Evaluating the Impact of Connected and Autonomous Vehicles on the Resilience of Belgian Road Networks

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ABSTRACT

The emergence of Connected and Automated Vehicles (CAVs) has brought about significant transformations in the transportation industry, leading to noteworthy effects on various aspects, including the resilience of road networks. CAVs have the ability to receive and transmit real-time information about road conditions, enabling them to avoid congestion caused by disruptions and optimize their routes to enhance the network's resilience through rerouting. Moreover, these vehicles also have a considerable impact on road capacity, which contributes to strengthening the overall resilience of the network. Consequently, it is crucial to evaluate the influence of CAVs on the resilience of road networks. However, to the best knowledge of the authors, there is currently a lack of studies that comprehensively assess the resilience of large-scale road networks, considering all dimensions of resilience, such as redundancy, robustness, and recovery speed. Therefore, this paper aims to evaluate the impact of CAVs on the resilience of a large-scale road network in Belgium. The study contributes to the existing literature by employing a simulation-based method to quantify the resilience triangle of the network, encompassing all dimensions of network resilience. The results of this study demonstrate that the presence of CAVs can significantly enhance network resilience in various scenarios, varying in a range of 4.4% for a 10% penetration rate to 59.9% for a 100% penetration rate. These findings can provide valuable insights to researchers and policymakers involved in the deployment of autonomous vehicles.

Keywords: Road Network Resilience, Connected and Autonomous Vehicles (CAVs), Traffic Simulation, Road Network Performance

1-INTRODUCTION

The contemporary road transport system faces numerous challenges that have the potential to impact its resilience. Among these challenges, the introduction of innovative technologies, including Connected and Autonomous Vehicles (CAVs), stands out as one of the most significant. CAVs are vehicles equipped with advanced technologies that enable them to communicate with each other and their surrounding environment, as well as operate autonomously without direct human input. The technology powering CAVs consists of two essential components: automation and connectivity. Automation integrates decision-making and control systems between humans and machines to operate the vehicle, ranging from complete manual control (level 0) to full autonomy (level 5). This hierarchy represents the degree of collaboration between humans and machines in controlling the vehicle. The second component, connectivity, enables the vehicle to communicate with various elements, including infrastructure (V2I), other vehicles (V2V), and pedestrians (V2P).

While there is ongoing debate regarding the effects of CAVs on road networks, they are anticipated to offer several benefits. Firstly, due to their automation, CAVs can enhance road capacity, resulting in changes in link travel times that affect the route choices of both CAVs and Human Driven Vehicles (HDVs). Secondly, as traffic management centers can control CAVs, they have access to comprehensive information about the road network's status, allowing for different route choice principles compared to HDVs. Finally, the connectivity feature of CAVs enables them to respond to traffic congestion or disruptions promptly by adjusting their routes (rerouting capability). Consequently, evaluating road network performance, specifically road network resilience, becomes a pressing topic of research when disruptions occur in the road network and new types of users coexist.

This study aims to develop a novel evaluation framework for road network resilience that considers the presence of CAVs and their coexistence with HDVs within the road network. When investigating the impact of CAVs on road network resilience, it is important to acknowledge that while some studies have suggested that CAVs can enhance resilience (as noted in (Khan et al., 2016)), there is currently no comprehensive research that has assessed the full range of potential impacts of CAVs on 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, focusing solely on CAVs' impact on traffic headway and overlooking other factors such as their routing behavior. Similarly, Zou and Chen (Zou & Chen, 2021) proposed an optimization model for post-disaster recovery scheduling that accounts for CAVs but only considered the difference in route choice and driving behavior between CAVs and HDVs, without incorporating features such as CAV rerouting behavior.

Furthermore, although previous studies have highlighted the need for a comprehensive examination of network resilience, encompassing the dimensions of robustness, redundancy, resourcefulness, and recovery (known as 4R) (Bruneau et al., 2003), most prior studies have focused on only one dimension of network resilience. Moreover, studies on road network resilience that do consider recovery often have limitations, focusing primarily on link-level evaluations during the post-crisis stage rather than network-level evaluations during crisis. Hence, this study contributes to the existing literature by: 1) evaluating the impact of CAVs on a large-scale road network (Belgium) while considering all potential impacts of CAVs, including different driving and route choice behaviors; and 2) proposing a novel framework for road network resilience evaluation that simultaneously considers robustness, redundancy, and recovery through simulation-based methods.

In the subsequent sections of this study, the concept of resilience in the context of transportation networks is initially examined in Section 2. Following that, in Section 3, the methodology for assessing network resilience is presented. Section 4 covers the development of a traffic simulation model for Belgium, as well as the modeling of CAVs and HDVs in the traffic simulation. Finally, Section 5 provides the results of the network resilience assessment. Section 6 concludes this study.

