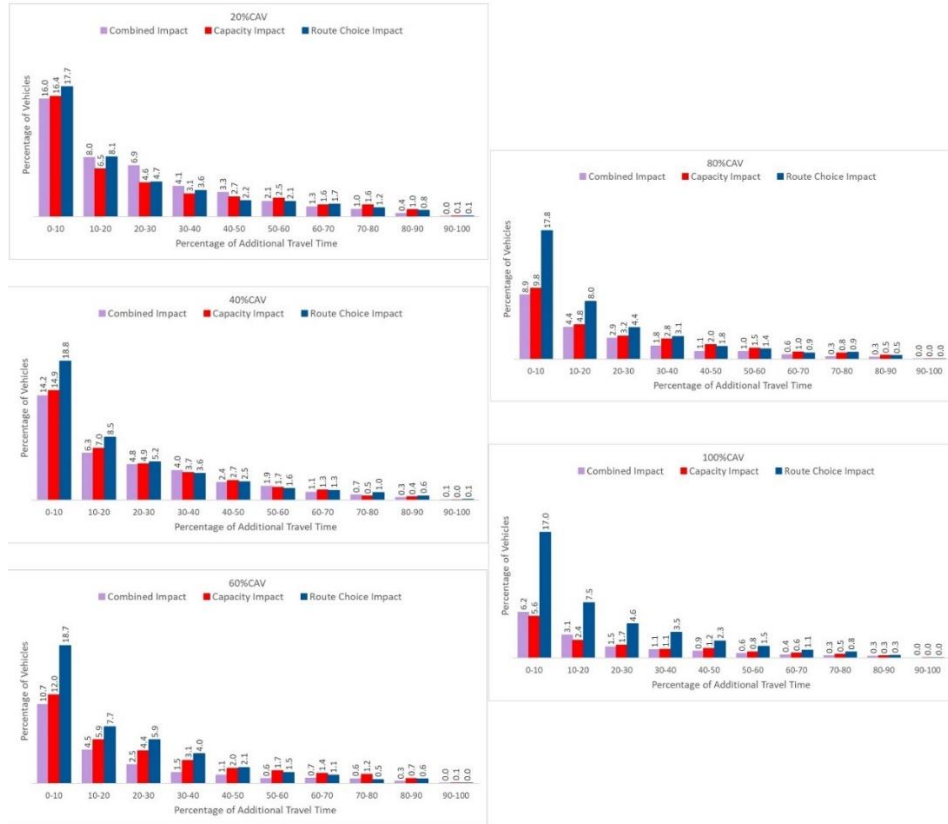


Figure 3-10: Travel Time Heterogeneity (Additional) (Random Network)
(source: Author)

By examining Figure 3-10, it can be concluded that when all vehicles in the network are CAVs, certain percentages experience travel times that are longer, such as 6.2% experiencing a 10% longer travel time, 3.1% experiencing a 20% longer travel time, 1.5% experiencing a 30% longer travel time, 1.1% experiencing a 40% longer travel time, 0.9% experiencing a 50% longer travel time, 0.6% experiencing a 60% longer travel time, 0.4% experiencing a 70% longer travel time, 0.3% experiencing an 80% longer travel time, and 0.3% experiencing a 90% longer travel time compared to when only HDVs are present. As a result,

the overall travel time of the entire network improves by 48.9%. This figure can provide valuable insights for policymakers in implementing CAVs in road networks, which can be easily extracted through simulation methods.

3.3.3.2 Sioux Falls Network

The second case study is the Sioux Falls network, which is displayed in Figure 3-5 (b). In this case, a total of 36,000 vehicles were simulated, with their origins and destinations determined according to the demand pattern described in LeBlanc's study (LeBlanc, Morlok, and Pierskalla 1975). The Sioux Falls network is a well-known and widely used benchmark in transportation research. Many researchers have used this network to test and compare various traffic assignment algorithms. By using the Sioux Falls network, a basis for comparing the proposed algorithm against existing models is provided. Choosing a widely recognized test case like Sioux Falls enhances the reproducibility of results. Other researchers can easily replicate the experiments on the same network, enabling direct comparisons with the proposed algorithm. Also, as real data is available for Sioux Falls network, testing the proposed algorithm on a realistic road network helps validate its performance in a setting that mirrors actual traffic conditions.

Mesoscopic simulation was used for this case study, utilizing the mesoscopic feature of SUMO. The study analyzed six different scenarios, and the convergence pattern for all scenarios (scenarios 1 to 6) is depicted in Figure 3-11. As mentioned before, it was assumed that CAVs exhibit different driving and route choice behavior. CAVs follow SO with rerouting capability, while HDVs follow UE. Additionally, CAVs have a lower headway in the meso simulation. The simulation results (Table 3-8) indicate that in the full automation scenario (scenario 6), the TTT has the minimum value in comparison with other PRs of CAVs. The percentage of TTT reduction varies between 8.2% to 27.2%. Also, the average speed and distance traveled rise as the PR of CAVs increases.

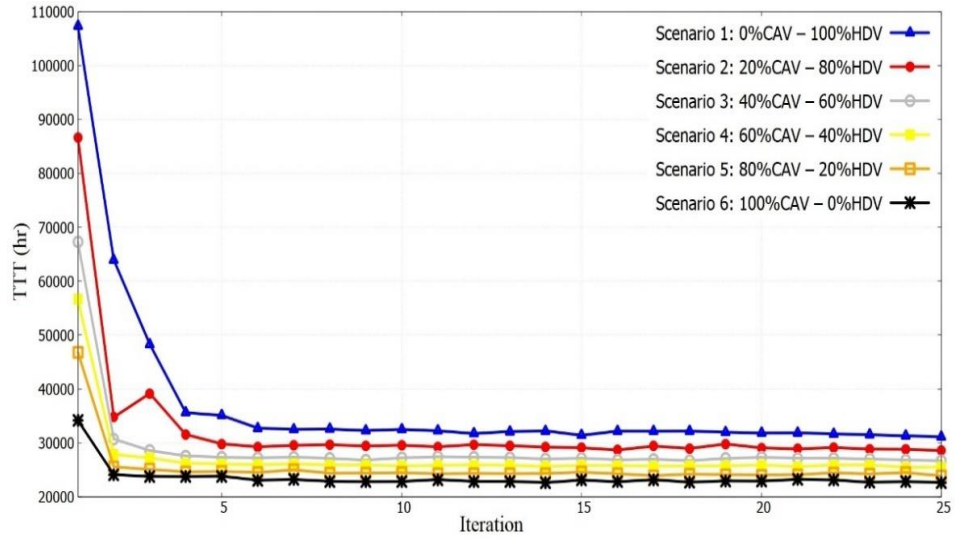


Figure 3-11: Convergence patterns for Sioux Falls network (source: Author)

Table 3-8: Simulation Results for Sioux Falls Network

Scenario	Hybrid Gap	Total Travel Time (hr.)	Average Speed (km/h)	TTT improvement (%)	Computational Time (min)
1	4.44	31111.94	43.56	-	14
2	3.41	28566.56	45.57	8.2	14
3	3.11	26670.89	46.87	14.3	15
4	2.83	25475.60	47.95	18.1	15
5	2.51	23862.69	49.17	23.3	16
6	2.12	22636.86	49.93	27.2	16

Figure 3-12 depicts the volume on the Sioux Falls network for different PRs of CAVs, categorized based on both colors and width, where thicker links indicate higher volume. Analyzing the differences in traffic volumes, this figure reveals that vehicles are distributed throughout the entire network in scenarios with high penetration rates of CAVs, avoiding selfish routing. CAVs select unused links, minimizing the travel time for the entire

network. Additionally, in scenarios with high PRs of CAVs, the links' capacity increases, which can lead to a higher number of links with high volume. The same links can service more vehicles in less time compared to scenarios with lower PRs of CAVs. Just like in the previous case study, various scenarios were performed to examine the isolated impact of various CAV-related driving and route choice behaviors. The results are presented in Figure 3-13.

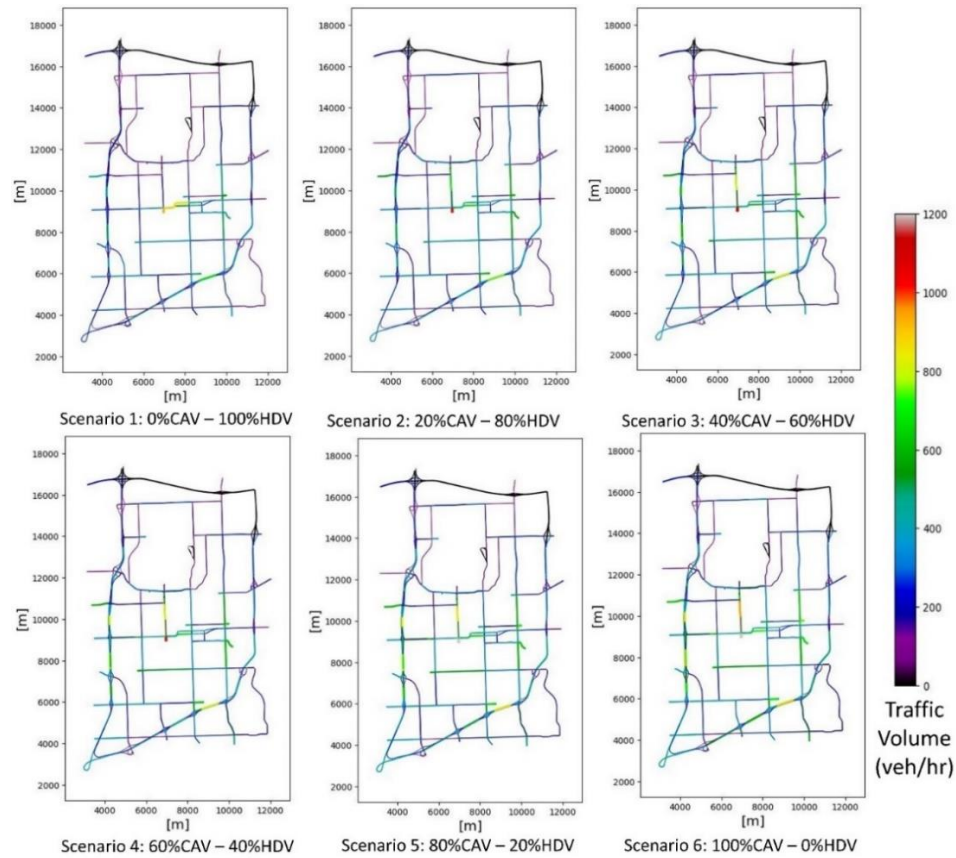


Figure 3-12: Traffic volume of Sioux Falls network (source: Author)

The improvement in TTT was observed in different settings of CAV impact, ranging from 10.1% for the isolated impact of CAV-specific route choice behavior, 20.2% for the isolated impact of CAV-specific driving

behavior, and reaching a maximum of 27.2% for the combined impact of both CAV-specific route choice and driving behaviors.

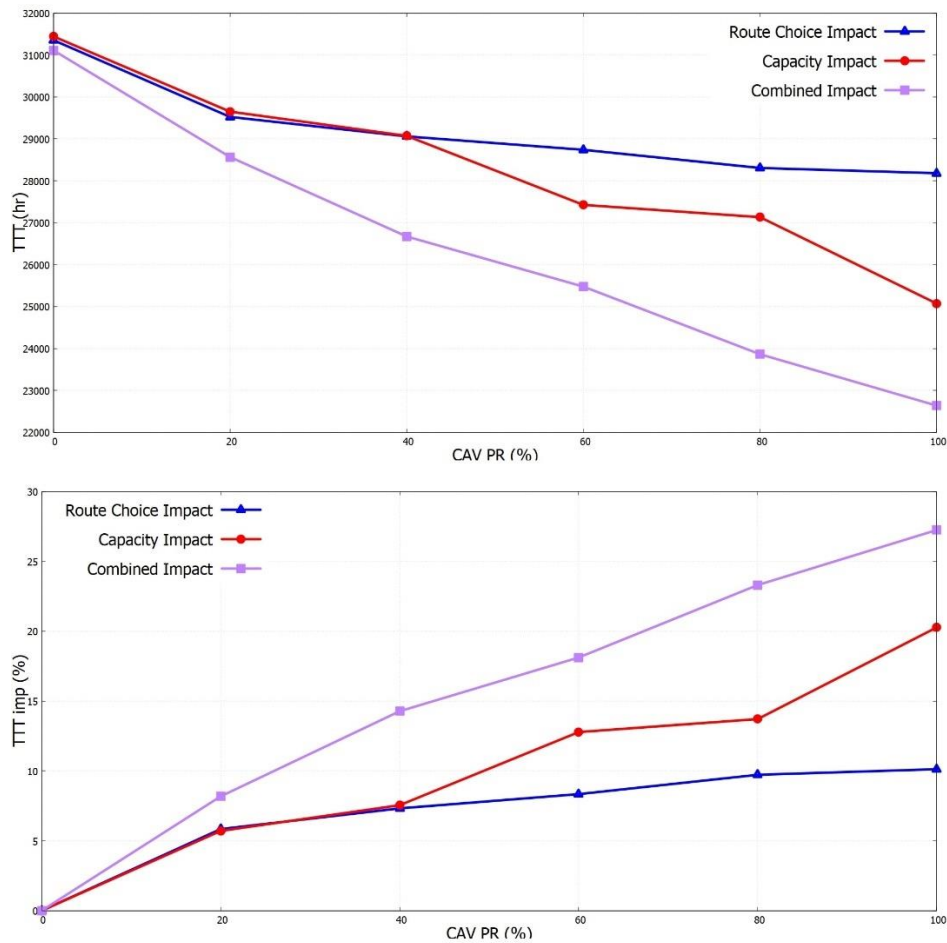


Figure 3-13: Impact of CAVs on TTT for different setting (Sioux Falls) (source: Author)

In Figure 3-14, the amount of reduced travel time experienced by the vehicles when there are CAVs in the road network is shown. Additionally, Figure 3-15 illustrates the amount of added travel time experienced by vehicles when CAVs are present in the network. Analyzing Figure 3-14 reveals that when CAVs exhibit different route choice and driving behavior

compared to HDVs, 17.1% of them experience a 10% improvement in their travel time. Furthermore, 12.8% experience a 20% improvement, 10.1% experience a 30% improvement, 7.4% experience a 40% improvement, 6.2% experience a 50% improvement, 5.1% experience a 60% improvement, 3.6% experience a 70% improvement, 2.2% experience an 80% improvement, 1.6% experience a 90% improvement, and finally, 0.4% experience a 100% improvement in their travel time compared to when all vehicles are HDVs.

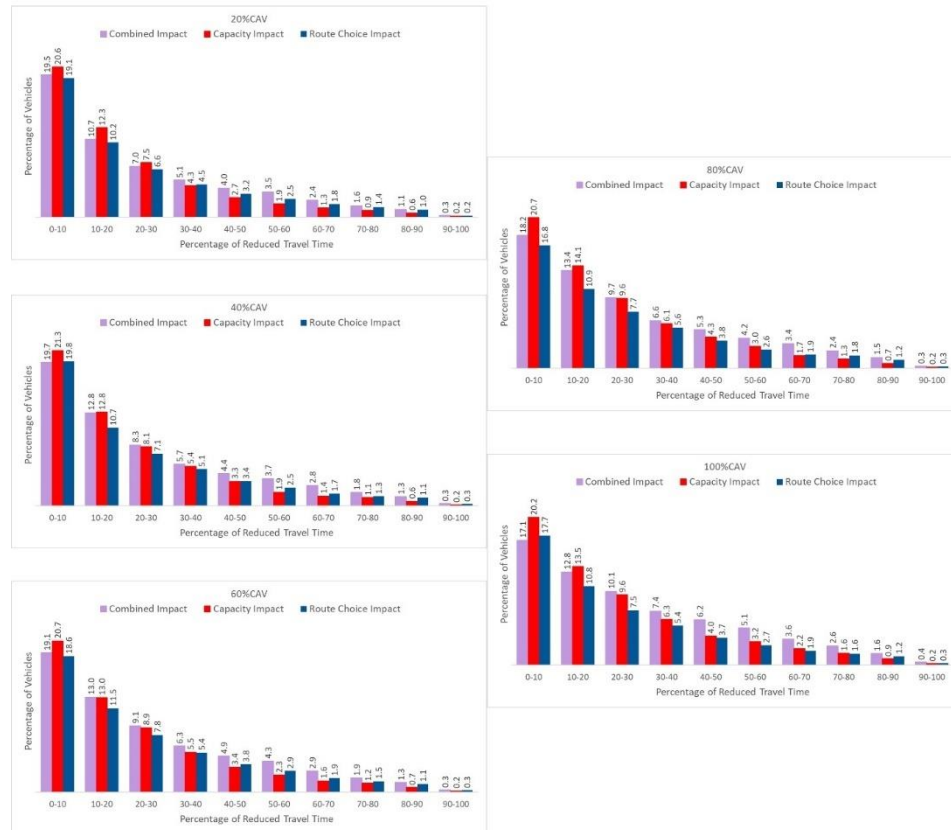


Figure 3-14: Travel Time Heterogeneity (Reduced) (Sioux Falls Network)
(source: Author)

Additionally, examining Figure 3-15 indicates that when all vehicles are CAVs, only 0.2% of vehicles experience a travel time that is 90% longer than when CAVs are not present. Furthermore, 12.6% of vehicles only experience a travel time that is 10% longer than under 100%HDV conditions. These results can be highly valuable for analyzing the policy sensitivity in CAV PRs which is easily measured using the simulation-based method.

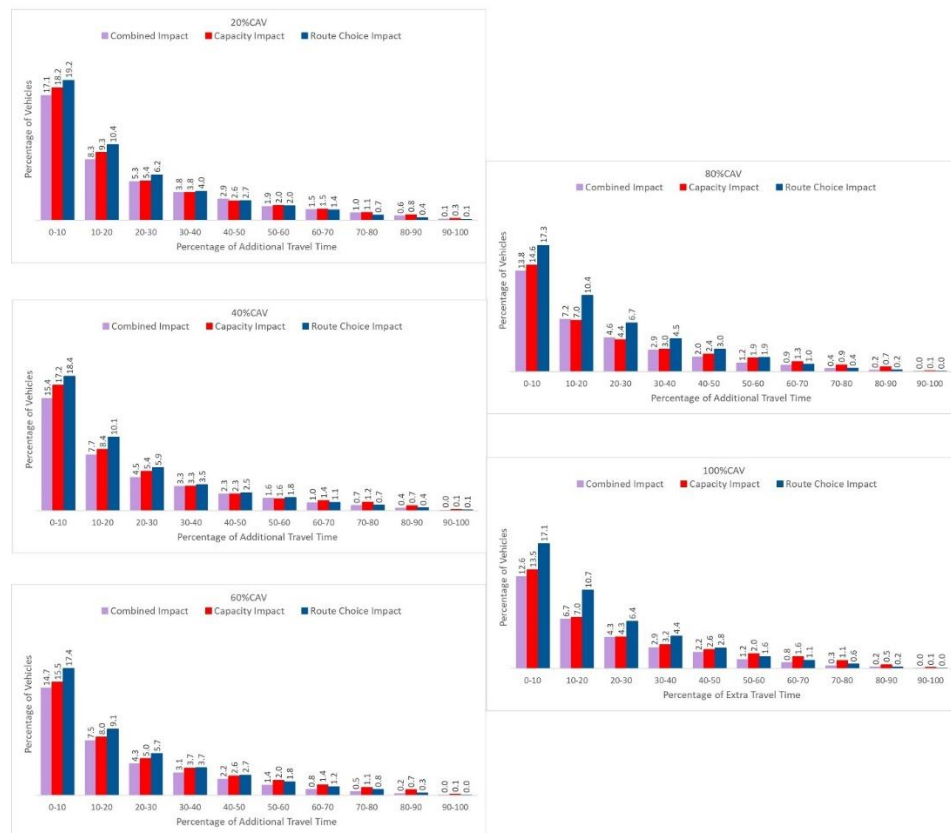


Figure 3-15: Travel Time Heterogeneity (Additional) (Sioux Falls Network)
(source: Author)

3.4. Summary

This chapter introduces the types of users considered to investigate the resilience of Belgium's network, which include HDVs and CAVs. The traffic flow modeling approach for these two types of users is also discussed. The assumption made is that CAVs have safer and more efficient driving behaviors than HDVs. To account for this assumption, the car-following and lane-changing models in microscopic scale traffic simulation are modified. Then, based on the results of the microsimulation, the parameters of queuing model in mesoscopic simulation are calibrated.

Subsequently, as it is assumed that CAVs exhibit different route choice behaviors compared to HDVs, an algorithm for solving the multi-class traffic assignment problem of mixed traffic flow is presented. The MS-TAP-M problem involves assigning two classes of vehicles, each with unique route preferences and driving behaviors. It is assumed that CAVs adhere to the SO principle and have the capability to reroute, while HDVs follow UE routines. The solution framework is an iterative process that involves path selection and dynamic network loading. Starting from an initial solution, the framework updates the path flow distribution in each iteration using a path-swapping algorithm. At the end of each iteration, a convergence criterion is calculated to determine when the algorithm should terminate. The assumption that CAVs follow SO and can change them based on real-time traffic information seems plausible, assuming they're linked to a central traffic management hub. However, predicting whether CAV users would consistently prioritize shorter travel times over user experience remains uncertain. Investigating this further is crucial, considering the potential for CAV occupants to use their time differently. Yet, as CAVs are not fully integrated or regulated in the market, making definitive statements about their behavior is challenging. The algorithm discussed in this section offer a way to simulate various setting of CAVs.

To the best of the author's knowledge, the proposed solution framework for MS-TAP-M is the first open-source algorithm that can be executed in both micro and meso scale simulation. This algorithm considers the

rerouting capability of CAVs, as well as their unique route preferences and driving behaviors. The solution framework is called "*dualIterateMix*" and is freely available under the EPLv2 license on GitHub at <https://github.com/eclipse/sumo/blob/main/tools/assign/dualIterateMix.py> and in the Appendix A of this thesis. This tool can be used by researchers and decision-makers to investigate the impacts of CAVs on the road network under various scenarios. *dualIterateMix* supports different assumptions on CAVs' route choice and driving behavior, providing flexibility in analyzing the potential effects of CAVs on traffic flow.

Finally, the proposed algorithm is tested on two network types: a random network and a classic Sioux-Falls network. The simulation results revealed that as the proportion of CAVs in the network increased, the travel time of vehicles decreased. The most significant improvement in TTT was observed in scenarios where CAVs had both unique route choices and driving behaviors, with a 48.9% improvement in the Random network and a 27.2% improvement in the Sioux Falls network. The second most significant impact on TTT was seen in scenarios where CAVs had only different driving behaviors, resulting in a 32.6% improvement in the Random network and a 20.2% improvement in the Sioux Falls network. In contrast, the smallest effect on TTT was observed in scenarios where CAVs had only unique route choice behaviors, resulting in a 15.8% improvement in the Random network and a 10.1% improvement in the Sioux Falls network. These results offer valuable insights into the potential of CAVs and could be useful for researchers and decision-makers seeking to understand the effects of CAVs on transportation systems. This section investigated travel time heterogeneity, yielding valuable insights into the extra and reduced travel time imposed by CAVs on all vehicles.

In the next section, the algorithm presented in this section is used to obtain the Belgium network's resilience in the presence of CAVs.

4. Resilience Evaluation Framework

This chapter begins by examining the concept of resilience. A literature review is presented, which covers the concept of resilience, different methods for assessing it, and various types of measures used to evaluate resilience. The chapter concludes by discussing the issues related to assessing resilience in the presence of CAVs and how this study addresses these concerns by introducing a new criterion. The information presented in this chapter is drawn from the following publications:

- Bamdad Mehrabani, B., Sgambi, L., Madani, N. Assessing the environmental aspects of road network resiliency, Springer, Cham, 2022. 978-3-031-11231-7 ; 978-3-031-11232-4. 8 p. https://doi.org/10.1007/978-3-031-11232-4_7. (Mehrabani, Sgambi, and Madani 2022).
 - Bamdad Mehrabani, B., Pel, A., Calvert, S., Sgambi, L., and Snelder, M. Assessing road network resilience in the era of Connected and Autonomous Vehicles (Belgium road network). Transportation Research Board 103rd Annual Meeting (USA, Washington DC, from 07/01/2024 to 11/01/2024).
-

4.1. Resilience Concept and Background

This section begins by providing an explanation of the concept of resilience and its historical development. Following that, various methods for evaluating resilience are introduced. Next, the available measures for assessing resilience and its different dimensions are reviewed. This is followed by a discussion of the resilience triangle concept. Finally, the gaps in previous studies related to evaluating resilience are addressed.

The term "resilience" originates from the Latin word "resiliere," which means to "bounce back" (Hosseini, Barker, and Ramirez-Marquez 2016). This term refers to an entity or system's ability to return to its normal condition after experiencing disruptive events. For many years, researchers from various fields have utilized the concept of resilience in their studies. In fact, the concept of resilience was first introduced in ecology in the 1970s (Holling 1973). Despite the evolution of the concept of resilience since the 1970s, many researchers have concluded that there is no single definition of resilience. Therefore, each researcher has provided a specific definition of resilience based on their project's objectives and the type of infrastructure under study (Gauthier, Furno, and El Faouzi 2018; Lhomme et al. 2013). In the context of transportation systems, resilience is defined as "the ability to prepare for changing conditions and withstand, respond to, and recover rapidly from disruptions" (FHWA 2015).

In Table 4-1, the studies which investigate road network resilience are reviewed. This table also shows the measures and methods that are used by previous studies. Based on this table, there have been five distinct approaches proposed for analyzing the resilience of transportation networks (Liu and Song 2020; Serdar, Koç, and Al-Ghamdi 2022). These approaches include Big Data analysis (Liu and Song 2020), graph theory (Gauthier et al. 2018; Sgambi et al. 2021), optimization models (Omer, Mostashari, and Nilchiani 2013), simulation-based models (Aghababaei, Costello, and Ranjitkar 2020), and miscellaneous methods (Calvert and Snelder 2018). Big Data analysis requires a significant amount of data and is not efficient when no data is available. Graph-based methods are simple

and popular, with roads considered bi-directional links and intersections as nodes. However, these methods are usually demand-insensitive and pay less attention to recovery simulation. They also often assume complete removal of nodes or links and cannot consider different traffic modes or the specific characteristics of one system in relation to another (Gauthier et al. 2018; Liu and Song 2020). Optimization models ensure the best results are achieved in terms of resilience under budget constraints and are usually used in the design phase. Simulation models of resilience analyze road traffic and simulate partial or total malfunctions in one or more roads, making them effective in analyzing the behavior of a specific network. Additionally, simulation models of resilience can evaluate specific driving and routing behavior of road users, such as CAVs (Liu and Song 2020; Sun, Bocchini, and Davison 2020). The present study employs the simulation-based approach, as it can model the detailed behavior of CAVs, which cannot be captured by other available methods.

When examining the impact of CAVs on road network resilience, it is important to note that while some studies have suggested that CAVs can enhance resilience (as mentioned in (Khan et al. 2016)), there is currently no comprehensive research that has assessed the impact of CAVs on all aspects of resilience. For instance, Ahmed et al. (Ahmed et al. 2019) analyzed the effect of varying CAV penetration rates in mixed traffic environments on road network resilience using mathematical models and graph theory and found that CAVs could improve disaster recovery efforts.

However, their study only considered CAVs' effect on traffic headway, and neglected other factors such as their routing behavior. Additionally, (Zou and Chen 2021) proposed an optimization model for post-disaster recovery scheduling that accounts for CAVs, but only modeled the difference between CAVs and HDVs in terms of their route choice and driving behavior, without including features such as CAV rerouting behavior.

Table 4 1: Review of Previous Studies on Road Network Resilience Evaluation

Author	Methodology		Category of resilience index		Type of Disruption		Resilience Stage		Resilience Index	Note
	Graph theory based	Optimization based	Probability-based	Simulation-based	Miscellaneous based	Topology-based	Traffic-related	Socioeconomic		
Aydin et al., 2018	✓			✓	✓	✓	✓	✓	✓ - Centrality measures ✓ - Connectivity measures	- Network distances
Donovan & Work, 2017	✓								✓ - The distribution of pace between city regions	- The pace deviations after disruptions
Ganin et al., 2017		✓			✓	✓	✓	✓	✓ - Efficiency: the average annual delay per peak period auto commuter ✓ - Resilience: the change in efficiency resulting from roadway disruptions	
Kaviani et al., 2017	✓				✓	✓	✓	✓	$\text{Total Travel Time(no guidance)} - \text{Total Travel Time (Guidance)}$ $\text{Improvement} = \frac{\text{Total Travel Time(No Guidance)}}{\text{Total Travel Time(Guidance)}}$	
Maria Nogal et al., 2017	✓				✓	✓	✓	✓	✓ - the normalized area over the exhaustion curve	
Amini et al., 2018		✓			✓	✓	✓	✓	✓ - weighted space-mean flow over average trip length	
Calvert & Snelder, 2018				✓		✓			$\text{Index} = \frac{k}{k_{crit}}$ $\text{Resistance} = \left[\frac{q + \psi^q}{v} \right] \frac{v_{crit}}{q_{cap}(g, h) \cdot f + \psi^{cap}}$ $\text{Recovery} = \left[\frac{q + \Delta q}{v_{eq}(q)} \right] \frac{v_{crit}}{q_{cap}(g, h) \cdot f - q_{ed}}$ Q: Flow V: Speed ψ^q: Volatility of flow q_{cap}: Road capacity g: Road characteristic h: Traffic characteristic ψ^{cap}: Volatility of capacity f: Temporal capacity reductions Δq: flow volatility q_{ed}: capacity drop v_{eq}: speed, derived from fundamental diagram	
Cauthier et al., 2018		✓	✓	✓	✓	✓			$PL(l, \delta) = \sum_{i=1}^n \frac{c_i^0(l) - c_i^0}{n}$ - $PL(l, \delta)$ is the overall performance loss when link l is disrupted at level δ (seconds/kilometer) - $c_i^0(l)$ is the travel cost of vehicle v when link l is disrupted at δ level (seconds/kilometer) - c_i^0 is the travel cost of vehicle v in the base case (seconds/kilometer) - n is the number of vehicles in the network	
Liao et al., 2018	✓			✓	✓	✓			$Rl = E \left[\int_0^T \frac{AP(t)}{TP(t)} dt \right]$ - $AP(t)$ actual performance function curve; $TP(t)$ target performance function curve; T a given time interval from disaster occurrence to complete restoration Performance measures: coping capacity (connectivity); robustness (travel time); flexibility (delay)	
Twumasi-Boakye & Sobajito, 2018		✓	✓	✓	✓				$PI_{VHT} = \frac{\sum_{i=1}^n \omega_i \cdot \frac{AP(t)}{TP(t)} dt}{\sum_{i=1}^n \omega_i \cdot VDT_{i,j}}$ - VDT: vehicle distance traveled; VHT: vehicle hours traveled $PI_{HFF} = \frac{\sum_{i=1}^n \omega_i \cdot \frac{CSPD_{i,j}}{VHT_{i,j}}}{\sum_{i=1}^n \omega_i \cdot \frac{CSPD_{i,j}}{VHT_{i,j}}}$ - CSPD = congested speed; FFS: free flow speed Performance measure = $\phi_k = \frac{PI_{after_shock}}{PI_{before_shock}}$; $R_k = \int_{t_0}^{t_1} [100 - \phi_k(t)] dt$	
Tang & Heinemann, 2018			✓						- Congestion index	
Balal et al., 2019	✓		✓	✓	✓	✓			- Queue length - Segment speed - Frontage road delay - Segment travel time - Detour route delay	

Table 4 1: Review of Previous Studies on Road Network Resilience Evaluation

Author	Methodology		Category of resilience Index		Type of Disruption		Resilience Stage	Resilience Index	Note
	Graph theory based	Optimization based	Probability-based	Simulation-based	Miscellaneous	Topology-based	Traffic-related	Socioeconomic	
Maria Nogal & Homfi, 2019	✓					✓		✓	Resilience of perturbation: $\int_{t_0}^{t_1} (1 - \psi_k(t)) dt$; t_0, t_1 initial and final time intervals of disruptive event; Resilience of recovery: $\chi_k^t = \max \left\{ \left(1 - \frac{t_{rec}}{T_{th}} \right) 100; 0 \right\}$; t_{rec} : time required to recover another equilibrium state; T_{th} is a temporal threshold associated with the largest acceptable time for recover
Das, 2020		✓		✓		✓	✓	✓	Resilience = $\frac{\text{Ideal Functionality} - \text{loss}}{\text{Ideal Functionality}}$; $Q(t) = \sum_{ij} \frac{1}{T_{ij}^0} O_{ij} t$; T_{ij}^0 travel time; O_{ij} number of trips
Cu et al., 2020	✓		✓	✓	✓	✓	✓	✓	- Topology-based resilience
Li et al., 2020	✓		✓	✓	✓	✓	✓	✓	- Accessibility
Sgambini et al., 2021	✓		✓	✓	✓	✓	✓	✓	- Increase in kilometers travelled
Wang et al., 2020	✓		✓	✓	✓	✓	✓	✓	- Response Time - Recovery Rate - Recovery Rate
M. T. S. Aghababaei et al., 2021		✓		✓		✓	✓	✓	$Robustness_{ij}(t_c) = \frac{Flow_{ij}(t_c)}{Flow_{ij}(t_0)}$ $Redundancy_{ij}(t_c) = \frac{Average Travel Time_{ij}(t_c)}{Average Travel Time_{ij}(t_0)}$ (Post disaster condition) $Reliability_{ij}(t_c) = Robustness_{ij}(t_c) * Redundancy_{ij}(t_c)$ $Trip Resilience = Reliability_{ij}(t_c)$ $Normalised Trip Resilience = \frac{Reliability_{ij}(t_c) dt}{\Delta t} * 100$
Martín et al., 2021	✓		✓		✓	✓	✓	✓	Potential Accessibility: $PA_i = \sum_j \frac{P_{ij}}{P_i}$; P_i resident population; T_{ij} : travel time Accessibility: $A_s = \frac{\sum PA_i P_i}{\sum P_i}$; Percentage of accessibility change: $Ac_c = \frac{A_0 - A_c}{A_0} * 100$
Zou & Chen, 2021	✓		✓		✓	✓	✓	✓	$R = \frac{1}{(q - \frac{1}{2})} \int_{t_0}^{t_1} Q_i dt$; $Q_i = \frac{TTC_{i,post}}{TTC_i}$; TTC: Total Travel Cost
Z. Liu et al., 2022		✓		✓		✓	✓	✓	$Robustness = R_{rob} = \frac{1}{2} \left(\frac{S^d}{S} + \frac{P^d}{P} \right)$; S quantitative index of road network structure, F quantitative index of road network function, S^d destroyed part of S, and P^d represents the destroyed part of F. $Recovery = R_{rec} = \frac{1}{2} \left(\frac{S^r}{S} + \frac{P^r}{P} \right)$; S^r the recovered part of S, and P^r the recovered part of F $Rapidity = R_{rap} = t_1 - t_0$; t_1 : end time of cascading failure, t_0 : start time of cascading failure $Performance = R_{per} = \frac{1}{2} \left(\frac{S^r}{S} + \frac{P^r}{P} \right)$; S^r structurally normal part road network after cascading failure; F^m functionally normal part of the urban road network after cascading failure
Niu et al., 2022	✓			✓	✓	✓	✓	✓	$\alpha = \tan^{-1} \frac{S_{journal} - S_{lowest}}{T_{lowest} - T_{begin}}$ $\beta = \tan^{-1} \frac{S_{recovery} - S_{lowest}}{T_{recovery} - T_{lowest}}$ $\alpha_i = \tan^{-1} \frac{S_{T_i} - S_{lowest}}{T_{T_i} - T_{lowest}}$, $T_i < T_{lowest}$ $\beta_i = \tan^{-1} \frac{S_{T_i} - S_{lowest}}{T_i - T_{lowest}}$, $T_i > T_{lowest}$

In road network studies, resilience is introduced as one of the road network performance elements. Generally, road network performance includes eleven elements which are (Rivera-Royero et al. 2022):

1. Connectivity.
2. Redundancy.
3. Accessibility.
4. Reliability.
5. Connectivity reliability.
6. Travel time reliability.
7. Capacity reliability.
8. Flexibility.
9. Robustness.
10. Vulnerability; and
11. Resilience.