2- RESILIENCE CONCEPT AND BACKGROUND

The term "resilience" originates from the Latin word "resiliere," which means to "bounce back" (Hosseini et al., 2016). This term refers to an entity's 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 resiliency. Therefore, each researcher has provided a specific definition of resilience based on their project's objectives and the type of infrastructure under study (Gauthier et al., 2018; Lhomme et al., 2013). In the context of transportation systems, resiliency is defined as "the ability to prepare for changing conditions and withstand, respond to, and recover rapidly from disruptions" (FHWA, 2015).

There have been five distinct approaches proposed for analyzing the resiliency of transportation networks (Liu & Song, 2020; Serdar et al., 2022). These approaches include Big Data analysis (Liu & Song, 2020), graph theory (Gauthier et al., 2018; Sgambi et al., 2021), optimization models (Omer et al., 2013), simulation-based models (M. T. Aghababaei et al., 2020), and miscellaneous methods (Calvert & 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 & 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 resiliency 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 resiliency can evaluate specific driving and routing behavior of road users, such as connected and autonomous vehicles (CAVs) (Liu & Song, 2020; Sun et al., 2020). The present study employs the simulation-based approach. 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 enable the calculation of various traffic-related metrics (e.g., average speed), providing a comprehensive perspective on the impact of CAVs on road network resilience.

According to Sun et al. (Sun et al., 2020), resilience measures for transportation infrastructure can be broadly categorized into three groups: 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) and 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 1 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 1, 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.

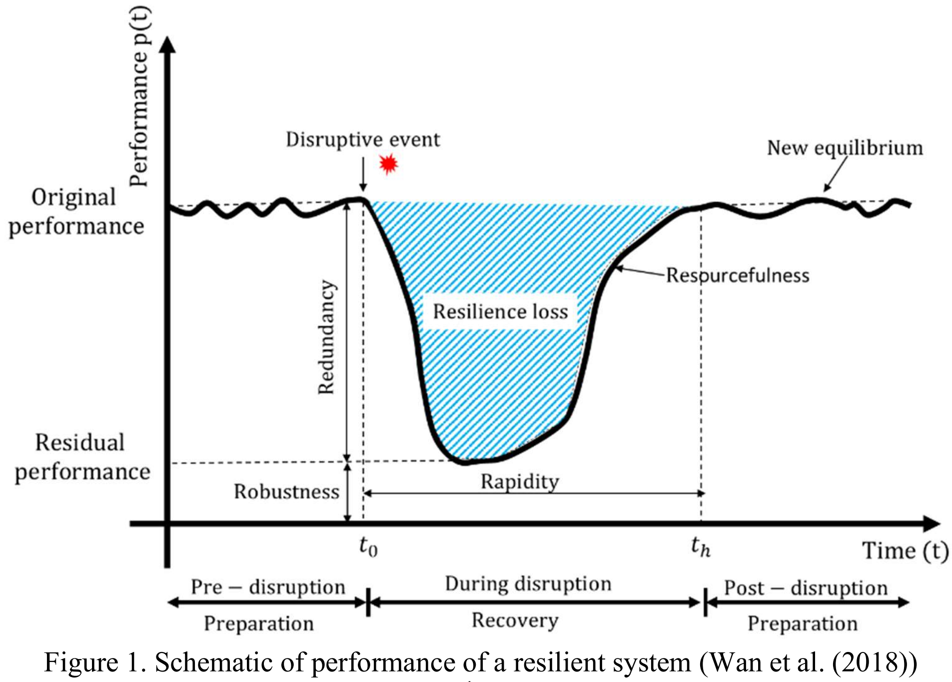


Figure 1. Schematic of performance of a resilient system (Wan et al. (2018))

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

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

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 indicator to quantify the resilience triangle. Despite previous research suggesting network-level measures for evaluating road network resilience, Balal et al.'s measures only focus on the link level and fail to offer a holistic understanding of network-level resilience. This means they do not capture the full extent of how the closure of a road or link can impact other areas of the transportation network. 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 (M. T. S. 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 (M. T. S. Aghababaei et al., 2021; Das, 2020; Niu et al., 2022; Nogal et al., 2017; Twumasi-Boakye & 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 summary, there are several gaps in the existing research on road network resilience. Most studies that examine the recovery speed of the network focus solely on the link level and concentrate on the post-crisis stage rather than the crisis itself. Furthermore, although certain measures, such as total travel time, are correlated with recovery time, they fail to capture the immediate impact of disruptions and the network's evolution. This study aims to address these gaps by introducing a novel performance indicator based on simulation-based methods. Subsequently, this performance indicator is utilized to construct a resilience triangle at the network level for a large-scale road network in Belgium. Additionally, the study calculates the resilience loss using the proposed measure for the given network. This approach enables an investigation into the speed of network response, the immediate impact of disruptions, and the network's evolution during different phases of disruption, encompassing not only natural disasters but also other scenarios. To the best of the authors' knowledge, this is the first instance where a traffic-related measure of resiliency has been introduced at the network level to examine resilience across various disruption phases in the presence of CAVs.

3- RESILIENCE EVALUATION FRAMEWORK

This section outlines the methodology for plotting the resilience triangle and calculating the resilience loss, 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 authors 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 et al., 2018a; 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., 2018b; Geroliminis & 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.