These concepts have many common and overlapping elements and sometimes they are considered as one another components. For example, Murray-Tuite (Murray-Tuite 2006), identified 10 key dimensions for resilience: redundancy, diversity, efficiency, autonomous components, strength, collaboration, adaptability, mobility, safety, and ability to recover quickly. Rashidy (El Rashidy 2014) considered redundancy, mobility, vulnerability, reliability, diversity, and recovery as resilience characteristics. Besides, Taylor (Taylor 2017), mentioned four key dimensions of resilience: robustness, redundancy, resourcefulness, and recovery. These four dimensions were originally introduced by Bruneau et al. (Bruneau et al. 2003) (known as 4R). In a study by Wan et al. (Wan et al. 2018) key characteristics of resilience are named as vulnerability, adaptability, robustness, preparedness, redundancy, response, and recovery. By focusing on traffic flow rather than the network infrastructure, Calvert and Snelder (Calvert and Snelder 2018), state resistance and recovery as two main parts of road resilience. Also, Ahmed and Dey (Ahmed and Dey 2020) considered travel time, reliability, vulnerability, restoration time, travel demand, budget, capacity, accessibility, shortest path, and resilience triangle as resilience quantification factors. In another

study by Aghababaei et al. (Aghababaei, Costello, and Ranjitkar 2021), robustness, redundancy and recovery are considered as resilience elements. By reviewing road network performance concepts, Rivera-Royero et al. (Rivera-Royero et al. 2022) considered robust and flexible networks as resilience network. They mentioned that reliability, accessibility, and redundancy are among the concepts which highly impact resilience. Therefore, it can be briefly concluded that distinct dimensions for resilience have been considered in previous studies and accordingly different measures exists.

According to Sun et al. (Sun et al. 2020), resilience measures for transportation infrastructure can be broadly categorized into three groups (as shown in Table 4-1): traffic-related, topology-based, and socioeconomic. The first two categories, traffic-related and topology-based, are also known as functionality-related resilience metrics. Traffic-related measures focus on traffic flow features and system capacity, with examples including travel time, throughput, and outflow. On the other hand, topology-based measures utilize graph theory to measure topological characteristics and often focus on connectivity and centrality. However, these measures do not account for dynamic and driving behavior related impacts of the network. Socioeconomic measures, the third category, are based on the socioeconomic benefits of a resilient transportation infrastructure, such as reduced emissions and lower economic costs. These benefits are highly dependent on the available resources. The present study will concentrate on traffic-related measures. Several studies have examined traffic-related measures to evaluate the resilience of the road network. One widely used tool for assessing resilience is the resilience triangle, which encompasses three features: reducing failure probabilities, minimizing the consequences of failures, and reducing the time to recovery.

The original definition of the resilience triangle was proposed by (Bruneau et al. 2003) which is shown in Figure 4-1.

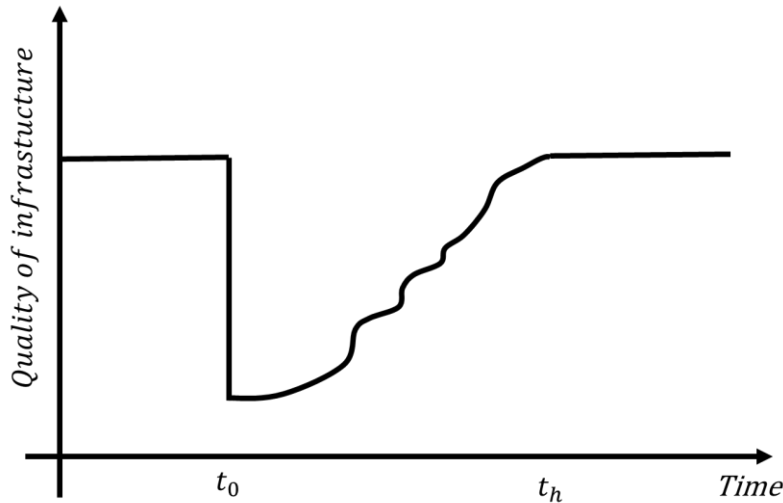


Figure 4-1: Original Resilience Triangle (Source : Bruneau et al. 2003)

The resilience triangle has since been refined by various researchers. For example, Wan et al. (Wan et al. 2018) conducted a literature review to incorporate additional characteristics of resilience into the resilience triangle, including vulnerability, adaptability, preparedness, redundancy, response, and recovery. From the literature (Bruneau et al. 2003; Taylor 2017), the most crucial characteristics of resilience that can be integrated into the resilience triangle are robustness, redundancy, resourcefulness, and recovery speed. Figure 4-2 illustrates these characteristics, and their definitions are derived from Wan et al. (Wan et al. 2018):

- **Robustness:** The ability to withstand or absorb disturbances and remain intact when exposed to disruptions.
- **Redundancy:** It indicates the ability of certain components of a system to take over the functions of failed components without adversely affecting the performance of the system itself.
- **Resourcefulness:** The availability of materials, supplies, and crews to restore functionality in a study of transportation resilience.
- **Rapidity:** it contains a hidden meaning of recovery, but with more emphasis on the speed to recover.

The resilience triangle is a concept that describes how a system's functionality can be affected by a sudden disruption. The resilience triangle explain that the system experiences a sudden drop in functionality at a specific time (t_0), but then gradually recovers until it returns to its primary level of functionality (t_h). This is illustrated in Figure 4-2, which depicts the resilience triangle consisting of three edges. The first edge represents the initial decrease in functionality at time t_0 , the second edge shows the recovery time ($t_h - t_0$), and the slope of the third edge represents the speed of recovery (Sun et al. 2020). Using this figure, it is possible to mathematically quantify resilience by integrating the area of the resilience triangle. This provides an estimate of the resilience loss caused by the disruptive event (as shown in Equation 1). A system that is highly resilient will have a low value of resilience loss.

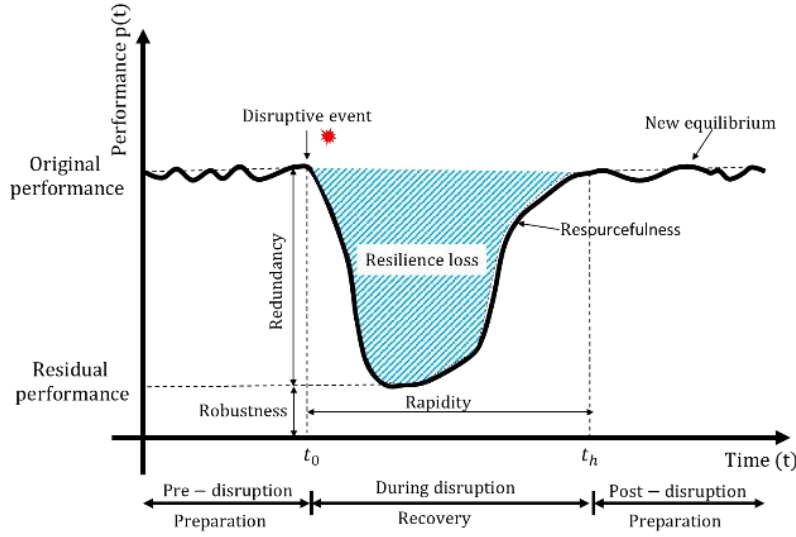


Figure 4-2: Schematic of performance of a resilient system (Source: Wan et al. (2018))

$$\text{Resilience loss} = \int_{t_0}^{t_h} [100 - P(t)] dt \quad (4 - 1)$$

$$\text{Resilience index} = \frac{\int_{t_0}^{t_h} [P(t)] dt}{t_h - t_0} \quad (4 - 2)$$

Where $P(t)$ is an indicator for the quality of infrastructure. Usually in road network resilience studies, $P(t)$ is considered as a performance indicator: segment travel time, queue length, segment delay, etc.

Establishing an appropriate performance indicator for the road network is crucial for measuring the resilience triangle effectively. Balal et al. (Balal et al. 2019) utilized segment travel time, detour route delay, queue length, segment speed, and frontage road delay as performance measures to quantify the resilience triangle. However, these measures are only at the link level and do not provide a comprehensive view of the network-level resilience (i.e., the ripple effects of road/link closure on other parts of the transportation network). Previous research recommends network-level measures for road network resilience evaluation. Additionally, most studies that use resilience-triangle-related measures only calculate one dimension of resilience, such as redundancy or robustness, and may not consider the recovery of the network (Aghababaei et al. 2021). However, previous studies have emphasized that recovery and rapidity are critical components of road network resilience, particularly in the context of new technologies like CAVs (Ahmed et al. 2019). Another limitation of studies that use the resilience triangle to evaluate road resilience is that they typically focus on natural hazards (e.g., earthquakes, floods) that result in structural collapse or significant changes in travel demand (Aghababaei et al. 2021; Das 2020; Niu et al. 2022; Nogal et al. 2017; Twumasi-Boakye and Sobanjo 2018). These studies usually assume a pre-defined recovery strategy (based on resourcefulness) and then calculate the (un)resilience index. Thus, they have not investigated the immediate impact of road/link closure and how performance evolves during different disruption phases.

In brief, the studies on road network resilience that use traffic-related measures have several gaps. Most studies do not consider the recovery speed of the network, are limited to the link level, and focus on the post-crisis stage rather than during the crisis. Although some measures based on total travel time are correlated with recovery time, they do not capture the immediate impact of disruption and the evolution of the network. This study addresses these gaps by introducing a new measure of network

functionality based on simulation-based methods and using it to plot the resilience triangle at the network level for a large-scale road network in Belgium. This approach allows for investigating the rapidity of the network, the immediate impact of disruption, and the evolution of the network during different phases of disruption, not limited to natural disasters. To the best of the authors' knowledge, this is the first time a traffic-related measure of resilience has been introduced at the network level to study resilience in different phases of disruption.

4.2. Road Network Resilience Evaluation Methodology

This section outlines the methodology for plotting the resilience triangle, starting with the selection of an appropriate performance indicator.

While many studies have used total travel time as a performance indicator, this has limitations. For example, it does not capture the immediate impact of sudden incidents on the network, and it does not reflect the recovery time, or rapidity, of the network. Additionally, total travel time is heavily influenced by the travel times of specific origin-destination pairs and may not be generalizable to other patterns. Therefore, the author chose a new performance indicator based on simulation-based methods that measures network functionality and captures the evolution of the network during different phases of disruption. This allows for a more comprehensive understanding of the network's resilience and enables the plotting of the resilience triangle at the network level.

Based on the explanation provided in the preceding section, the performance indicator needs to encompass all aspects of resilience, including robustness, redundancy, and rapidity. It's worth noting that this study does not consider resourcefulness, as it is solely reliant on the availability of resources and, therefore, falls outside the scope of this research. Additionally, given the research objectives, the performance indicator must also account for the impact of CAVs on the resilience of the road network.

The performance of a road network can be quantified as the number of completed trips within a unit of time, also referred to as the outflow of the network (Amini, Tilg, and Busch 2018; Knoop 2017). In essence, this indicates the number of vehicles that can be accommodated by the road network. However, in the event of an incident, the impact on the outflow cannot be immediately observed. Only when the affected vehicles reach their destination can the effect on the outflow be noticed. Additionally, determining the outflow of the network in practice can be challenging. Therefore, this study employs a surrogate measure of outflow. Previous research (Amini et al. 2018; Geroliminis and Daganzo 2008; Knoop 2017) has demonstrated that the performance of the network is closely related to its production in equilibrium conditions. Network production refers to the internal flows in the network. Furthermore, it has been established that the production of a network is dependent on its accumulation, which refers to the number of vehicles in the network. The advantages of using accumulation as the performance indicator are twofold: Firstly, it can be easily measured in practice, assuming a good coverage of detectors in the network. Secondly, the impact of incidents on accumulations can be detected much faster than on outflow or travel time, as it is dynamically impacted by any incident. Therefore, this study considers accumulation as the performance indicator for the formation of the resilience triangle.

$$A_t = V_t^i + V_t^o \quad (4 - 3)$$

Where A_t is the accumulation of the network at time t , V_t^i is the number of vehicles in the network at time t , and V_t^o is the number of vehicles waiting for insertion to the network at time t . In this performance indicator definition, not only is the number of vehicles within the network taken into account, but also the number of vehicles waiting for insertion. The reason for this inclusion is to account for the effect of blockages in the insertion links.

To construct the resilience triangle using accumulation, the first step is to simulate a base case scenario in which no disruptions occur. The accumulation of the network at each time interval, typically 5 minutes, is then plotted. Following this, another simulation is conducted for a scenario

in which a disruption occurs, and the corresponding accumulation is plotted. The area between the accumulation curve of the base case scenario and the accumulation curve of the disrupted scenario is defined as the resilience loss. A smaller area between the two curves indicates a higher level of resilience in the network. Figure 4-3 presents a sample resilience triangle using accumulation, where the X-axis represents the accumulation in the network, and the Y-axis represents the time interval. The resilience loss formulation can be defined as follows:

$$RL = \int_{t_0}^{t_h} A_t^d(t)dt - \int_{t_0}^{t_h} A_t^b(t)dt \quad (4-4)$$

Here, RL is the resilience loss, and $A_t^d(t)$ and $A_t^b(t)$ are the accumulation of disrupted and base case scenarios at time t , respectively.

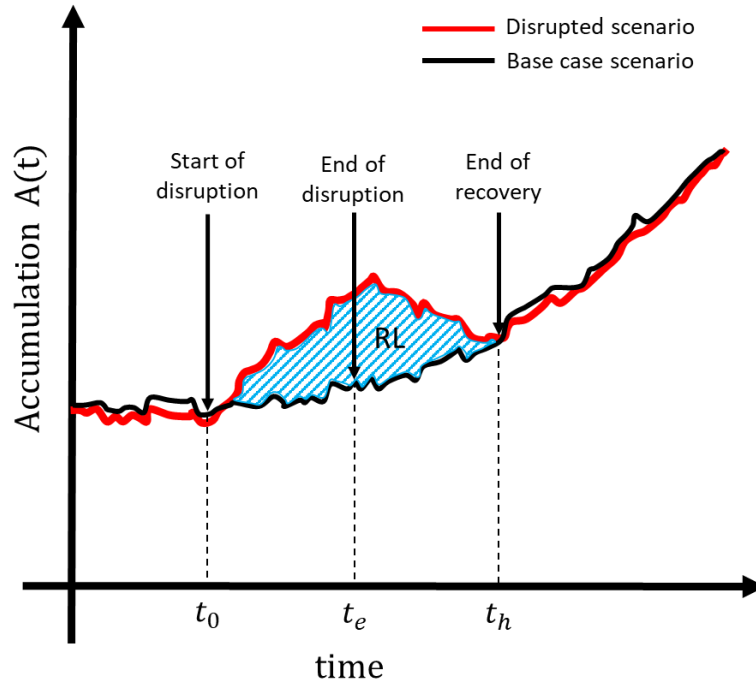


Figure 4-3: Road network resilience triangle using accumulation (source: Author)

Using accumulation as the performance indicator to draw the resilience loss triangle allows us to account for all aspects of resilience, including redundancy, robustness, and recovery. This approach also enables the measurement of the impact of CAVs on the resilience of the entire network, particularly given their rerouting capability. CAVs can avoid congested and disrupted roads, which can result in an increase in the outflow of the network, as represented by the accumulation measure. This increase in outflow is associated with higher network performance, indicating a more resilient network. Therefore, the use of accumulation as a performance indicator can help to quantify the benefits of CAVs for enhancing network resilience, particularly in response to disruptive events.

4.3. Summary

In this chapter, it was mentioned that the existing metrics are insufficient to measure the immediate impact of CAVs on disruptions. As a result, a new metric called Resilience Loss (RL) has been introduced to examine the impact of CAVs on the resilience of the road network. The RL metric utilizes the resilience triangle concept and measures the area between the accumulation curve of the disrupted scenario and the accumulation curve of the undisturbed scenario. The smaller the area between these two curves, the more resilient the system is. One of the advantages of taking accumulation as network performance metric is that it can instantly demonstrate the occurrence of a disruption. For instance, when a link is closed, the accumulation in the system quickly increases. Moreover, this metric can easily quantify the impact of rerouting CAVs using online data. If self-driving vehicles can reroute, they can reduce the accumulation of the system and alleviate network congestion compared to when self-driving cars are not present in the network. In the next chapter, the RL metric presented in this chapter will be used to assess the network resilience of Belgium in various scenarios. It's important to highlight that in this study, accommodation has been utilized to evaluate network resilience. However, for future studies, it is suggested to explore alternative criteria for assessing network resilience, such as the number of completed trips, for a more comprehensive analysis.

5. Belgium Road Network Resilience Evaluation

In this chapter, the author employs a combination of tools including the travel demand matrix from Chapter 2, the multi-class traffic assignment problem solving tool from Chapter 3, and the new resilience measure from Chapter 4 to evaluate the resilience of Belgium's transportation network. The chapter begins by introducing various scenarios used to assess the network's resilience and subsequently presents resilience values for Belgium's transportation network under different scenarios. The basis for this chapter is an article that the author refers to.

- Bamdad Mehrabani, B., Pel, A., Calvert, S., Sgambi, L., and Snelder, M. Assessing road network resilience in the era of Connected and Autonomous Vehicles (Belgium road network). Transportation Research Board 103rd Annual Meeting (USA, Washington DC, from 07/01/2024 to 11/01/2024).
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5.1. Malfunction Scenarios

In network resilience studies, different types of disruptions can be classified as natural disasters (e.g., floods, earthquakes, storms), abnormal events (e.g., accidents, road maintenance sites), and man-made disasters (e.g., cyber-attacks). The recovery period for natural disasters can range from several weeks to several months, while the recovery time for abnormal events can vary from a few hours to several days. This study has taken into account accident scenarios to assess the network's resilience. However, when simulating accidents in large networks like Belgium, it is imperative to identify where these accidents take place within the network. To this end, a critical link analysis was performed. The critical links were determined by identifying the shortest paths during peak hour period. The significance of each link was determined by counting the number of times it appeared in the shortest paths of all trips. As a result, links can be sorted based on their importance.

Accidents at critical links in the network are considered as the disruption scenarios. The simulation covers a 3-hour, during rush hours, and the accidents happen one hour after the start of the simulation. The first 15 minutes of this simulation have been considered as the warm-up time. The occurrence of an accident takes place one hour after the end of the warm-up time and last for 30 minutes in one direction. These accidents result in the closure of two lanes in the related highway, which can be considered as minor accidents.

Minor accidents on highways can have a substantial impact on traffic flow, often resulting in the closure of lanes and causing disruptions that range from a few minutes to several hours. In this study, we specifically focus on incidents with a duration of 30 minutes. This time frame was chosen based on the significant influence that even minor accidents can have on the flow of traffic when two out of three lanes are temporarily closed. Despite their seemingly brief nature, these incidents can lead to congestion, delays, and ripple effects on overall road network efficiency.

Figure 5-1 illustrated the importance of each link in Belgium road network.