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

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 the number of vehicles within the network is 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, which can significantly impact the network's performance.

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 1 minute, 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 2 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:

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

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.

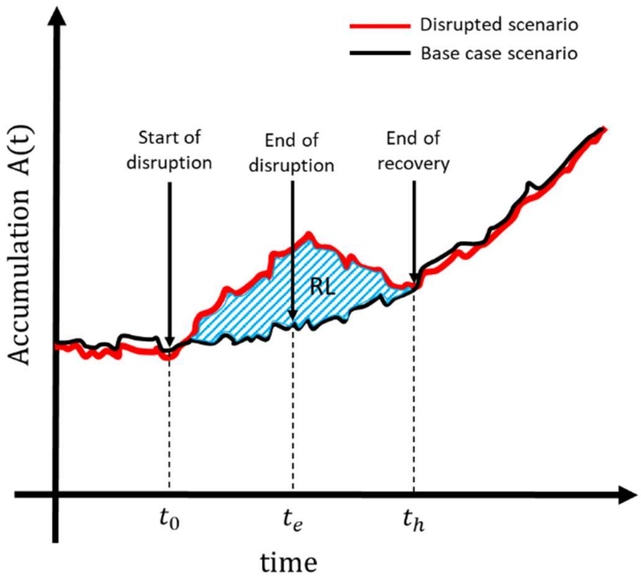


Figure 2. Road network resilience triangle using accumulation

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 are capable of avoiding 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- TRAFFIC SIMULATION MODEL DEVELOPMENT

4-1- Case Study

Belgium, a European country with a population of 11.5 million and a land area of 30,688 km², is divided into three regions: Flanders, Wallonia, and the Brussels-Capital Region (OECD, 2022). The country has a well-developed and well-connected transport network, including national roads spanning 13.2 thousand kilometers, five international airports, a usable rail network of 3,602 kilometers, and five seaports (Statista, 2009, 2020). Among EU countries, Belgium ranks 7th in terms of passenger-kilometers, and its motorway network is the third densest in Europe (Decoster et al., 2020). It also has over eight international E-roads connecting eastern and western Europe, as well as southern and northern Europe. To simulate the Belgium road network, the Simulation of Urban Mobility (SUMO) was used. The network was generated using data from the Open Street Map (OSM) file, and it includes Motorway, Trunk, and Primary roads for outer-city roads like highways and provincial and regional roads. However, inner-city traffic roads are not included. A probabilistic travel demand model was developed to generate demand data between cities, which was previously calibrated and validated in the authors' previous work (Mehrabani et al., 2023). The same traffic simulation model is used in this study. For more information on the travel demand model of Belgium, please refer to the above mentioned article. Figure 3 shows the peak hour traffic volume simulated for Belgium.

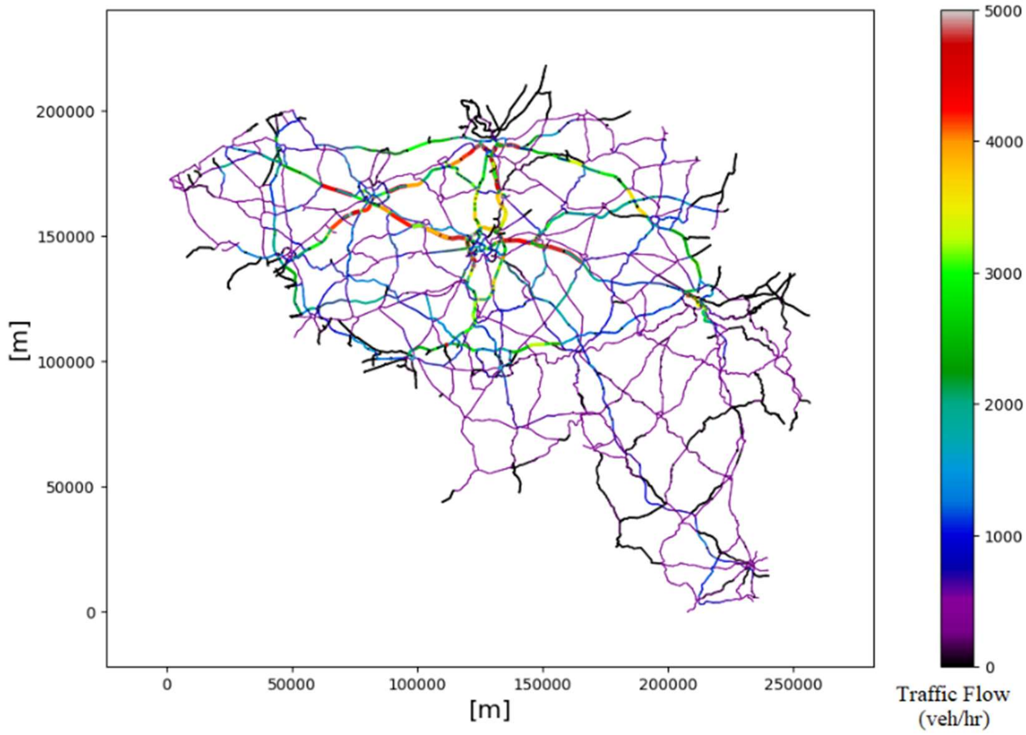


Figure 3: Simulated peak hour traffic flow of the Belgium road network

4-2- Traffic Simulation Model

The simulation includes two types of vehicles: HDVs and CAVs. HDVs are operated by human drivers who can receive information from navigation apps but require a human to control the vehicle. CAVs, on the other hand, are equipped with advanced technologies, including internet connectivity, sensors, and artificial intelligence, that enable them to operate without human input. CAVs have various features, such as the ability to sense and respond to their environment, navigate roads, make decisions, and communicate with other vehicles and infrastructure. The study models the differences between CAVs and HDVs based on their driving behavior and route choice.

In the contect of driving behaviour, this study uses the traffic simulation software SUMO to model traffic flow at the mesoscopic scale. The mesoscopic model in SUMO is based on a queue-based approach developed by Eissfeldt (Eissfeldt, 2004). 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 distinct 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 4.

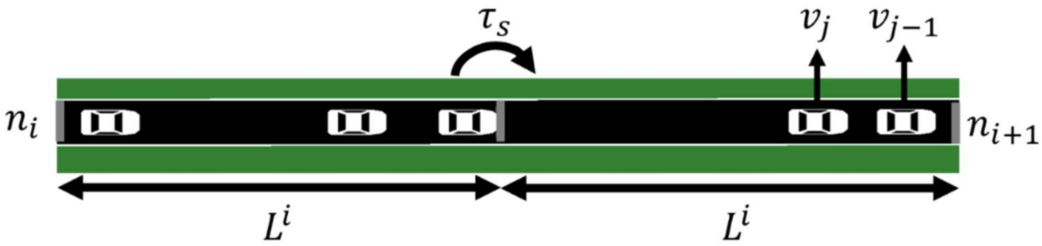
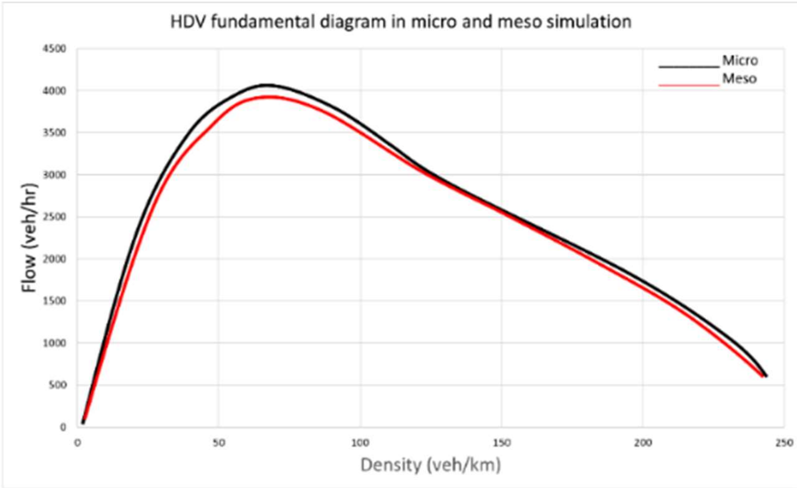


Figure 4: Sketch of queuing model in SUMO

The driving behavior of CAVs is focused on their full automation feature (level 5), which results in safer and quicker driving. Automation technology allows CAVs to react faster, enabling them to follow leading vehicles at a closer distance than HDVs. Consequently, CAVs are assumed to have shorter time headways (Karbasi et al., 2022). Specifically, CAVs and HDVs are distinguished based on their queuing model parameters, with different minimum headway (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). 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' knowledge, there has been no previous investigation of modeling CAVs using an Eissfeldt queuing model in the SUMO software. Thus, in this study, the authors calibrated the parameters of the mesoscopic model for CAVs and HDVs based on previous studies that model CAVs and HDVs at the microscopic level. Specifically, CAVs and HDVs are distinguished based on their queuing model parameters, with different queue (τ) values applied to each vehicle class.