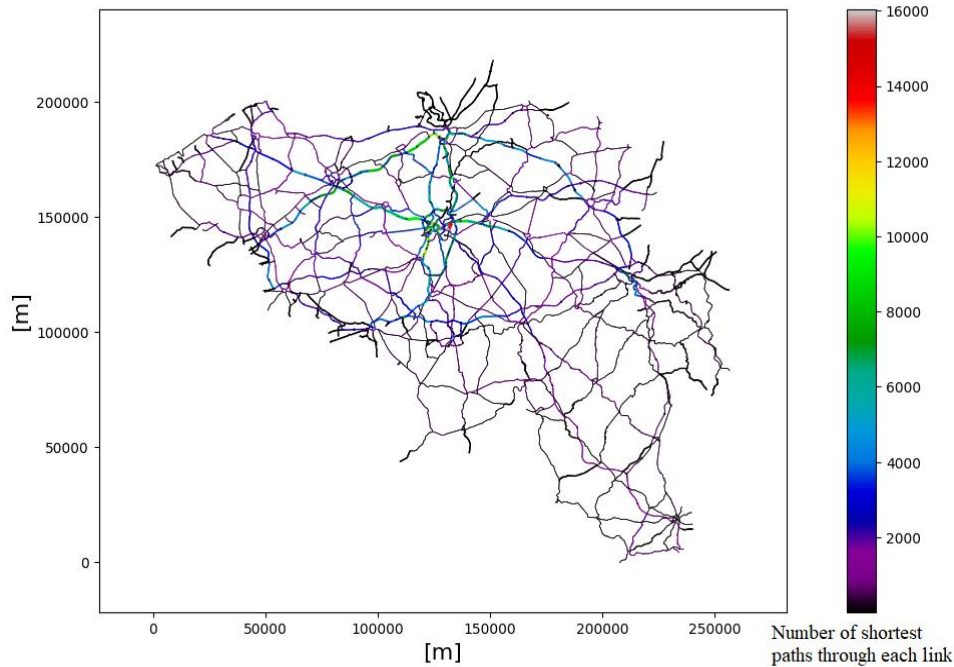


Figure 5-1: Belgium Links Importance (source: Author)

By examining the impact of these 30-minute closures caused by minor accidents, we aim to gain insights into the broader implications for network resilience analysis and explore potential impacts of CAVs to mitigate the consequences of such disruptions on highways. To evaluate the network's resilience under various scenarios, the cumulative occurrence of accidents was simulated, starting with the most critical link. This approach provides insight into the network's behavior when the most critical links are affected first and can help plan preventative and adaptive measures. Table 5-1 shows the simulated scenarios and their settings.

Table 5-1: Malfunction scenarios

Scenario	CAV percentage	HDV percentage	Disrupted links	Scenario	CAV percentage	HDV percentage	Disrupted links
1	0	100	0 (base case)	29	0	100	Top 4 critical link
2	10	90		30	10	90	
3	20	80		31	20	80	
4	40	60		32	40	60	
5	60	40		33	60	40	
6	80	20		34	80	20	
7	100	0		35	100	0	
8	0	100	Top 1 critical link	36	0	100	Top 5 critical link
9	10	90		37	10	90	
10	20	80		38	20	80	
11	40	60		39	40	60	
12	60	40		40	60	40	
13	80	20		41	80	20	
14	100	0		42	100	0	
15	0	100	Top 2 critical link	43	0	100	Top 10 critical link
16	10	90		44	10	90	
17	20	80		45	20	80	
18	40	60		46	40	60	
19	60	40		47	60	40	
20	80	20		48	80	20	
21	100	0		49	100	0	
22	0	100	Top 3 critical link				
23	10	90					
24	20	80					
25	40	60					
26	60	40					
27	80	20					
28	100	0	Duration of Simulation : 3-hr; Duration of Incident: 30 Min				

5.2. Simulation Results and Discussion

This study uses the traffic simulation software SUMO to model traffic flow at the mesoscopic scale. In these simulations, we have studied two types of

users: CAVs and HDVs. As previously mentioned, we assume that CAVs have faster and safer driving behavior and are following SO principles along with rerouting capabilities. The difference in driving behavior between CAVs and HDVs has been taken into account by modifying the queue model at the meso-scale level. To achieve the mixed equilibrium of CAVs and HDVs, the multi-class traffic assignment problem algorithm outlined in Chapter Four has been utilized.

Thus, the multiclass traffic assignment problem of mixed traffic flow for different penetration rate of CAVs has been solved. The convergence criterion presented in Chapter Four was utilized for these simulations, and the iteration with the least hybrid gaps was taken as the base case scenario. After obtaining the base case scenarios for each penetration rate, then simulations for each disrupted scenario were conducted in order to form the accumulation curve. By comparing each disrupted scenario's accumulation curve and its base case scenario's accumulation curve, it is possible to calculate the resilience loss of each scenario. In this section, first the traffic results for each of the base case scenarios at various penetration rates are presented, followed by the accumulation curve and the value of the resilience loss being investigated.

5.2.1 Base-Case Model

The convergence pattern of the base case scenario at varying penetration rates is illustrated in Figure 5-2. The graph indicates that the 100% HDV scenario exhibits the greatest gap, while the 100% CAV scenario demonstrates the smallest gap. This suggests that a network consisting entirely of CAVs results in a smaller discrepancy between the optimal and attained solutions. This phenomenon could be attributed to the ability of CAVs to be rerouted prior to or after entering the network.

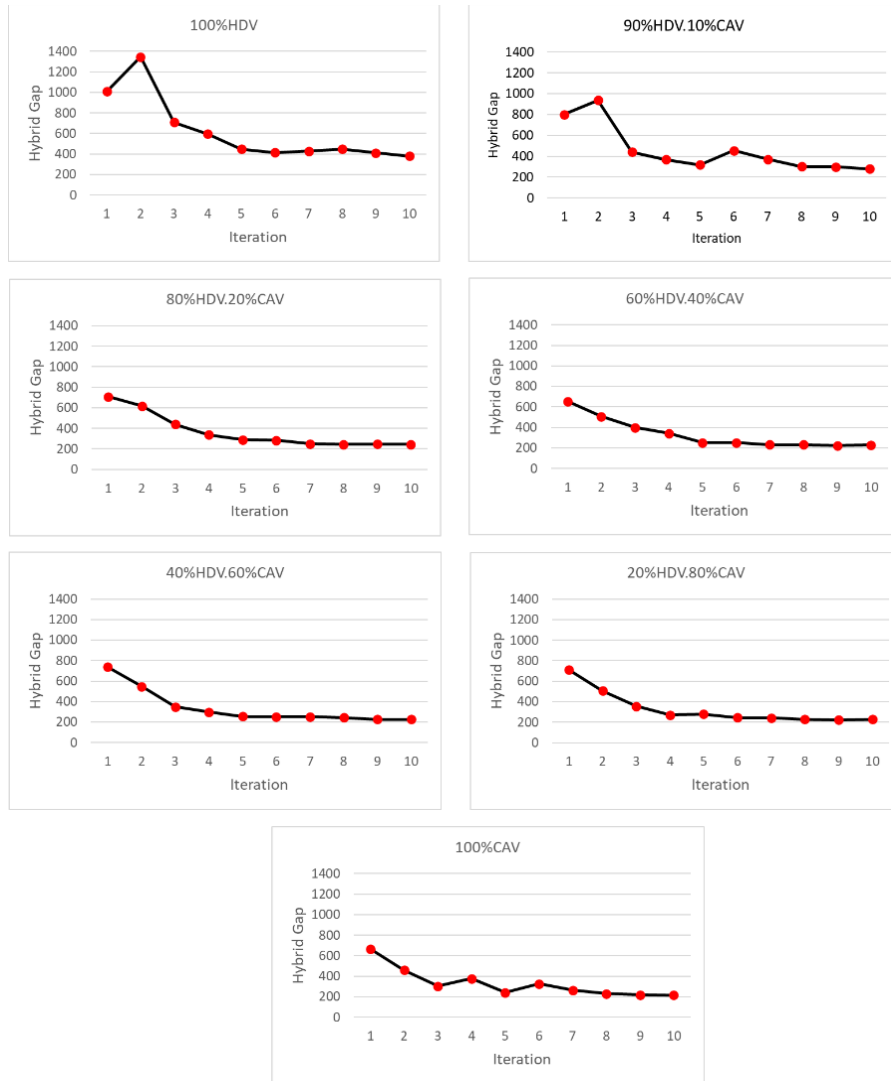


Figure 5-2: Convergence pattern for Base-Case models (source: Author)

To explore the influence of CAVs on travel time and network performance in the absence of any unexpected events, Figure 5-3 has been presented. Upon reviewing the figure, it becomes evident that as the percentage of

CAVs penetration rate increases, the overall travel time of the network reduces. The degree of enhancement in the total travel time of the network when CAVs are present varies between 2.7% (at a penetration rate of 10%) and 10.9% (at a penetration rate of 100%).

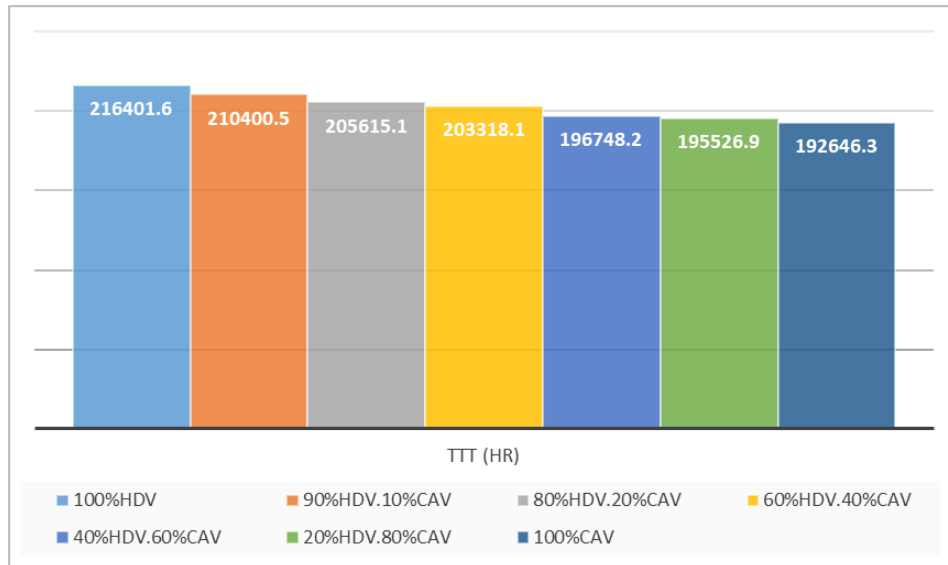
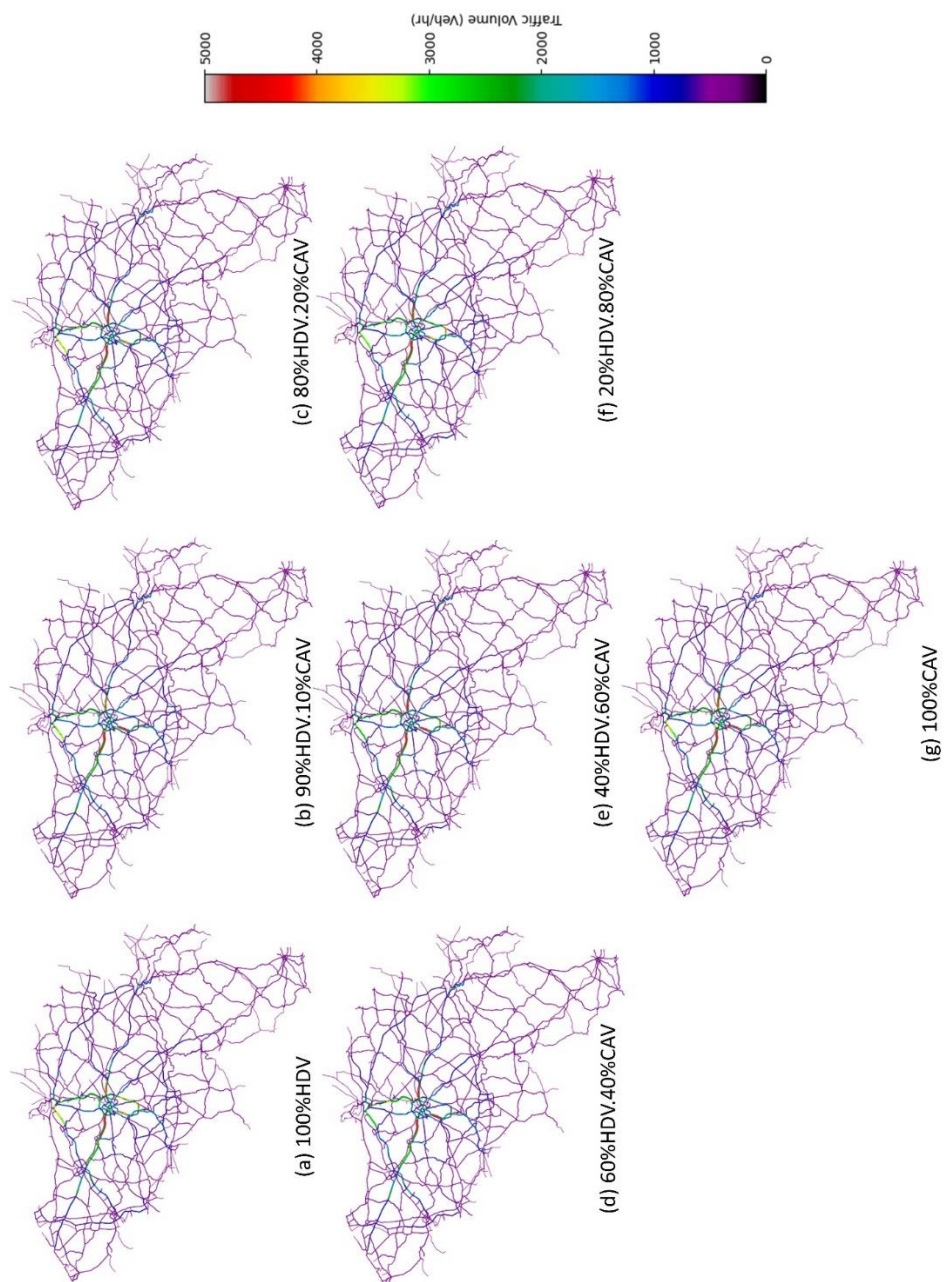


Figure 5-3: Total travel time in different penetration rate of CAVs (source: Author)

In order to obtain a more precise evaluation of the network's performance under varying levels of CAVs penetration, different penetration rates have been examined, and their corresponding network volumes are depicted in the provided Figure 5-4. As depicted in the figure, the path selection pattern undergoes a change with an increase in CAVs penetration, leading to fluctuations in the number of vehicles on each highway. This suggests that the network volume varies at different levels of CAVs penetration, as traffic tends to opt for routes that minimize the overall travel time of the network.

Figure 5-4: Belgium traffic volume in different penetration rate of CAVs (source: Author)



To explore the influence of CAVs on travel time and network performance Table 8 have been presented. As seen in Table 5-2, to achieve convergence on the Belgium road network (which is a large-scale network) during the peak hours (with over 243,000 vehicles), between 6.5 to 8 hours is required, which is an acceptable computational time considering the size of the network.

Scenario	Hybrid Gap	Total Travel Time (hr.)	Average Speed (km/h)	TTT improvement (%)	Computation Time (min)
1	380	216401.63	72.8	-	391
2	279	210400.53	72	2.7	421
3	244	205615.14	72.4	7.9	448
4	229	203318.06	73.1	6.04	453
5	228	196748.17	74.2	9.08	467
6	227	195526.90	74.8	9.64	474
7	215	192646.34	75.2	10.97	484

Table 5-2: Simulation Results (Base-case model)

5.2.2 Disrupted Model

Table 5-3 provides an overview of traffic metrics at different PR of CAVs in disrupted scenarios.

As observed in table 5-3, an increase in the percentage of CAVs leads to a decrease in the total travel time of the network. This can be attributed to the fact that CAVs adhere to the SO, which prioritizes optimizing the travel time of the entire network. In disrupted scenarios, reducing the total travel time by increasing the percentage of CAVs may be due to the fact that these vehicles are connected to each other. Therefore, when a sudden incident occurs in the network, these vehicles can notify each other of the incident, and as a result, vehicles that have not yet reached the incident can change their route (rerouting capability). Having reviewed the simulation results for the base-case scenario, the next step is to evaluate the resilience of the Belgian network.

100%HDV		60%HDV.40%CAV		100%CAV	
Scenario	TTT (min)	Scenario	TTT (min)	Scenario	TTT (min)
1 link Closure	13076523	1 link Closure	12360555	1 link Closure	11727832
2 Link Closure	13117268	2 Link Closure	12392351	2 Link Closure	11760581
3 Link Closure	13165122	3 Link Closure	12395149	3 Link Closure	11807367
4 link Closure	13260307	4 link Closure	12498335	4 link Closure	11874124
5 Link Closure	13316268	5 Link Closure	12502181	5 Link Closure	11892919
10 Link Closure	13463633	10 Link Closure	12571591	10 Link Closure	11900310
90%HDV.10%CAV		40%HDV.60%CAV			
Scenario	TTT (min)	Scenario	TTT (min)		
1 link Closure	12737497	1 link Closure	11834474		
2 Link Closure	12745272	2 Link Closure	11871907		
3 Link Closure	12839657	3 Link Closure	11907132		
4 link Closure	13010625	4 link Closure	11911474		
5 Link Closure	13064213	5 Link Closure	11976920		
10 Link Closure	13236609	10 Link Closure	11986508		
80%HDV.20%CAV		20%HDV.80%CAV			
Scenario	TTT (min)	Scenario	TTT (min)		
1 link Closure	12447666	1 link Closure	11840927		
2 Link Closure	12479101	2 Link Closure	11859870		
3 Link Closure	12489484	3 Link Closure	11870081		
4 link Closure	12494796	4 link Closure	11875285		
5 Link Closure	12592035	5 Link Closure	11926337		
10 Link Closure	12834344	10 Link Closure	11954628		

Table 5-3: Simulation Results (Disrupted scenarios)

Figure 5-5 displays the accumulation curve for both disrupted scenarios and the non-disrupted scenario, across all penetration rates of CAVs. Given that the accumulation curve is the same for all disrupted and non-disrupted scenarios prior to the occurrence of the incident in a specific penetration rate, as shown in Figure 5-6, for the sake of simplicity the first hour of the simulation is not shown because it remains consistent across all scenarios. As depicted in the figure, the accumulation curve for all scenarios prior to an incident is consistent for each CAV penetration rate. However, following a disruption, indicated by the closure of the lane, the accumulation curve begins to diverge from the accumulation curve of the base-case scenario. The rise in accumulation in disrupted scenarios, as compared to non-disrupted scenarios, is to be expected as a disruption in the network leads to an increase in the travel time of vehicles, resulting in longer trips. Consequently, the number of completed trips within a given timeframe reduces, leading to an immediate increase in the number of vehicles in the network or accumulation after the incident.