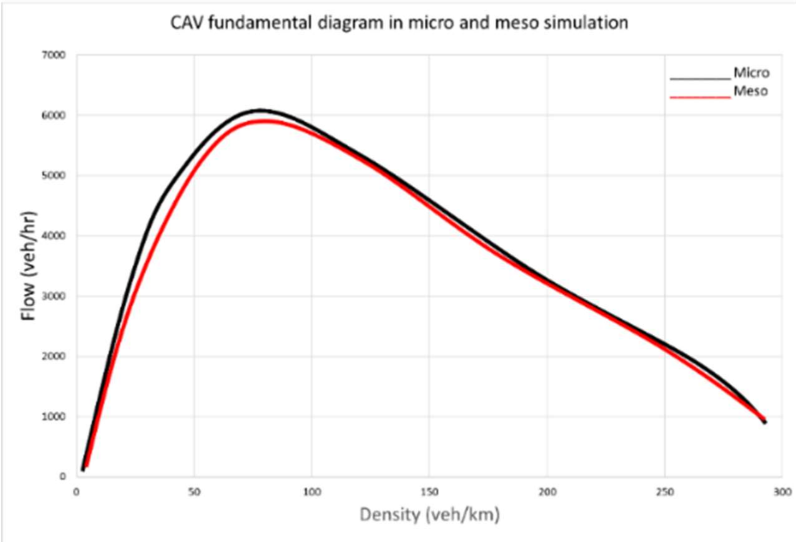


Figure 5: Fundamental diagrams in micro & meso simulations

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). 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 (Karbasi et al., 2022), 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 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. The FDs generated at the meso and micro scales for CAVs and HDVs are shown in Figure 5 using the calibrated parameters.

In the context of route choice behavior, it is assumed that CAVs are under the control of a central traffic management system, which guides them to follow the route that minimizes the overall travel time of the system, utilizing real-time information about the road network (known as the system optimal principle). On the other hand, HDVs adhere to the user equilibrium principle, where each driver selects a route that minimizes their individual travel time without considering the impact on the overall system. Furthermore, it is assumed that a portion of CAVS (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. Similarly, a percentage of HDVs (50%) possess the ability to reroute before entering the network using navigation applications (e.g. google map, waze, etc.), and they also follow the user equilibrium principle. 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 .

In situations where the network consists of only one type of user (e.g., exclusively HDVs or exclusively CAVs), the dynamic Traffic Assignment Problem (TAP) can be solved by applying one of the principles of Wardrop (either user equilibrium or system optimal). However, when both HDVs and CAVs coexist in the network, the TAP becomes a multiclass problem involving mixed traffic flow. 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. To tackle the multiclass TAP involving mixed traffic flow, the authors have utilized a simulation-based approach that was developed in their previous research. Consequently, in order to obtain the results, the multiclass traffic assignment problem for mixed traffic flow has been solved iteratively for each scenario until convergence is achieved. For a comprehensive explanation of how to solve the multiclass TAP and how to model the variations in driving and route choice behavior between CAVs and HDVs, it is recommended to refer to the previous publication by the authors (Bamdad Mehrabani et al., 2023)

4-3- Disruption Scenarios

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. 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 up to the 10 most critical links. 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 1 shows the simulated scenarios and their settings.

Table 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- RESULT AND DISCUSSION

Table 2 provides an overview of the traffic metrics produced at different penetration rates of CAVs in all scenario. As observed in the table, 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 particular, 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).

Table 2: Simulation Results

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

Figure 6 displays the accumulation curves (resilience triangle) for a base scenario and the disrupted scenarios in which the 1 to 10 most critical links are closed, across 0%, 10%, 20%, 40%, 60%, 80% and 100% 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 partition rate, for the sake of simplicity two out of three hours of simulation time are displayed. 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, 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 the non-disrupted scenario, 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.

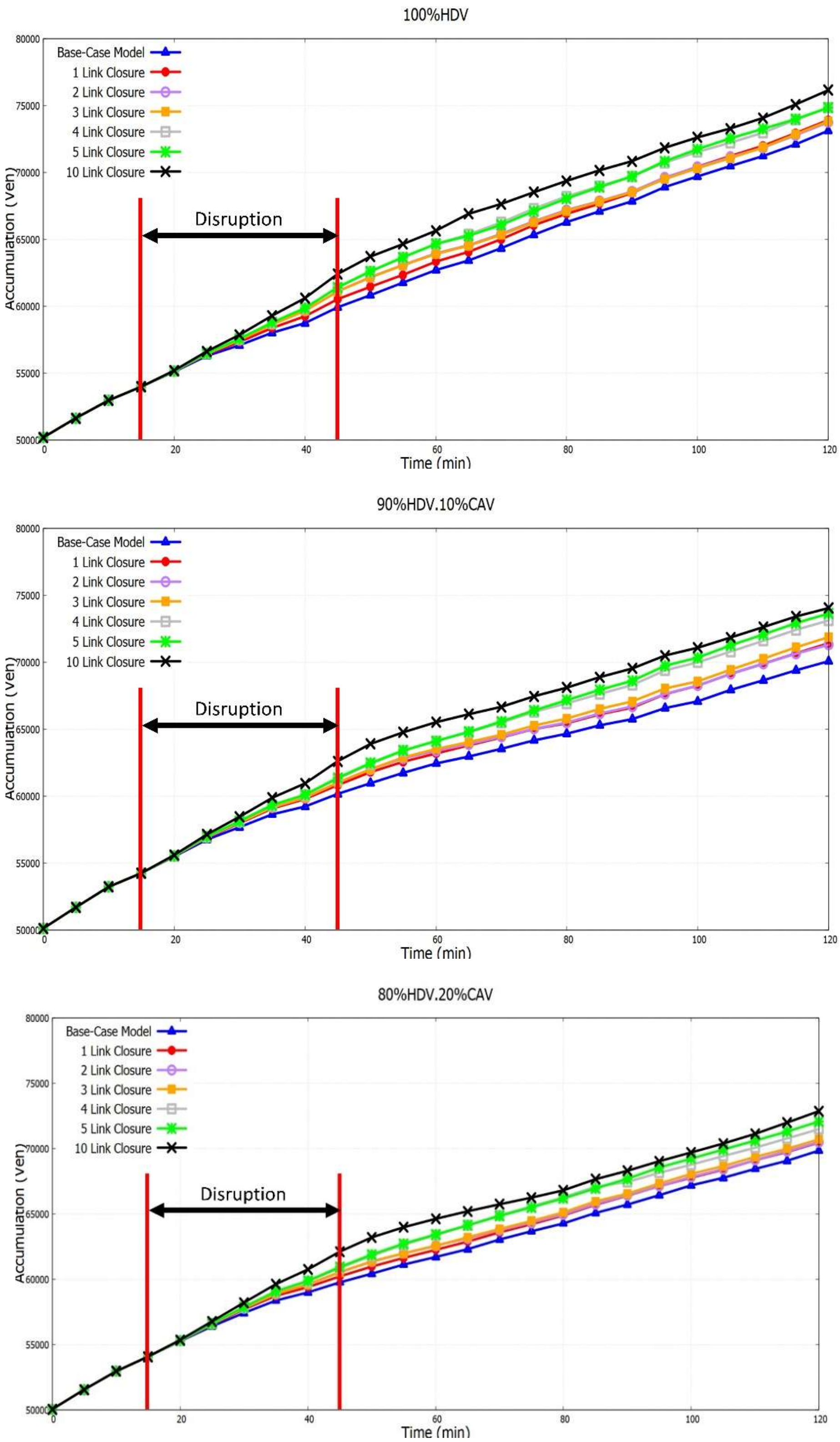


Figure 6: Accumulation Curve (resilience triangle) for all scenarios

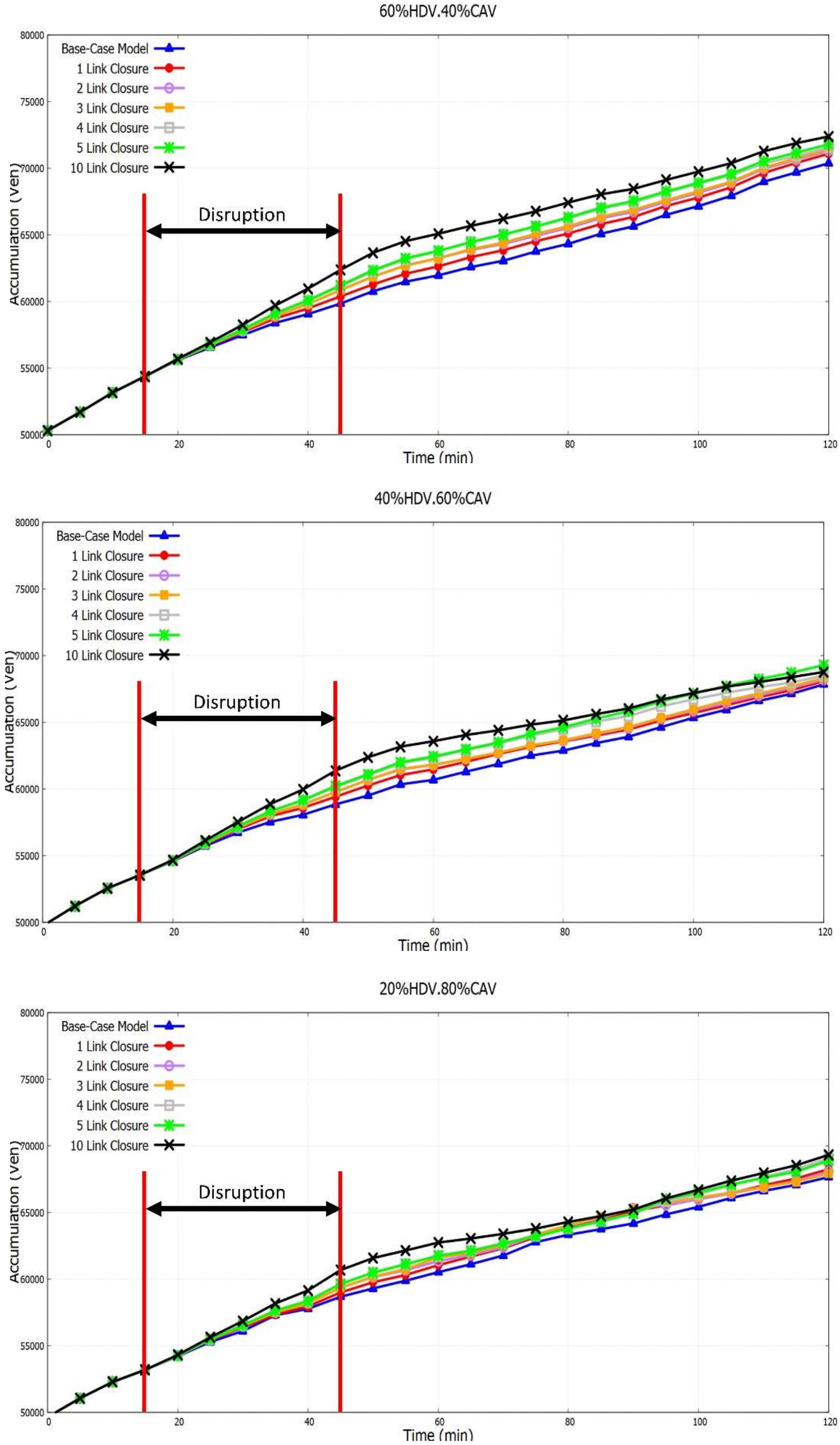


Figure 6: Accumulation Curve (resilience triangle) for all scenarios

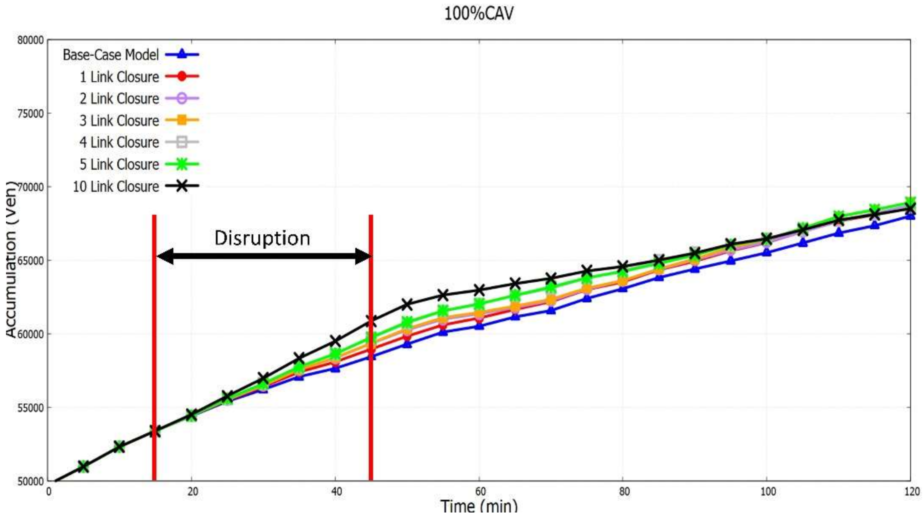


Figure 6: Accumulation Curve (resilience triangle) for all scenarios

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 Figure 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 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 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.