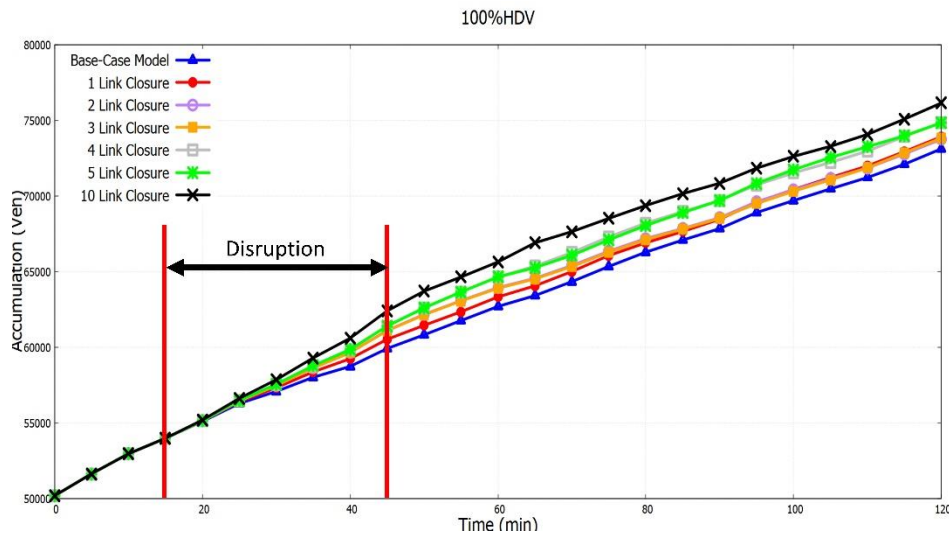


Figure 5-5: Accumulation Curve for all scenarios (source: Author)

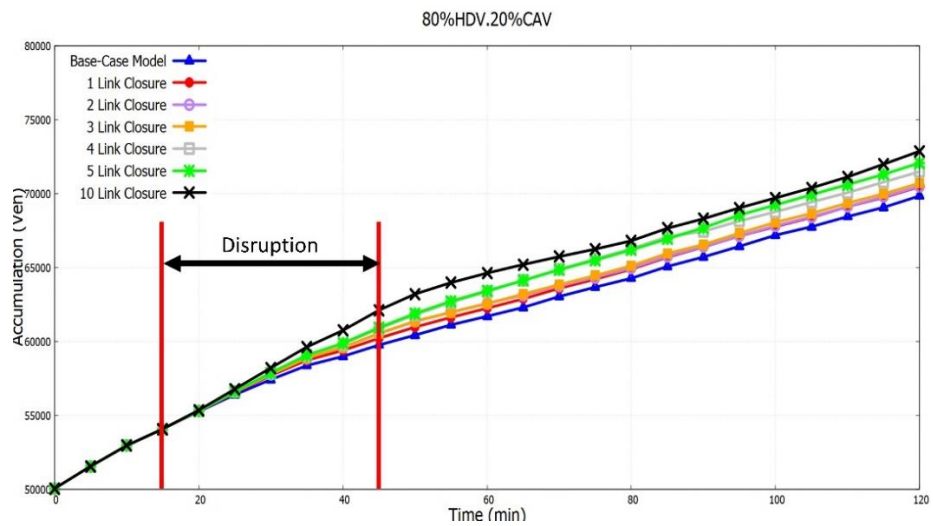
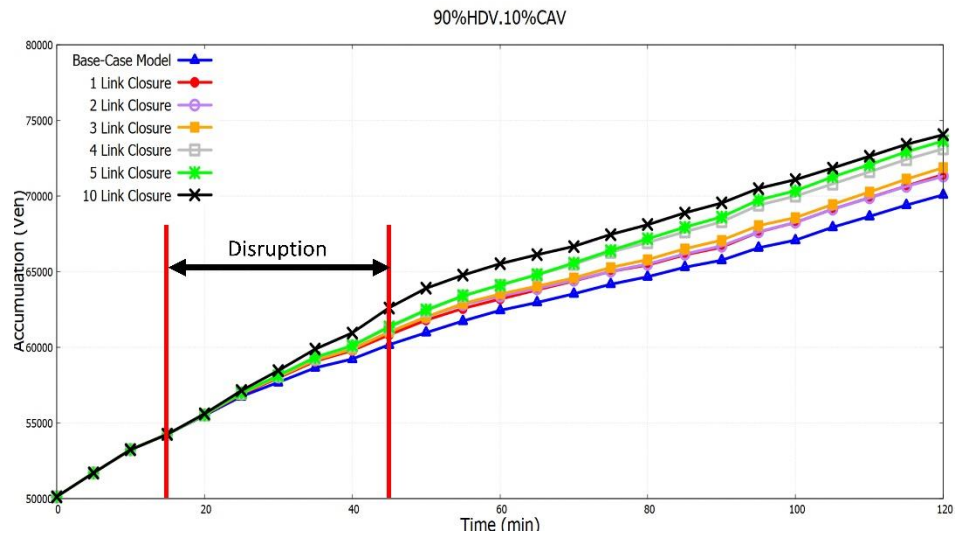


Figure 5-5: Accumulation Curve for all scenarios (source: Author)

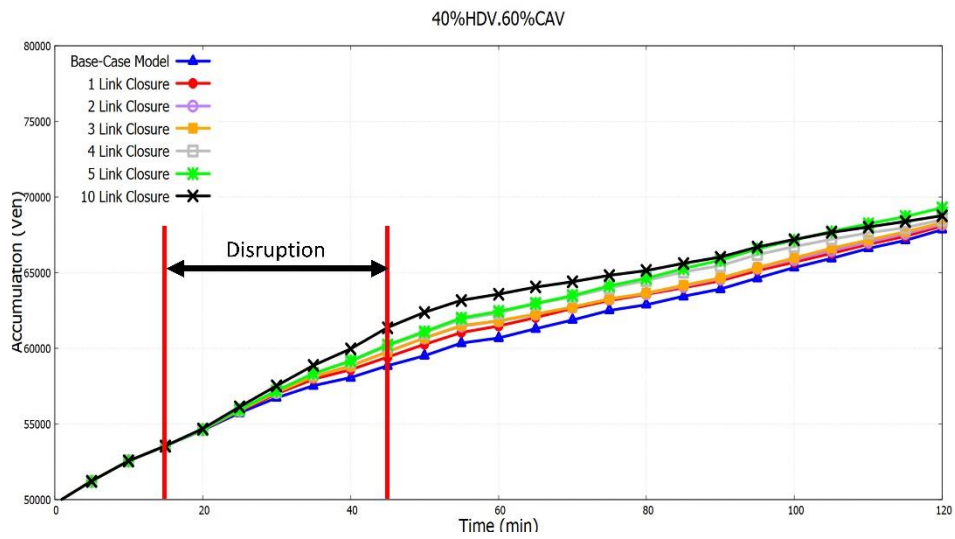
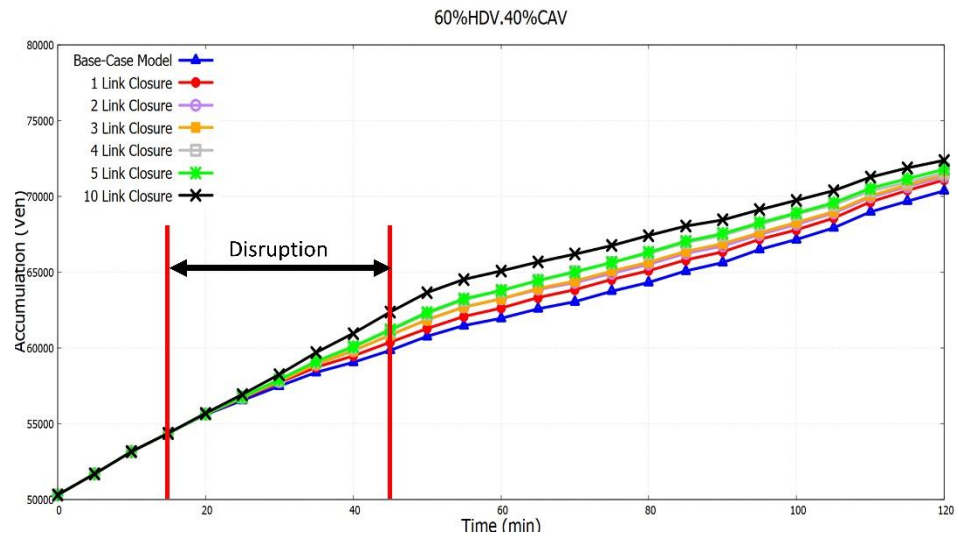


Figure 5-5: Accumulation Curve for all scenarios (source: Author)

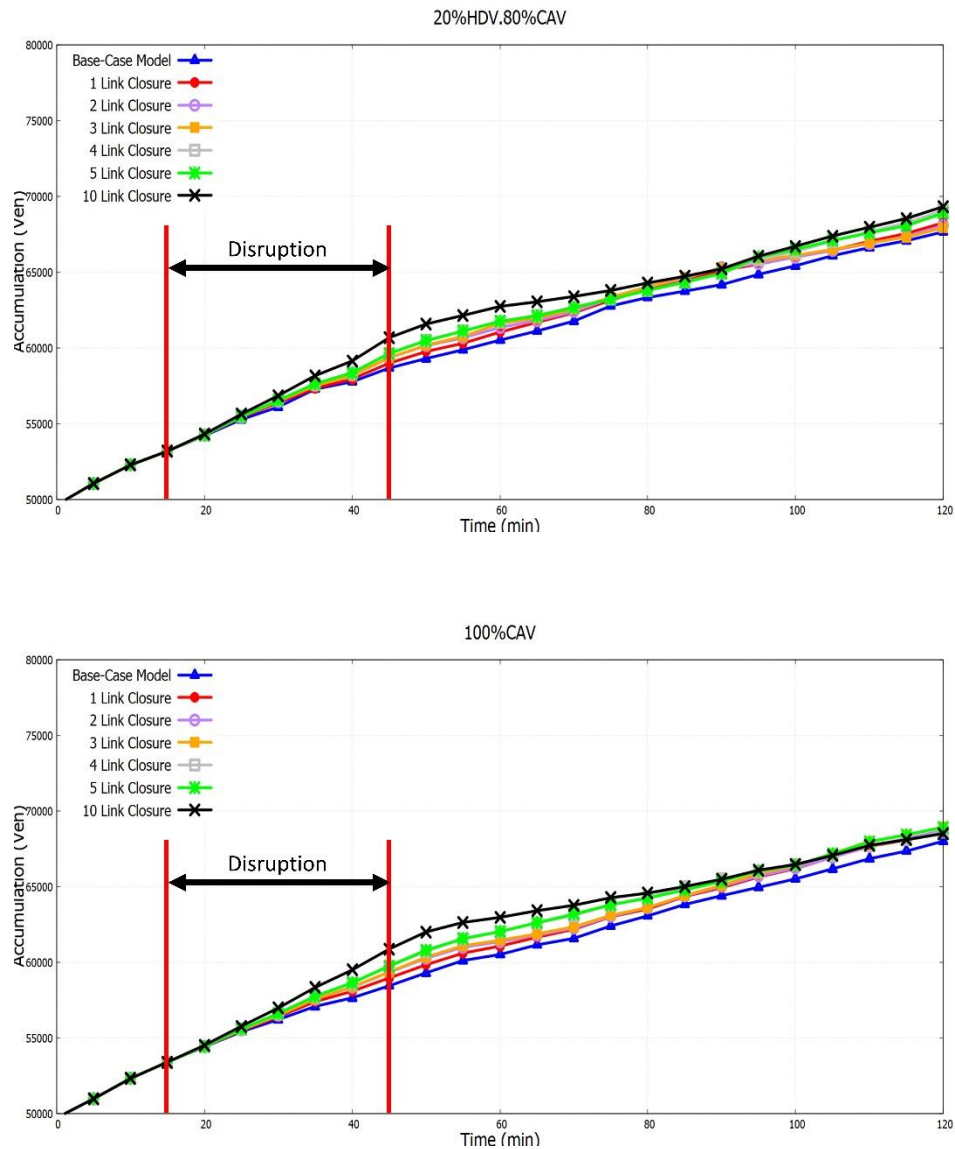


Figure 5-5: Accumulation Curve for all scenarios (source: Author)

When analyzing accumulation in various scenarios, a crucial consideration is whether the accumulation curve returns to its initial state

after the disruption. If the curve does return to its initial state, then the system has fully recovered; however, if the curve does not return to its initial state until vehicles enter the network, then the system has not fully recovered. Examining the Figure 5-6, we can see that when only HDVs are present in the network, the distance between the disruptive accumulation scenarios and the base case scenario is significant, and these curves do not return to their original state until the end of the peak hour. However, as the percentage of CAVs increases in the network, the distance between the accumulation curves of the disruptive scenarios and the base case scenario decreases. It is noteworthy that when all vehicles are CAVs, the distance between these curves is insignificant, and after the disruption ends, the accumulation curve of the disruptive scenarios returns to its initial state. This finding suggests that the presence of CAVs in the network results in faster network recovery time and hence increases the network's resilience.

Another noteworthy observation in the accumulation curve is the change in the network accumulation values in different scenarios with varying CAVs penetration rates. As illustrated in Figure 5-6, an increase in the CAVs penetration rate results in a decrease in the network accumulation value in all disruptive scenarios. For instance, the network accumulation value ranges between 50,000 and 75,000 in all scenarios with 100% HDV, while it ranges between 50,000 and 70,000 in scenarios involving 100% CAVs. Considering that the number of vehicles in all scenarios is identical, and only the CAVs penetration rate varies, it can be inferred that the completed trip rate increases with an increase in the CAVs penetration rate, leading to a reduction in the network accumulation value for a specific period. In other words, the network performance improves with an increase in the CAVs penetration rate. In summary, after analyzing Figure 5-6, it can be conclusively stated that the inclusion of CAVs has a positive impact on both the rapidity and redundancy of the network. The term rapidity refers to the duration required for the system to revert to its initial state before an incident occurs, while redundancy denotes the extent of performance reduction after an incident. The existence of CAVs has resulted in the network returning to its initial state at a quicker pace and

experiencing a lower level of performance degradation following an incident when compared to situations without CAVs. This indicates the significance of CAVs in the redundancy and resilience of transportation road networks. The network's resilience loss was determined and illustrated in Figure 5-6 to measure the network's resilience under various scenarios.

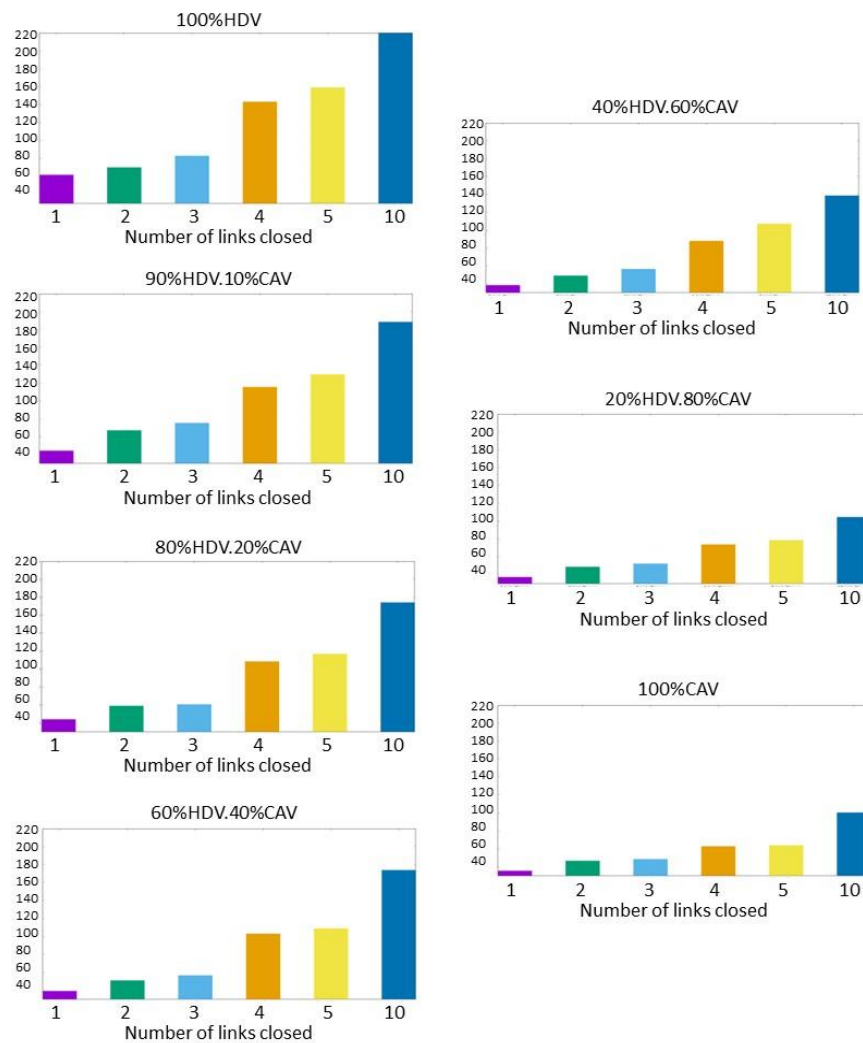


Figure 5-6: Resilience Loss for all scenarios (Veh. Min x1000) (source: Author)

A careful examination of this figure reveals that as the number of CAVs increases, the network's resilience loss reduces in different disruption situations. In other words, the network's resilience improves with an increase in the deployment of CAVs. Two factors may contribute to this trend. Firstly, CAVs rely on SO principles to navigate through the network and have the ability to reroute in real-time (both pre-trip and en-route). CAVs continuously gather updated information and are promptly notified in the event of an incident. If a quicker route is available, they reroute and take the new detour. Secondly, the driving behavior of CAVs improves the network's capacity and enhances its overall performance, leading to a rise in the completed trip rate. To better understand the impact of CAVs on network resilience, the percentage improvement in network resilience at various CAVs penetration rates compared to when all vehicles are HDV is shown in the Table 5-4.

Table 5-4: Percentage of improvement in resilience in different penetration rate of CAVs

	10%	20%	40%	60%	80%	100%
<i>1 link Closure</i>	28.5	28.9	36.6	37.8	39.6	42.5
<i>2 Link Closure</i>	4.4	15.9	27.3	30.1	30.3	33.4
<i>3 Link Closure</i>	9.4	27.0	31.8	32.1	36.9	41.6
<i>4 link Closure</i>	19.3	24.3	28.1	38.6	48.4	56.2
<i>5 Link Closure</i>	18.5	26.6	31.6	32.6	50.6	59.9
<i>10 Link Closure</i>	14.2	20.7	20.8	36.9	52.4	54.3

According to the findings presented in Table 5-3, an increase in the percentage of CAVs in all the studied disruption scenarios corresponds to an increase in the resilience value of the network. Notably, the scenario involving lane closures in the top five most critical links exhibits the most

significant improvement in network resilience, with a 59.9% enhancement achieved at a 100% CAVs penetration rate. Conversely, the scenario involving lane closures in only the two most critical links exhibits the lowest improvement in network resilience, with a mere 4.4% improvement observed at a 10% CAVs penetration rate. These results underscore the critical role of CAVs in enhancing the overall resilience of the transportation network during disruptive events.

In investigating the resilience improvement percentages within the Belgian network, it is crucial to note that a simple correlation between the number of links affected by an incident and the percentage of improvement may not be apparent. Our study's simulation results indicate that this expected effect does not occur. Specifically, when an incident arises in only one link at a 10% penetration rate of CAVs, network resilience improves by 28.5%. However, when the incident occurs in two links, network resilience improves by a mere 4.4%. One plausible explanation is that the ranking of link criticality may differ based on network resilience criteria versus the shortest path criteria. Consequently, a new criticality ranking for links based on the resilience loss criterion could be introduced. However, such a proposal falls outside the scope of this study.

It is essential to note that the results of the resilience evaluation can have various applications. For instance, by eliminating cumulative links and calculating the resilience loss resulting from the removal of each link, one can investigate the link criticality and determine whether the link criticality ranking derived from resilience loss results aligns with the ranking obtained from the shortest paths or not. Additionally, considering that the scenarios utilized in this study, involving minor incidents, lead to the closure of lanes on highways, the interpretations and findings of this study can be applied to any incident causing lane closures. Moreover, given that the methodology presented in this study for assessing resilience is based on traffic simulation, it can be employed to examine network resilience under conditions where other incidents occur (such as adverse weather conditions). In other words, the impact of other incidents can

easily be simulated in traffic simulation. For instance, if we aim to assess network resilience under adverse weather conditions, we can simulate it by reducing the vehicle speed at the network level or by decreasing link capacities at the network level. In this way, the level of network resilience can be examined using the measure proposed in this study.

5.3. Summary

This chapter presents an analysis of network resilience in Belgian roadways, using simulation scenarios and advanced modeling techniques. The chapter begins by introducing the scenarios for which network resilience has been measured, followed by a presentation of simulation results. The modeled disruption scenarios in this study have focused on minor accidents. However, it is recommended that in future studies, using the tools provided in this thesis, other scenarios be simulated as well. A total of 49 different simulation scenarios were examined, and the results were presented in two parts: the base case scenario and the disrupted scenario. The chapter employs a range of modeling tools presented in previous chapters, including the base case model presented in chapter 2, the traffic assignment tool presented in chapter 3, and the new method for assessing network resilience presented in chapter 4.

The simulation results demonstrate that as the percentage of CAVs penetration increases, both in scenarios without disruption and in scenarios with disruption travel time decreases. Additionally, as the percentage of CAVs penetration increases, the network resilience in all scenarios improves. The enhancement of network resilience is attributed to the route selection behavior of CAVs and their different driving behaviors, which are safer and faster compared to HDVs. The route selection behavior of CAVs is based on the system optimal, and they have the ability to reroute when an incident occurs on the network.

In conclusion, this chapter provides a comprehensive analysis of the impact of CAVs on network resilience, demonstrating that their

introduction can significantly improve the overall performance of the roadway network. The findings of this study have important implications for transportation planning and policymaking, as they suggest that the widespread adoption of CAVs could help to mitigate congestion, reduce travel time, and improve air quality in urban areas.

6. Conclusion and Recommendation

This chapter discusses the results of the study. It begins by presenting the main findings and limitations of the study. Then, the overall results of the study and how they can be applied in practice are examined. Finally, the limitations of the study are discussed, and suggestions for future studies are presented.

The modern transportation system is facing new challenges as technology continues to advance and shape the way we move from one place to another. Among these challenges, CAVs are considered the most important. CAVs are the vehicles which has two main features: connectivity, and autonomously. Connectivity refers to the ability to communicate with other vehicles, infrastructure, and devices, providing real-time data that can improve safety and efficiency. Autonomously, on the other hand, refers to the fact that CAVs can operate without human input, relying on sensors, cameras, and algorithms to make driving decisions.

CAVs are outfitted with an array of sensors, integrated cameras, in-vehicle computing systems, high-precision GPS technology, satellite receivers, and short-range radars, collectively facilitating the execution of either entire or partial driving responsibilities. The European automotive market has already witnessed the introduction of vehicles providing driver assistance at levels 1 and 2 of automation. Presently, vehicles featuring self-driving capabilities at levels 3 and 4 are undergoing testing and are anticipated to become commercially available between 2020 and 2030. Moreover, fully automated vehicles operating at level 5 are projected to enter the market starting in 2030 (European Parliament 2019).

CAVs have the potential to revolutionize transportation, they also pose new challenges. These include concerns about data privacy and cybersecurity, as well as legal and ethical issues surrounding liability in the event of accidents. Additionally, there are questions about how these vehicles will interact with traditional cars, pedestrians, and bicyclists on the road. As the technology continues to evolve, it will be important for policymakers and industry leaders to work together to address these challenges and ensure that the benefits of CAVs are realized while minimizing their risks.

As these vehicles can communicate with each other and with the surrounding infrastructure, they can be highly intelligent and efficient. They can improve safety, reduce congestion, and increase road capacity.

However, it is important to evaluate the impact of CAVs on road network resilience, as they will co-exist with other road users.

While CAVs have many benefits, they also have features that can impact road network resilience. One key advantage of CAVs is their ability to have their route choices controlled by a traffic management center, setting them apart from HDVs. This could result in a scenario where different types of road users with varying road preferences coexist simultaneously. Another feature of these vehicles is their rerouting capability. CAVs can reroute themselves when a disruption happens on the road network, which can affect the resilience of the network. Additionally, CAVs can communicate with each other to optimize their route choices, which can lead to less congestion and improve the resilience of the network. Therefore, it is crucial to assess whether the resilience of the road network improve in the presence of CAVs. The objective of this study is to investigate the impact of CAVs on road network resilience.

To achieve this goal the Simulation-based approach of resilience evaluation is taken. To simulate the resilience of the network, a base case model of the Belgian road network was first constructed, which should resemble the real network as closely as possible. Therefore, validation and calibration are necessary. The next step involves solving the problem of traffic assignment when CAVs are present in the network. In this study, it is assumed that the driving behavior and route choice behavior of CAVs are different from those of HDV, resulting in a mixed traffic flow. Consequently, a new framework is proposed for solving the problem of multiclass traffic assignment of mixed traffic flow. Finally, a new methodology for investigating the resilience of the network is presented in this study which can capture the impact of CAVs. Our study has shown that CAVs can significantly impact the resilience of the road network.

The following subsection describes the questions that are answered in this study to achieve its objective.

6.1. Main Findings and Scientific Contributions

This section presents a summary of the primary discoveries unveiled in the thesis and provides responses to all research inquiries posed in chapter one.

1. How to model travel demand for Belgium road network?

Developing large-scale models for transportation and estimating travel demand in large networks has always been challenging, as it requires a large amount of data to develop such models. In this study, an alternative method for classical travel demand models is presented. The proposed model in this study, named the probabilistic travel demand model, only considers passenger car vehicle-kilometers travelled, the number of trucks yearly trips, population of the cities, and the distance between the cities as input data and then uses a probabilistic approach to estimate the number of trips between cities for the Belgian network. This model was calibrated and validated based on real data in this study, and the results showed that the proposed model is very close to reality. The development of this model was explained in chapter 2. This model is the first probabilistic travel demand model developed at the national level and is among the contributions of this study. However, it should be noted that in order to simplify the travel demand model, numerous assumptions have been made (discussed in previous chapters). These assumptions need to be further examined in future studies.

2. How to model CAVs and HDVs in road networks?

Another important aspect in developing large scale traffic simulations is to properly simulate the motion of CAVs and HDVs and the difference between them. In this study, the differences between CAVs and HDVs were examined from two perspectives: their driving behavior and their route choice behavior. It was assumed that CAVs have a faster and safer driving behavior than HDV. To achieve such driving behavior, the model parameters of the queuing model were calibrated on a mesoscopic scale by using the simulation results in the microscale. In terms of route choice

behavior, it was assumed that CAVs follow the system optimal principles while HDVs follow the user equilibrium principles. It was also assumed that CAVs have the ability of rerouting. As a result, it is crucial to solve the traffic assignment problem for a mixture of CAVs and HDVs. This study addresses this challenge by presenting a solution framework for the Multiclass Simulation-based Traffic Assignment Problem for the Mixed traffic flow of CAVs and HDVs (MS-TAP-M). The MS-TAP-M problem involves assigning two classes of vehicles, each with unique route preferences and driving behaviors. The solution framework is an iterative process that involves path selection and dynamic network loading. Starting from an initial solution, the framework updates the path flow distribution in each iteration using a path-swapping algorithm. At the end of each iteration, a convergence criterion is calculated to determine when the algorithm should terminate. To the best of the author's knowledge, the proposed solution framework for MS-TAP-M is the first open-source algorithm that can be executed in both micro and meso scale simulation. This algorithm takes into account the rerouting capability of CAVs, as well as their unique route preferences and driving behaviors. The development of this algorithm was presented in chapter three. This study assessed the effectiveness of the proposed solution framework in two case studies, one at the micro scale and one at the meso scale. This algorithm is the main contribution of this study as it is the first solution framework for MS-TAP-M that considered most of the possible feature of CAVs.

3. How to assess the resilience of road networks in the presence of CAVs?

Given that CAVs exhibit different routing and driving behaviors compared to conventional vehicles, it is necessary to develop new methods to assess network resilience that can capture the impact of CAVs on the road network. As a result, this study presents a new criterion for forming a resilience triangle. The accumulation of vehicles in the network was used to quantify resilience loss, with the area between the accumulation curve of disrupted scenarios and the base case scenario (without disruption) considered as resilience loss. This criterion can effectively account for the

impact of CAVs on network resilience, as it allows for an examination of network performance in each time interval after an incident occurs. Therefore, the effect of CAVs rerouting ability can be easily measured. This methodology is the first study to examine the instant impact of rerouting actions on network resilience using this approach. The methodology was described in Chapter 4. To assess the impact of autonomous vehicles on the resilience of road networks, specific assumptions have been made regarding the driving behavior and route selection of CAVs. Therefore, these recommendations are contingent upon considering these assumptions. However, the tools provided in this study can be used for modeling with other assumptions related to the driving behavior and route selection of CAVs.

4. How the resilience value of the Belgian road network is altered concerning CAVs?

Given the provided explanations, investigating the resilience of road networks in the presence of CAVs is of utmost importance. Therefore, in this study, utilizing the base-case model presented in Chapter 2, the solution framework of the multiclass traffic assignment problem presented in Chapter 3, and the methodology for assessing network resilience presented in Chapter 4, the resilience of Belgian road networks was examined under various scenarios. In summary, it can be stated that as the penetration rate of CAVs increases, the resilience of the network improves.

6.2. Overall Conclusion

In this section, we present the overall conclusions of this study, followed by an explanation of how the study's results can be applied in reality (application of this study's results in reality). In summary, in addition to the numerical results of the resilience assessment of the Belgium network presented in this study, the methodological frameworks proposed can provide valuable assistance to researchers and decision-makers in the transportation industry in the deployment of CAVs.

In this section, 9 overall conclusion of the study is presented:

The first conclusion of this study is that, despite relying on numerous assumptions in developing the probabilistic travel demand model and acknowledging its limitations (such as not accounting for intra-city traffic, a concern addressed in previous sections), the model demonstrates a noteworthy capability to represent reality. This is evidenced by the favorable validation results, where the model's performance, assessed through the comparison of simulated travel time for origin-destination pairs with real-time data from Google Maps, proves to be satisfactory. The probabilistic travel demand model, utilized in this research, has the potential for further enhancement in future studies. This model can be used for strategic planning or examining various scenarios for the overall performance of the Belgian road network.

The second conclusion is that mesoscale simulation is a suitable substitute for microscale simulation when working on large-scale networks. This is because mesoscale simulation provides reasonable accuracy in simulating different classes of vehicles while having an acceptable computational cost. This makes it a practical choice when working on large-scale networks. Furthermore, it is worth noting that mesoscale simulation has shown promising results in simulating traffic flow dynamics and driver behavior. By considering the interaction between vehicles and the surrounding environment, mesoscale simulation can capture emergent phenomena such as traffic jams. This can provide valuable insights for transportation planning and management. In addition, mesoscale simulation can be used for studying the impact of different policies and interventions on traffic flow. This can inform decision-making and help optimize transportation systems. Overall, mesoscale simulation offers a powerful tool for studying traffic flow dynamics and optimizing transportation systems. Its ability to balance accuracy and computational cost makes it a practical choice for large-scale networks.

The third conclusion drawn from this study is that the multiclass traffic assignment problem solution framework presented in this research is among the useful tools for investigating the impact of CAVs on network performance. This tool has the capability of solving the traffic assignment

problem both at the micro and meso scales, and its performance has been examined in various networks. Therefore, this tool can be used by other researchers and decision-makers to deploy autonomous vehicles more efficiently. This study contributes to the growing body of research on the potential benefits and challenges of deploying CAVs in transportation systems. The traffic assignment problem solving tool developed in this research provides a valuable resource for future studies on CAVs' impact on network performance, and the findings can inform the design of policies and strategies for deploying CAVs more efficiently and effectively. For the development of the traffic assignment solution framework, certain assumptions have been formulated concerning the driving conduct and route preferences of CAVs. It remains indeterminate whether these assumptions are accurate, as there are currently no CAVs operational on the designated route. Nevertheless, the traffic assignment solution framework presented here is versatile and can be applied to model scenarios incorporating alternative assumptions pertaining to the driving behavior and route choices of CAVs.

The fourth conclusion drawn from this study is that there are several benefits to implementing CAVs in the transportation network. Specifically, the base case model used in the analysis demonstrates that CAVs can significantly reduce travel time. The magnitude of the improvement in travel time ranges from 2.7% at a 10% CAV penetration rate to 10.9% at a 100% CAV penetration rate. Overall, these findings highlight the potential of CAVs to significantly improve transportation efficiency and sustainability. The findings of this study provide valuable insights into the potential benefits of CAVs in reducing traffic congestion and improving network performance. The results show that, under certain conditions, CAVs can significantly reduce travel time, delay, and fuel consumption compared to conventional vehicles. These benefits are particularly evident in highly congested networks, where CAVs can optimize their speed and trajectory to avoid traffic congestion. The study highlights the importance of considering the heterogeneity of CAVs in traffic flow modeling. The results show that the performance of CAVs varies significantly depending on their level of automation, communication capabilities, and behavioral

characteristics. Therefore, it is essential to account for these factors in traffic flow modeling to accurately evaluate the impact of CAVs on network performance.

The fifth conclusion drawn from this study is that the magnitude of improvement facilitated by CAVs on travel time and other traffic-related parameters within road networks is contingent upon the configurations of these CAVs. The findings of this investigation demonstrate that the extent of the influence exerted by CAVs is most pronounced when these vehicles exhibit safer and faster driving behaviors in comparison to conventional vehicles (e.g., with reduced headway) and when they demonstrate different route choice behavior (adherence to SO and the ability of rerouting). Subsequently, the highest degree of impacts occurs when CAVs exhibit solely distinct driving behaviors. The minimum impact incurred by CAVs on network travel time transpires when they manifest different route choice behavior. Hence, it can be deduced that until such time that CAVs possess both distinct driving behaviors and differential route choice behaviors in comparison to HDVs, we are unable to observe substantial effects of CAVs on network travel time. For instance, TTT improved across various CAV impact scenarios: 10.1% for CAV route choice, 20.2% for CAV driving behavior, and a peak of 27.2% for combined route choice and driving impacts. It is important to note that the improvement in travel time mentioned here stems from the assumptions made in this study. Therefore, in future research, it is crucial to examine other assumptions that may conflict with those made in this study. This exploration will contribute to a comprehensive understanding of the impact of CAVs on road networks.

The sixth conclusion of this research asserts that the integration of CAVs into the network requires specialized methods for studying their impact. Consequently, this study has employed a new method for examining network resilience in the presence of CAVs, which effectively measures their impact on network resilience. This method is capable of accurately displaying the network performance, i.e., accumulation, at any given time interval. By comparing the accumulation curves of scenarios with and without disruptions, the value of resilience loss can be measured. As

network accumulation can be obtained using detector data or traffic control center data, the proposed method can be utilized to measure network resilience in real-world scenarios. To apply this method in practical cases, we need to compare the network accumulation during normal times (without disruptions) with network accumulation during abnormal times. Consequently, both real-time and strategic actions can be taken to enhance network resilience. The present study has employed this methodology to examine network resilience on intercity highways, but it is equally applicable to investigate network resilience in other networks such as urban networks.

The seventh conclusion from this study suggests that the presence of CAVs within a network can significantly enhance the network's resilience. The improved resilience means that scenarios with higher CAVs penetration rates result in lower resilience losses. This improvement in network resilience is due to the ability of CAVs to enhance both the redundancy and rapidity of the network. It is worth noting that the extent of this improvement varies, with a range of 4.4% for a 10% penetration rate to 59.9% for a 100% penetration rate, depending on the different scenarios of lane closures. It is important to note that this study assumes CAVs exhibit faster and safer driving behavior and have different route selection behavior than regular vehicles. Furthermore, CAVs have rerouting capabilities that contribute to the enhancement of network resilience. Therefore, the improved resilience observed in our study is primarily due to these assumptions.

The eighth finding of this study suggests that the resilience results of the network can be used to examine the criticality of links. This can be achieved by individually closing each link and subsequently calculating the resilience index of the network after the closure of each link. Specifically, the network resilience analysis results showed that the ranking of link criticality using the number of shortest paths passing through each link does not necessarily align with the criticality results of links using the increase or decrease in overall network resilience after removing a link. To elaborate, while the number of shortest paths passing through a link is a

commonly used metric to determine the importance of a link in a network, the results of this study demonstrate that this metric may not fully capture the criticality of links. In contrast, the change in the overall network resilience after removing a link provides a more comprehensive understanding of the impact of link removal on the network's functionality and criticality. Therefore, the findings of this study suggest that both metrics should be considered when examining the criticality of links in a network. Furthermore, the results indicate that network resilience analysis can be a valuable tool for identifying critical links in a network, particularly in the context of mitigating potential network failures.

6.3.Limitations and Recommendation

The limitations of this study and recommendations for addressing these limitations in future studies are presented below.