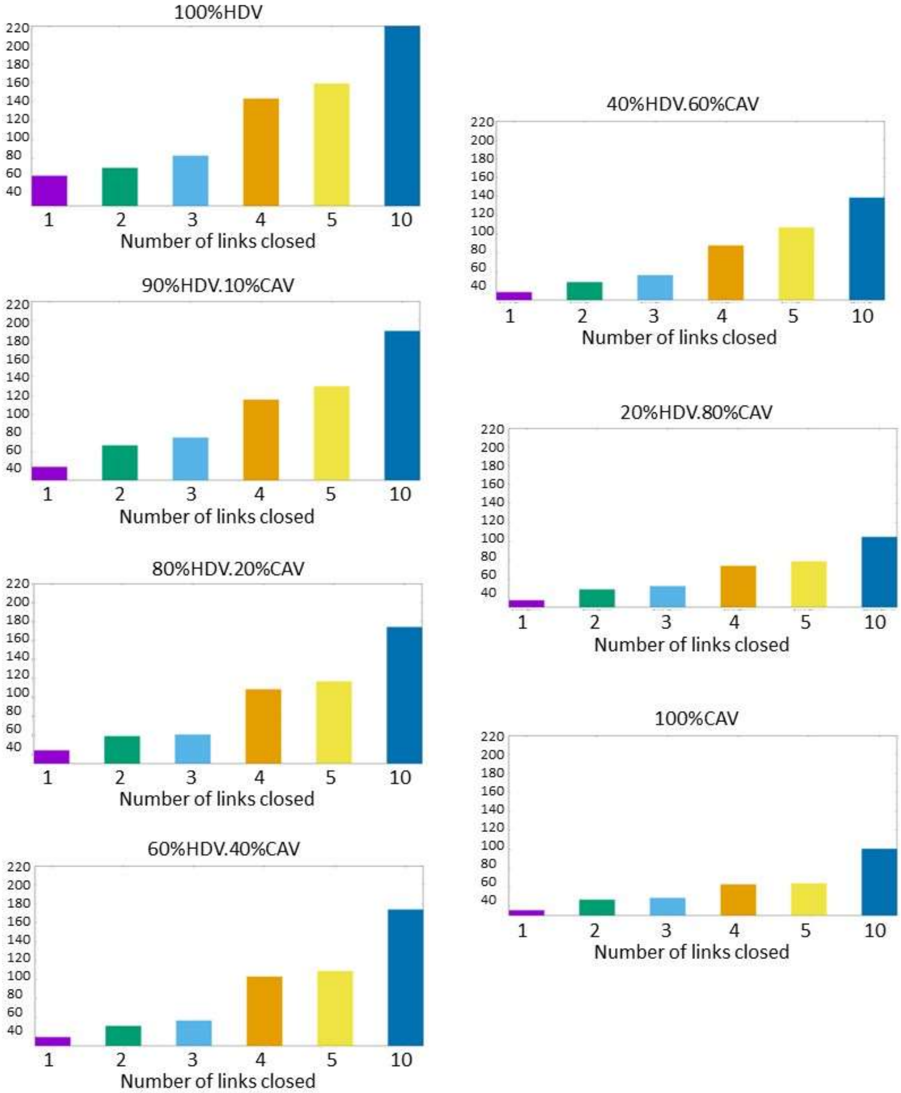


Figure 7: Resilience Loss for all scenarios (Veh. Min x1000)

The network's resilience loss was determined and illustrated in Figure 7 to measure the network's resilience under various scenarios. 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 system optimal principles to navigate through the network and have the ability to reroute in real-time. 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.

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 3.

Table 3: Percentage of improvement in resilience in different penetration rate of CAVs

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

According to the findings presented in Table 3, an increase in the percentage of CAVs in all of 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.

6- CONCLUSION

While there are numerous advantages to CAVs, it is important to acknowledge the features that can influence the resilience of road networks. One notable benefit of CAVs is their ability to have their routes directed by a traffic management center, distinguishing them from HDVs. Consequently, this could give rise to a scenario where diverse road users, each with distinct preferences, coexist simultaneously. Another characteristic of CAVs is their capacity to adapt their routes in response to disruptions within the road network, thereby affecting its overall resilience. Furthermore, CAVs possess the ability to communicate with one another, allowing for optimized route choices, reduced congestion, and an enhanced network resilience. Consequently, it becomes crucial to evaluate whether the presence of CAVs truly improves the resilience of road networks. Hence, the primary objective of our study is to investigate the impact of CAVs on the resilience of road networks.

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 used which were previously calibrated and validated in authours previous work (Mehrabani et al., 2023). 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. Thus, the multiclass traffic assignment problem of mixed traffic flow was solved for each scenario. Finally, a new methodology for investigating the resilience of the network is presented in this study which can capture the impact of CAVs. 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.

A total of 49 different simulation scenarios were examined, which demonstrate that as the percentage of CAVs penetration increases, both in scenarios without disruption and in scenarios with disruption, travel time decrease. The 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 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.

In conclusion, this paper 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. This method was used to assess the impact of CAV’s on the resilience. Depending on penetration rate of CAVs the resilience can be improved by more than a factor 2. The findings of this study have important implications for transportation planning and policy-making, as they suggest that the widespread adoption of CAVs could help to mitigate congestion, reduce travel time, and improve air quality in urban areas.

The findings of this study on network resilience depend on the scenarios outlined in the research. This means that changes to the scenarios will likely affect the variations in network resilience. However, the methodologies provided are versatile and can be used to evaluate network resilience across different scenarios in future studies. In this study, accumulation was used as a performance metric for the network. Future research is encouraged to use other performance metrics, such as space-mean flow, and compare these results to those of the current study. The framework used here to assess the resilience of the Belgian road network could be applied to other networks to evaluate their resilience. This study emphasizes the potential of the proposed framework for wider application in assessing the resilience of various networks. It assumes that Connected and Autonomous Vehicles (CAVs) have rerouting capabilities, significantly enhancing network resilience in their presence. Future studies should focus on developing a CAV rerouting system for various disruption scenarios to identify the optimal rerouting strategy. Such strategies should aim to maximize network resilience. Specifically, it is recommended to create a traffic management system for CAVs that activates during disruptions, building on the tools and findings of this study. The proposed CAV rerouting system would allow vehicles to detect and avoid congested areas, thus improving resilience amid unpredictable events like accidents or road closures. Additionally, developing this system would enable network operators to respond proactively to disruptions by diverting traffic, reducing congestion, and lessening the negative effects on the network's overall performance. Therefore, the results of this study are expected to significantly influence the design and operation of future CAV networks.

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8- AUTHOR CONTRIBUTIONS

Behzad Bamdad Mehrabani contributed to the conceptualization of the study, developed the methodology, conducted the investigation, curated the data, wrote the original draft, and created the visualizations. Luca Sgambi contributed to validation of the results, reviewed, and edited the writing, provided supervision, managed the project administration, and acquired the funding. Adam Pel assisted with the methodology, validated the results, performed formal analysis, curated the data, and reviewed and edited the writing. Simeon Calvert assisted with the methodology, validated the results, and reviewed and edited the writing. Maaike Snelder contributed to the conceptualization of the study, developed the methodology, validated the results, analyzed, and interpreted the data, and reviewed and edited the writing. All authors reviewed the results and approved the final version of the manuscript.

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