Probabilistic Travel Demand Model:

- As the transit traffic from/to neighborhood countries are not considered in the travel demand model, further studies could aim to expand the scope of data collection and analysis to provide a more comprehensive understanding of traffic patterns in the region.
- As the behavior of both passenger cars and heavy vehicles in terms of origin and destination are assumed to be the same, further research is necessary to investigate the differences between passenger cars and heavy vehicles destination selection.
- Due to the considerable difficulty in accessing urban traffic data, intra-city traffic has not been modeled in this study. To achieve more accurate results in future studies, it is essential to incorporate intra-city traffic into the simulation model.

Assumptions on CAVs route choice and driving behavior:

- The assumption of CAVs adhere to SO and have rerouting capabilities, can be justify by assuming CAVs are connected to a traffic management center so they have the ability to receive real-

time information about traffic conditions, enabling them to make optimal route choices. However, this assumption can be highly challenging. This is because many CAV users in the future may not prefer a route with longer travel times (SO and not UE). Nevertheless, this question should be thoroughly investigated in future studies, taking into account the value of time for CAV users. Considering that CAV users can utilize their time for other tasks, this aspect needs a comprehensive examination. However, since these vehicles have not yet fully entered the market and are not regulated, a definite opinion on their behavior cannot be provided. The advantage of the algorithms presented in this study is that they allow for the simulation of different assumptions.

- The assumption that CAVs can reroute during driving or before entering the network aligns with the potential benefits of connected vehicles adapting to changing traffic conditions in real time. However, if there are communication disruptions, the effectiveness of the system may be compromised.
- Assuming CAVs exhibit faster, and safer driving behavior is grounded in the capabilities of automated driving systems, which can react faster than human drivers and adhere more consistently to safety protocols. The assumption depends on the reliability of CAV technology. If there are malfunctions or technical issues, the safety and speed advantages may not be realized.

Multi-class traffic assignment solution framework:

- In this study, the local approximation of marginal travel time has been used. Future studies should estimate the global approximation of marginal travel time.
- This study postulates that CAVs exhibit superior driving behaviors in terms of both safety and speed compared to human-driven cars. The assumption is that CAVs adhere to a system optimal while HDVs follow a user equilibrium. Given this premise, it is recommended that future research explore additional hypotheses related to CAVs. The potential benefits of CAVs are numerous,

with safety being a key factor. By eliminating human error, CAVs have the potential to significantly reduce accidents and fatalities on the road. In addition, CAVs have the potential to increase the efficiency of transportation systems, reducing congestion and travel time. However, there are also potential challenges and limitations to the widespread adoption of CAVs. One concern is the lack of trust in the technology, which may lead to resistance from consumers. In addition, there are legal and regulatory barriers that must be addressed to ensure the safe and effective integration of CAVs into existing transportation systems. Overall, the potential benefits of CAVs are significant, and further research is needed to fully understand their capabilities and limitations. By exploring additional hypotheses related to CAVs, researchers can help pave the way for the safe and efficient implementation of this technology.

- Owing to the importance of the demand level in traffic assignment, researchers are encouraged to assess the impact of different demand levels on the proposed solution framework.

Resilience evaluation framework:

- The results presented in this study regarding network resilience are contingent upon the scenarios defined within this research. This implies that if the description scenarios change, the degree of variation in network resilience will inevitably change as well. Nevertheless, considering that the provided methodologies are applicable under any scenario, they can be utilized in future studies to assess network resilience in different scenarios.
- In this study, accumulation has been utilized as a performance metric for the network. It is suggested that future research should employ other network performance metrics such as space-mean flow and compare their results to those obtained in this study.
- The present study utilized a framework to examine the resilience of the Belgian road network. The findings suggest that this framework could be applied to other network systems to assess their resilience.

Thus, this study highlights the potential of the proposed framework for broader applicability in evaluating the resilience of various network.

- This research assumes that CAVs are equipped with rerouting capabilities, which has a substantial impact on enhancing network resilience in the presence of CAVs. It is recommended that future studies focus on developing a CAVs rerouting system for different disruption scenarios to achieve the optimal strategy for rerouting CAVs. These rerouting strategies should be designed in a manner that optimizes network resilience. In essence, it is suggested to create a traffic management system for CAVs that is activated when disruptions occur in future studies, using the tools and findings of the present study as a basis. To elaborate, the proposed CAV rerouting system will enable vehicles to detect and avoid congested areas in the network, thereby enhancing network resilience in the presence of unpredictable events such as accidents or road closures. Moreover, developing such a system will enable network operators to respond to disruptions proactively by diverting traffic, reducing congestion, and mitigating the adverse impacts of disruptions on the network's overall performance. Therefore, the findings of this study are expected to have significant implications for the design and operation of future CAV networks.

In summary, this thesis emphasizes that despite extensive efforts in developing a calibrated and validated model for the Belgian road network in this study, the Belgian demand model possesses some limitations, as discussed in previous chapters. Consequently, the main contribution of this thesis lies in presenting methodologies that can be applied to any road network. Thus, a multiclass traffic assignment solution framework for mixed traffic flow is proposed, easily applicable to diverse network configurations. Additionally, a novel method for assessing network resilience is introduced, which can be obtained using simulation software for any given network.

6.4. List of Publications

Contributions included in this PhD thesis are as follow:

Journal Papers:

- Bamdad Mehrabani, B., Erdmann, J., Sgambi, L., Seyedabrishami, S., & Snelder, M. (2023). A multiclass simulation-based dynamic traffic assignment model for mixed traffic flow of connected and autonomous vehicles and human-driven vehicles. *Transportmetrica A: Transport Science*, 1-32. <https://doi.org/10.1080/23249935.2023.2257805>. (Bamdad Mehrabani et al. 2023)
- Karbasi, A. H., Bamdad Mehrabani, B., Cools, M., Sgambi, L., Saffarzadeh, M. (2022). Comparison of Speed-Density Models in the Age of Connected and Automated Vehicles, *Transportation Research Record*, <https://doi.org/10.1177/0361198122111853>. (Karbasi et al. 2022)
- Bamdad Mehrabani, B., Pel, A., Calvert, S., Sgambi, L., and Snelder, M. Assessing road network resilience in the era of Connected and Autonomous Vehicles (Belgium road network). Under preparation for journal submission.

Conference papers and posters:

- Bamdad Mehrabani, B., Pel, A., Calvert, S., Sgambi, L., and Snelder, M. Assessing road network resilience in the era of Connected and Autonomous Vehicles (Belgium road network). *Transportation Research Board 103rd Annual Meeting (USA, Washington DC, from 07/01/2024 to 11/01/2024)*.
- Bamdad Mehrabani, B., Sgambi, L., Maerivoet, S. and Snelder, M. Development, calibration, and validation of a large-scale traffic simulation model: Belgium road network. *SUMO User Conference, Berlin, from 02/05/2023 to 04/05/2023*, <https://doi.org/10.52825/scp.v4i.199> (Mehrabani, Sgambi, et al. 2023)

- Bamdad Mehrabani, B., Erdman, J., Sgambi, L., Snelder, M. A Multi-Class, Simulation-Based, Dynamic Traffic Assignment Model for Mixed Traffic Flow of Connected and Autonomous Vehicles and Human Driven Vehicles. Transportation Research Board 102nd Annual Meeting (USA, Washington DC, from 08/01/2023 to 12/01/2023). <http://hdl.handle.net/2078.1/274209>
- Bamdad Mehrabani, B., Erdmann, J., Sgambi, L., and Snelder, M. Proposing a Simulation-Based Dynamic System Optimal Traffic Assignment Algorithm for SUMO: An Approximation of Marginal Travel Time. SUMO User conference 2022, Berlin, Germany <https://doi.org/10.52825/scp.v3i>.(Mehrabani, Erdmann, et al. 2022)
- Bamdad Mehrabani, B., Sgambi, L. Assessment of the road network resiliency in the presence of road maintenance sites: An environmental perspective. The 100th Transportation Research Board Annual Meeting (Virtual Conference, United States of America, from 25/01/2021 to 29/01/2021). <http://hdl.handle.net/2078.1/242160>
- Karbasi, A., Bamdad Mehrabani, B., Saffarzadeh, M. Impact of Connected and Automated Vehicles on Capacity of single lane road based on macroscopic fundamental diagram. 2nd Conference on Environment, Civil, Architecture and Urban Development (Padua, Italy, 17/09/2020).(Karbasi et al. 2022)

Book Chapters:

- Bamdad Mehrabani, B., Sgambi, L., Madani, N. Assessing the environmental aspects of road network resiliency, Springer, Cham, 2022. 978-3-031-11232-4. 8 p. https://doi.org/10.1007/978-3-031-11232-4_7. (Mehrabani, Sgambi, et al. 2022)
- Bamdad Mehrabani, B., Sgambi, L., Garavaglia, E. and Madani, N. (2021), Modeling Methods for the Assessment of the Ecological Impacts of Road Maintenance Sites. Environmental Sustainability and Economy (ESEcon), Chapter 10, Elsevier, USA, <https://doi.org/10.1016/B978-0-12-822188-4.00009-9>. (Mehrabani et al. 2021)

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8. Appendix

dualIterateMix.py

A:

The *dualIterateMix.py* which is the solution framework for the multiclass traffic assignment problem of mixed traffic flow of CAVs and HDVs based on the SUMO traffic simulator is presented as follow. This tool is also freely available under the EPLv2 license on GitHub at <https://github.com/eclipse-sumo/sumo/blob/main/tools/assign/dualIterateMix.py>

```
598 lines (549 sloc) | 28.9 KB
1  #!/usr/bin/env python
2  # -*- coding: utf-8 -*-
3  # Eclipse SUMO, Simulation of Urban MObility; see https://eclipse.org/sumo
4  # Copyright (C) 2008-2023 German Aerospace Center (DLR) and others.
5  # This program and the accompanying materials are made available under the
6  # terms of the Eclipse Public License 2.0 which is available at
7  # https://www.eclipse.org/legal/epl-2.0/
8  # This Source Code may also be made available under the following Secondary
9  # licenses when the conditions for such availability set forth in the Eclipse
10 # Public License 2.0 are satisfied: GNU General Public License, version 2
11 # or later which is available at
12 # https://www.gnu.org/licenses/old-licenses/gpl-2.0-standalone.html
13 # SPDX-License-Identifier: EPL-2.0 OR GPL-2.0-or-later
14
15 # @file    dualIterateMix.py
16 # @author  Behzad Bamdad Mehrabani
17 # @author  Jakob Erdmann
18 # @date    2022-08-10
19
20 """
21 Run duarouter and sumo alternating to perform a mixed traffic assignment of user equilibrium and s
22 (Mixed traffic flow of Human Driven Vehicles (HDVs) and Connected and Autonomous Vehicle (CAVs)).
23 It is assumed that HDVs follow user equilibrium and CAVs follow system optimum.
24 """
25 from __future__ import print_function
26 from __future__ import absolute_import
27
28 import os
29 import sys
```

```

30 import subprocess
31 import glob
32 import argparse
33 import xml.etree.ElementTree as ET
34
35
36 from datetime import datetime
37 from costMemory import CostMemory
38 from dualIterate import addGenericOptions
39 from dualIterate import call
40 from dualIterate import get_scale
41 from dualIterate import get_dumpfilename
42 from dualIterate import get_weightfilename
43 from dualIterate import writeSUMOConf
44 from dualIterate import filterTripinfo
45 from dualIterate import assign_remaining_args
46 from dualIterate import get_basename
47 from dualIterate import calcMarginalCost
48 sys.path.append(os.path.dirname(os.path.dirname(os.path.realpath(__file__))))
49
50 import sumolib # noqa
51 from sumolib.options import ArgumentParser # noqa
52
53 DEBUGLOG = None
54 EDGEDATA_ADD = "edgedata.add.xml"
55
56
57 def initOptions():
58     argParser = ArgumentParser(
59         description=""" Any options of the form sumo--long-option-name will be passed to sumo.
60         These must be given after all the other options
61         example: sumo--step-length 0.5 will add the option --step-length 0.5 to sumo.""",
62         formatter_class=argparse.ArgumentDefaultsHelpFormatter)
63     addGenericOptions(argParser)
64
65     argParser.add_argument("--continue-on-unbuild", action="store_true", dest="continueOnUnbuild",
66                           default=False, help="continues on unbuild routes")
67     argParser.add_argument("-t", "--trips", type=ArgumentParser.route_file,
68                           help="trips in step 0 (either trips, flows, or routes have to be supplied)")
69     argParser.add_argument("-r", "--routes", type=ArgumentParser.route_file,
70                           help="routes in step 0 (either trips, flows, or routes have to be supplied)")
71     argParser.add_argument("-f", "--flows", type=ArgumentParser.route_file,
72                           help="flows in step 0 (either trips, flows, or routes have to be supplied)")
73     argParser.add_argument("-A", "--gA",
74                           type=float, default=.5, help="Sets Gawron's Alpha")
75     argParser.add_argument("-B", "--gBeta",
76                           type=float, default=.9, help="Sets Gawron's Beta")
77     argParser.add_argument("-E", "--disable-summary", "--disable-emissions", action="store_true",
78                           default=False, help="No summaries are written by the simulation")

```

```

79     argParser.add_argument("-T", "--disable-tripinfos", action="store_true", dest="noTripinfo",
80                           default=False, help="No tripinfos are written by the simulation")
81     argParser.add_argument("--tripinfo-filter", dest="tripinfoFilter", type=str,
82                           help="filter tripinfo attributes")
83     argParser.add_argument("--inc-start", dest="incStart",
84                           type=float, default=0, help="Start for incrementing scale")
85     argParser.add_argument("--inc-max", dest="incMax",
86                           type=float, default=1, help="Maximum for incrementing scale")
87     argParser.add_argument("--inc-base", dest="incBase", type=int, default=-1,
88                           help="Give the incrementation base. Negative values disable incremental")
89     argParser.add_argument("--incrementation", dest="incValue",
90                           type=int, default=1, help="Give the incrementation")
91     argParser.add_argument("--time-inc", dest="timeInc",
92                           type=int, default=0, help="Give the time incrementation")
93     argParser.add_argument("-f", "--first-step", dest="firstStep",
94                           type=int, default=0, help="First DUA step")
95     argParser.add_argument("-l", "--last-step", dest="lastStep",
96                           type=int, default=50, help="Last DUA step")
97     argParser.add_argument("--convergence-iterations", dest="convIt",
98                           type=int, default=10, help="Number of iterations to use for convergence")
99     argParser.add_argument("--max-convergence-deviation", dest="convDev",
100                           type=float, help="Maximum relative standard deviation in travel times")
101     argParser.add_argument("-D", "--districts", help="use districts as sources and targets",
102                           type=ArgumentParser.file, metavar="FILE")
103     argParser.add_argument("-x", "--vehroute-file", dest="routeFile", type=str,
104                           choices=['None', 'routesonly', 'detailed'],
105                           default='None', help="choose the format of the route file")
106     argParser.add_argument("-z", "--output-lastRoute", action="store_true", dest="lastroute",
107                           default=False, help="output the last routes")
108     argParser.add_argument("-K", "--keep-allroutes", action="store_true", dest="allroutes",
109                           default=False, help="save routes with near zero probability")
110     argParser.add_argument("--routing-algorithm", default="dijkstra", type=str, help="select the r")
111     argParser.add_argument("--max-alternatives-HDV", default=5, type=int, dest="max_alternatives_H")
112                           help="prune the number of alternatives to INT for HDV")
113     argParser.add_argument("--max-alternatives-CAV", default=5, type=int, dest="max_alternatives_C")
114                           help="prune the number of alternatives to INT for CAV")
115     argParser.add_argument("--skip-first-routing", action="store_true", dest="skipFirstRouting",
116                           default=False, help="run simulation with demands before first routing")
117     argParser.add_argument("--logit", action="store_true", default=False, help="use the logit mode")
118     argParser.add_argument("-g", "--logitbeta", type=float,
119                           default=0.15, help="use the c-logit model for route choice; logit model")
120     argParser.add_argument("-i", "--logitgamma", type=float, default=1., help="use the c-logit mod")
121     argParser.add_argument("-G", "--logittheta", type=float, help="parameter to adapt the cost uni")
122     argParser.add_argument("-J", "--addweights", type=str, help="Additional weights for duarouter")
123     argParser.add_argument("--convergence-steps", dest="convergenceSteps", type=int,
124                           help="Given x, if x > 0 reduce probability to change route by 1/x per s")
125                           "(Probabilistic Swapping (PSwap)). "
126                           "If x < 0 set probability of rerouting to 1/step after step |x|")
127     argParser.add_argument("--addweights.once", dest="addweightsOnce", action="store_true",

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```

128         default=False, help="use added weights only on the first iteration")
129     argParser.add_argument("--router-verbose", action="store_true",
130         default=False, help="let duarouter print some statistics")
131     argParser.add_argument("--weight-memory", action="store_true", default=False, dest="weightmem",
132         help="smooth edge weights across iterations")
133     argParser.add_argument("--pessimism", default=1, type=float,
134         help="give traffic jams a higher weight when using option --weight-mem")
135     argParser.add_argument("--clean-alt", action="store_true", dest="clean_alt",
136         default=False, help="whether old rou.alt.xml files shall be removed")
137     argParser.add_argument("--binary", dest="gzip", action="store_true", default=False,
138         help="alias for --gzip")
139     argParser.add_argument("--gzip", action="store_true", default=False,
140         help="writing intermediate and resulting route files in gzipped format")
141     argParser.add_argument("--dualog", default="dua.log", type=ArgumentParser.file,
142         help="log file path (default 'dua.log')")
143     argParser.add_argument("--log", default="stdout.log", type=ArgumentParser.file,
144         help="stdout log file path (default 'stdout.log')")
145     argParser.add_argument("--marginal-cost", action="store_true", default=False,
146         help="use marginal cost to perform system optimal traffic assignment")
147     argParser.add_argument("--marginal-cost-reverse", action="store_true", default=False,
148         help="use with mix option for reversing the marginal cost with original")
149     argParser.add_argument("--mix", action="store_true", default=False, help="performing mix traff")
150     argParser.add_argument("--marginal-cost.exp", type=float, default=0, dest="mcExp",
151         help="apply the given exponent on the current traffic count when comput")
152     argParser.add_argument("--remaining_args", nargs='*')
153     return argParser
154
155
156 def writeRouteConfHDV(duarouterBinary, step, options, dua_args, file,
157     output, routesInfo):
158     filename = os.path.basename(file)
159     filename = filename.split('.')[0]
160     cfgname = "%03i/iteration_%03i_%.duarcfg" % (step, step, filename)
161     args = [
162         '--net-file', options.net,
163         '--route-files', file,
164         '--output-file', output,
165         '--exit-times', str(routesInfo == "detailed"),
166         '--ignore-errors', str(options.continueOnUnbuild),
167         '--with-taz', str(options.districts is not None),
168         '--gawron.beta', str(options.gBeta),
169         '--gawron.a', str(options.gA),
170         '--keep-all-routes', str(options.allroutes),
171         '--routing-algorithm', options.routing_algorithm,
172         '--max-alternatives', str(options.max_alternatives_HDV),
173         '--weights.expand',
174         '--logit.beta', str(options.logitbeta),
175         '--logit.gamma', str(options.logitgamma),
176         '--random', str(options.absrand),

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```

177     '--begin', str(options.begin),
178     '--verbose', str(options.router_verbose),
179     '--no-step-log',
180     '--no-warnings', str(options.noWarnings),
181 ]
182 if options.districts:
183     args += ['--additional-files', options.districts]
184 if options.logit:
185     args += ['--route-choice-method', 'logit']
186 if options.MSA:
187     probKeepRoute = step/(step+1)
188     args += ['--keep-route-probability', str(probKeepRoute)]
189 if options.convergenceSteps:
190     if options.convergenceSteps > 0:
191         probKeepRoute = max(0, min(step / float(options.convergenceSteps), 1))
192     else:
193         startStep = -options.convergenceSteps
194         probKeepRoute = 0 if step > startStep else 1 - 1.0 / (step - startStep)
195     args += ['--keep-route-probability', str(probKeepRoute)]
196
197 if step > 0 or options.addweights:
198     weightpath = ""
199     if step > 0:
200         weightpath = get_weightfilename(options, step - 1, "dump")
201     if options.addweights and (step == 0 or not options.addweightsOnce):
202         if step > 0:
203             weightpath += ","
204             weightpath += options.addweights
205     args += ['--weight-files', weightpath]
206 if options.eco_measure:
207     args += ['--weight-attribute', options.eco_measure]
208 if 'CH' in options.routing_algorithm:
209     args += ['--weight-period', str(options.aggregation)]
210 if options.logittheta:
211     args += ['--logit.theta', str(options.logittheta)]
212 if options.end:
213     args += ['--end', str(options.end)]
214
215 args += ["--save-configuration", cfgname]
216
217 subprocess.call([duarouterBinary] + args + dua_args)
218 return cfgname
219
220
221 def writeRouteConfCAV(duarouterBinary, step, options, dua_args, file,
222                      output, routesInfo):
223     filename = os.path.basename(file)
224     filename = filename.split('.')[0]
225     cfgname = "%03i/iteration_%03i_%s.duarcfg" % (step, step, filename)

```

```

226     args = [
227         '--net-file', options.net,
228         '--route-files', file,
229         '--output-file', output,
230         '--exit-times', str(routesInfo == "detailed"),
231         '--ignore-errors', str(options.continueOnUnbuild),
232         '--with-taz', str(options.districts is not None),
233         '--gawron.beta', str(options.gBeta),
234         '--gawron.a', str(options.gA),
235         '--keep-all-routes', str(options.allroutes),
236         '--routing-algorithm', options.routing_algorithm,
237         '--max-alternatives', str(options.max_alternatives_CAV),
238         '--weights.expand',
239         '--logit.beta', str(options.logitbeta),
240         '--logit.gamma', str(options.logitgamma),
241         '--random', str(options.absrand),
242         '--begin', str(options.begin),
243         '--verbose', str(options.router_verbose),
244         '--no-step-log',
245         '--no-warnings', str(options.noWarnings),
246     ]
247     if options.districts:
248         args += ['--additional-files', options.districts]
249     if options.logit:
250         args += ['--route-choice-method', 'logit']
251     if options.MSA:
252         probKeepRoute = step/(step+1)
253         args += ['--keep-route-probability', str(probKeepRoute)]
254     if options.convergenceSteps:
255         if options.convergenceSteps > 0:
256             probKeepRoute = max(0, min(step / float(options.convergenceSteps), 1))
257         else:
258             startStep = -options.convergenceSteps
259             probKeepRoute = 0 if step > startStep else 1 - 1.0 / (step - startStep)
260         args += ['--keep-route-probability', str(probKeepRoute)]
261
262     if step > 0 or options.addweights:
263         weightpath = ""
264         if step > 0:
265             weightpath = get_weightfilename(options, step - 1, "dump")
266         if options.addweights and (step == 0 or not options.addweightsOnce):
267             if step > 0:
268                 weightpath += ","
269             weightpath += options.addweights
270         args += ['--weight-files', weightpath]
271     if options.eco_measure:
272         args += ['--weight-attribute', options.eco_measure]
273     if 'CH' in options.routing_algorithm:
274         args += ['--weight-period', str(options.aggregation)]

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275     if options.logittheta:
276         args += ['--logit.theta', str(options.logittheta)]
277     if options.end:
278         args += ['--end', str(options.end)]
279
280     args += ["--save-configuration", cfgname]
281
282     subprocess.call([duarouterBinary] + args + dua_args)
283     return cfgname
284
285
286 def calcMarginalCostReverse(step, options):
287     if step > 1:
288         if DEBUGLOG:
289             log = open("marginal_cost2.log", "w" if step == 2 else "a")
290             tree_sumo_cur = ET.parse(get_weightfilename(options, step - 1, "dump"))
291             tree_sumo_prv = ET.parse(get_weightfilename(options, step - 2, "dump"))
292             for interval_cur in tree_sumo_cur.getroot():
293                 begin_cur = interval_cur.attrib.get("begin")
294                 for interval_prv in tree_sumo_prv.getroot():
295                     begin_prv = interval_prv.attrib.get("begin")
296                     for edge_cur in interval_cur.iter('edge'):
297                         for edge_prv in interval_prv.iter('edge'):
298                             if begin_cur == begin_prv and edge_cur.get("id") == edge_prv.get("id"):
299                                 if edge_cur.get("traveltime") is not None and edge_prv.get(
300                                     "traveltime") is not None:
301                                     tt_cur = float(edge_cur.get("overlapTraveltime"))
302                                     edge_cur.set("traveltime", str(tt_cur))
303             tree_sumo_cur.write(get_weightfilename(options, step - 1, "dump"))
304
305         if DEBUGLOG:
306             log.close()
307
308
309 def calcMixTrips(step, options):
310     input_demands = options.trips.split(",")
311     input_demands_1 = options.routes.split(",")
312     routesSuffix = ".xml"
313     trips_CAV = ["%03i/%s_%03i.rou%s" % (step, get_basename(f), step, routesSuffix)
314                  for f in input_demands_1]
315     trips_HDV = ["%03i/%s_%03i.rou%s" % (step, get_basename(f), step, routesSuffix)
316                  for f in input_demands]
317     src_tree = ET.parse(str(trips_CAV[0]))
318     dest_tree = ET.parse(str(trips_HDV[0]))
319     src_root = src_tree.getroot()
320     dest_root = dest_tree.getroot()
321
322     # temporary remove vtypes
323     vType1 = dest_root.find("vType")

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324     dest_root.remove(vType1)
325     vType2 = src_root.find("vType")
326     src_root.remove(vType2)
327
328     for n in range(1000000):
329         src_tag = src_root.find('./vehicle')
330         if src_tag is None:
331             break
332         dest_root.append(src_tag)
333         src_root.remove(src_tag)
334
335     dest_root[:] = sorted(dest_root, key=lambda child: (child.tag, float(child.get("depart"))))
336     for n in range(1000000):
337         dest_tag_2 = dest_root.find('./vehicle')
338         if dest_tag_2 is None:
339             break
340         src_root.append(dest_tag_2)
341         dest_root.remove(dest_tag_2)
342
343     # Put the 'vType' element on HDV file
344     src_root.insert(0, vType1)
345     src_root.insert(1, vType2)
346     ET.ElementTree(src_root).write(os.path.join((str(trips_HDV[0]))))
347     # if DEBUGLOG:
348     #     log.close()
349
350
351 def main(args=None):
352     argParser = initOptions()
353
354     try:
355         options = argParser.parse_args(args=args)
356     except (NotImplementedError, ValueError) as e:
357         print(e, file=sys.stderr)
358         sys.exit(1)
359
360     if not options.net:
361         argParser.error("Option --net-file is mandatory")
362     if (not options.trips and not options.routes and not options.flows):
363         argParser.error(
364             "Either --trips, --flows, or --routes have to be given!")
365     duaBinary = sumolib.checkBinary("duarouter", options.path)
366     sumoBinary = sumolib.checkBinary("sumo", options.path)
367     if options.addweights and options.weightmemory:
368         argParser.error("Options --addweights and --weight-memory are mutually exclusive.")
369     if options.marginal_cost and not options.logit:
370         print("Warning! --marginal-cost works best with --logit.", file=sys.stderr)
371
372     # make sure BOTH binaries are callable before we start

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```

373     try:
374         subprocess.call(duaBinary, stdout=subprocess.PIPE)
375     except OSError:
376         sys.exit(
377             ("Error: Could not locate duarouter (%s).\nMake sure its on the search path or set env
378              variable DUAROUTER_BINARY\n") % duaBinary)
379     try:
380         subprocess.call(sumoBinary, stdout=subprocess.PIPE)
381     except OSError:
382         sys.exit(
383             ("Error: Could not locate sumo (%s).\nMake sure its on the search path or set environm
384              variable SUMO_BINARY\n") % sumoBinary)
385
386     sumo_args = assign_remaining_args(sumoBinary, 'sumo', options.remaining_args)
387     dua_args = assign_remaining_args(duaBinary, 'duarouter', options.remaining_args)
388     sys.stdout = sumolib.TeeFile(sys.stdout, open(options.log, "w+"))
389     log = open(options.dualog, "w+")
390     if options.zip:
391         if options.clean_alt:
392             sys.exit("Error: Please use either --zip or --clean-alt but not both.")
393         try:
394             subprocess.call("7z", stdout=open(os.devnull, 'wb'))
395         except Exception:
396             sys.exit("Error: Could not locate 7z, please make sure its on the search path.")
397         zipProcesses = {}
398         zipLog = open("7zip.log", "w+")
399         starttime = datetime.now()
400     if options.trips:
401         input_demands = options.trips.split(",")
402     if options.routes:
403         input_demands_1 = options.routes.split(",")
404     if options.trips and not options.routes:
405         print("Please insert HDVs trip by -t and CAVs trips by -r")
406     if options.routes and not options.trips:
407         print("Please insert HDVs trip by -t and CAVs trips by -r")
408     if options.weightmemory:
409         costmemory = CostMemory('traveltime', pessimism=options.pessimism, network_file=options.ne
410                                 )
411     routesSuffix = ".xml"
412     if options.gzip:
413         routesSuffix = ".gz"
414
415     if options.weightmemory and options.firstStep != 0:
416         # load previous dump files when continuing a run
417         print(">>> Reassembling cost-memory from previous iteration steps")
418         for step in range(0, options.firstStep):
419             dumpfile = get_dumpfilename(options, step, "dump")
420             print(">>> Loading %s" % dumpfile)
421             costmemory.load_costs(dumpfile, step, get_scale(options, step))

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422
423 # write detectorfile
424 with open(EDGEData_ADD, 'w') as fd:
425     vTypes = ' vTypes="%s" % ' '.join(options.measureVTypes.split(',')) if options.measureVTy
426     print("<a>", file=fd)
427     print(' <edgeData id="dump_%s" freq="%s" file="%s" excludeEmpty="true" minSamples="1"%s
428           options.aggregation,
429           options.aggregation,
430           get_dumpfilename(options, -1, "dump", False),
431           vTypes), file=fd)
432     if options.eco_measure:
433         print((' <edgeData id="eco_%s" type="hbefa" freq="%s" file="%s" ' +
434               'excludeEmpty="true" minSamples="1"%s/>') % (
435               options.aggregation,
436               options.aggregation,
437               get_dumpfilename(options, step, "dump", False),
438               vTypes), file=fd)
439     print("</a>", file=fd)
440
441 avgTT = sumolib.miscutils.Statistics()
442 for step in range(options.firstStep, options.lastStep):
443     current_directory = os.getcwd()
444     final_directory = os.path.join(current_directory, "%03i" % step)
445     if not os.path.exists(final_directory):
446         os.makedirs(final_directory)
447     btimeA = datetime.now()
448     print("> Executing step %s" % step)
449     # working on CAVs demand
450     router_demands = input_demands
451     simulation_demands = input_demands
452     # demand files have regular names based on the basename and the step
453     if not (options.skipFirstRouting and step == 0):
454         simulation_demands = ["%03i/%s_%03i.rou%s" % (step, get_basename(f), step, routesSuffi
455                               for f in input_demands]
456     if not ((options.skipFirstRouting and step == 1) or step == 0):
457         router_demands = ["%03i/%s_%03i.rou.alt%s" % (step-1, get_basename(f), step-1, routesS
458                               for f in input_demands]
459
460     if not (options.skipFirstRouting and step == options.firstStep):
461         # call duarouter
462         for router_input, output in zip(router_demands, simulation_demands):
463             print(">> Running router on %s" % router_input)
464             btime = datetime.now()
465             print(">>> Begin time: %s" % btime)
466             cfgname = writeRouteConfHDV(duaBinary, step, options, dua_args, router_input,
467                                         output, options.routefile)
468             log.flush()
469             sys.stdout.flush()
470             if options.marginal_cost_reverse:

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471         calcMarginalCostReverse(step, options)
472     call([duaBinary, "-c", cfgname], log)
473     if options.clean_alt and router_input not in input_demands:
474         os.remove(router_input)
475     etime = datetime.now()
476     print(">>> End time: %s" % etime)
477     print(">>> Duration: %s" % (etime - btime))
478     print("<<")
479     # working on HDVs demand
480     router_demands = input_demands_1
481     simulation_demands = input_demands_1
482     # demand files have regular names based on the basename and the step
483     if not (options.skipFirstRouting and step == 0):
484         simulation_demands = ["%03i/%s_%03i.rou%s" % (step, get_basename(f), step, routesSuffi
485             for f in input_demands_1]
486     if not ((options.skipFirstRouting and step == 1) or step == 0):
487         router_demands = ["%03i/%s_%03i.rou.alt%s" % (step-1, get_basename(f), step-1, routesS
488             for f in input_demands_1]
489
490     if not (options.skipFirstRouting and step == options.firstStep):
491         # call duarouter
492         for router_input, output in zip(router_demands, simulation_demands):
493             print(">>> Running router on %s" % router_input)
494             btime = datetime.now()
495             print(">>> Begin time: %s" % btime)
496             cfgname = writeRouteConfCAV(duaBinary, step, options, dua_args, router_input,
497                 output, options.routefile)
498             log.flush()
499             sys.stdout.flush()
500             if options.marginal_cost:
501                 calcMarginalCost(step, options)
502
503             call([duaBinary, "-c", cfgname], log)
504             if options.clean_alt and router_input not in input_demands_1:
505                 os.remove(router_input)
506             etime = datetime.now()
507             print(">>> End time: %s" % etime)
508             print(">>> Duration: %s" % (etime - btime))
509             print("<<")
510     # combining trips file
511     if options.mix:
512         calcMixTrips(step, options)
513     # simulation
514     simulation_demands = ["%03i/%s_%03i.rou%s" % (step, get_basename(f), step, routesSuffix)
515         for f in input_demands]
516     print(">>> Running simulation")
517     btime = datetime.now()
518     print(">>> Begin time: %s" % btime)
519     sumocfg = writeSUMOConf(sumoBinary, step, options, sumo_args,

```

```

520         ",".join(simulation_demands)) # todo: change 'grou.xml'
521     log.flush()
522     sys.stdout.flush()
523     call([sumoBinary, "-c", sumocfg], log)
524     if options.tripinfoFilter:
525         filterTripinfo(step, options.tripinfoFilter.split(","))
526     etime = datetime.now()
527     print(">>> End time: %s" % etime)
528     print(">>> Duration: %s" % (etime - btime))
529     print("<<")
530
531     if options.weightmemory:
532         print(">> Smoothing edge weights")
533         costmemory.load_costs(get_dumpfilename(options, step, "dump"), step, get_scale(options))
534         costmemory.write_costs(get_weightfilename(options, step, "dump"))
535         print(">>> Updated %s edges" % costmemory.loaded())
536         print(">>> Decayed %s unseen edges" % costmemory.decayed())
537         print(">>> Error avg:%.12g mean:%.12g" % (costmemory.avg_error(), costmemory.mean_error()))
538         print(">>> Absolute Error avg:%.12g mean:%.12g" %
539               (costmemory.avg_abs_error(), costmemory.mean_abs_error()))
540
541     if options.zip and step - options.firstStep > 1:
542         # this is a little hackish since we zip and remove all files by glob, which may have u
543         # also note that the 7z file does not have an "_" before the
544         # iteration number in order to be not picked up by the remove
545         for s in list(zipProcesses.keys()):
546             if zipProcesses[s].poll() is not None:
547                 for f in glob.glob("*.%03i*" % s):
548                     try:
549                         os.remove(f)
550                     except Exception:
551                         print("Could not remove %s" % f, file=zipLog)
552                 del zipProcesses[s]
553         zipStep = step - 2
554         zipProcesses[zipStep] = subprocess.Popen(
555             ["7z", "a", "iteration%03i.7z" % zipStep, "%03i" % zipStep], stdout=zipLog,
556             stderr=zipLog)
557
558     converged = False
559     if options.convDev:
560         sum = 0.
561         count = 0
562         for t in sumolib.output.parse_fast("%03i/tripinfo_%03i.xml" % (step, step),
563                                           'tripinfo', ['duration']):
564             sum += float(t.duration)
565             count += 1
566         avgTT.add(sum / count)
567         relStdDev = avgTT.relStdDev(options.convIt)
568         print("< relative travel time deviation in the last %s steps: %.05f" % (

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```

569         min(avgTT.count(), options.convIt), relStdDev))
570     if avgTT.count() >= options.convIt and relStdDev < options.convDev:
571         converged = True
572
573     print("< Step %s ended (duration: %s)" %
574           (step, datetime.now() - btimeA))
575     print("-----\n")
576
577     log.flush()
578     sys.stdout.flush()
579     if converged:
580         break
581     if options.zip:
582         for s in zipProcesses.keys():
583             zipProcesses[s].wait()
584             for f in glob.glob("*_%03i*" % s):
585                 try:
586                     os.remove(f)
587                 except Exception:
588                     print("Could not remove %s" % f, file=zipLog)
589             zipLog.close()
590     print("dua-iterate ended (duration: %s)" % (datetime.now() - starttime))
591
592     log.close()
593     sys.stdout.close()
594     sys.stdout = sys.__stdout__
595
596
597 if __name__ == "__main__":
598     main()

```


*.....it only matters what 's happening inside me, at the
moment when the world is passing by.....*

Dr. Farhang Bolakouee

