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DOI
10.1080/23249935.2024.2442576

Publication date
2024

Document Version
Final published version

Published in
Transportmetrica A: Transport Science

Transportmetrica A: Transport Science

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/ttra21

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To cite this article: Behzad Bamdad Mehrabani, Luca Sgambi, Adam Pel, Simeon Calvert & Maaike Snelder (18 Dec 2024): Impact of connected and autonomous vehicles on road network resilience in Belgium, Transportmetrica A: Transport Science, DOI: 10.1080/23249935.2024.2442576

To link to this article: https://doi.org/10.1080/23249935.2024.2442576

Published online: 18 Dec 2024.

TRANSPORTMETRICA A: TRANSPORT SCIENCE
https://doi.org/10.1080/23249935.2024.2442576

Impact of connected and autonomous vehicles on road network resilience in Belgium

Behzad Bamdad Mehrabani [a], Luca Sgambi [b], Adam Pel [c], Simeon Calvert [c] and Maaike Snelder [c,d]

[a]Transport and Mobility Leuven, Leuven, Belgium; [b]Louvain Research Institute for Landscape, Architecture, Built Environment (LAB), Université Catholique de Louvain, Louvain-la-Neuve, Belgium; [c]Transport & Planning Department, Delft University of Technology, Delft, Netherlands; [d]Netherlands Organization for Applied Scientific Research (TNO), The Hague, Netherlands

ABSTRACT

The advent of Connected and Automated Vehicles (CAVs) has ushered in substantial changes in the transportation sector, particularly impacting the resilience of road networks. CAVs can exchange real-time information about road conditions, allowing them to bypass congestion and optimise their routes, thereby enhancing network resilience through dynamic rerouting. Additionally, these vehicles significantly affect road capacity, further bolstering the overall resilience of the network. As a result, it is essential to assess the impact of CAVs on road network resilience comprehensively. However, to the best of the authors' knowledge, there is a notable gap in research that thoroughly evaluates the resilience of large-scale road networks, taking into account all dimensions of resilience, such as redundancy, robustness, and recovery speed. This paper aims to fill this gap by assessing the influence of CAVs on the resilience of a large-scale road network in Belgium. Utilising a simulation-based approach, the study quantifies the network's resilience triangle, addressing all facets of network resilience. The findings reveal that the integration of CAVs can markedly improve network resilience under various scenarios, with improvements ranging from 4.4% at a 10% penetration rate to 59.9% at full penetration. These insights are valuable for researchers and policymakers focused on the implementation of autonomous vehicles.

ARTICLE HISTORY
Received 25 July 2024
Accepted 7 December 2024

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

CONTACT Behzad Bamdad Mehrabani behzad.bamdad@tmleuven.be Transport & Mobility Leuven, Diestsesteenweg 71, 3010 Leuven, Belgium

autonomously without direct human input. These advanced capabilities represent a significant shift in vehicular technology, fundamentally changing how vehicles interact within the transportation network and with human drivers.

The technology underpinning CAVs comprises two critical elements: automation and connectivity. Automation encompasses a range of decision-making and control systems that coordinate human and machine inputs to operate the vehicle, progressing from complete human control (level 0) to full vehicle autonomy (level 5). This range delineates the levels of interaction and cooperation between human drivers and automated systems in vehicle management. At higher levels of automation, vehicles can perform complex driving tasks without human intervention, potentially reducing human error and enhancing safety. Connectivity, the second crucial component, facilitates communication between the vehicle and various external entities, including infrastructure (V2I), other vehicles (V2 V), and pedestrians (V2P). Additionally, connectivity enables vehicles to interact with cloud-based services and traffic management systems (V2C), enhancing overall traffic efficiency and safety. This interconnectedness allows for real-time data exchange, improving decision-making processes and responsiveness to dynamic road conditions. The integration of these technologies not only improves operational efficiency but also significantly enhances road safety and traffic management capabilities.

There is ongoing debate about the impact of CAVs on road networks, but they are expected to bring several advantages. Firstly, CAVs, through their automation, can increase road capacity, leading to alterations in link travel times, which in turn influence the routing decisions of both CAVs and Human Driven Vehicles (HDVs). An increase in road capacity means that more vehicles can travel smoothly without congestion, which can lead to shorter travel times and reduced delays. Secondly, traffic management centres, with the ability to control CAVs, can utilise extensive information about the road network's conditions, enabling them to implement different route choice strategies compared to HDVs. This centralised control can optimise traffic flows by redirecting vehicles to less congested routes, thereby balancing the network load. Lastly, the connectivity feature of CAVs allows them to swiftly respond to traffic congestion or disruptions by dynamically adjusting their routes (rerouting capability). As a result, assessing road network performance, particularly its resilience, becomes a critical area of research, especially in the context of network disruptions and the coexistence of diverse types of users.

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. While some studies suggest that CAVs can enhance resilience (Khan et al. 2016), comprehensive research assessing the full range of potential impacts of CAVs on resilience is still lacking. Most existing studies focus on specific aspects without considering the holistic functionalities of CAVs. Therefore, this study addresses this gap by 1- Assessing the impact of CAVs on a large-scale road network in Belgium, taking into account all potential effects, including varying driving and route choice behaviours. 2- Introducing a new framework for evaluating road network resilience that incorporates robustness, redundancy, and recovery using simulation-based methods.

In the following sections of this study, Section 2 begins with an examination of the concept of resilience within transportation networks. 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 modelling 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' is derived from the Latin word 'resiliere,' meaning to 'bounce back' (Hosseini, Barker, and Ramirez-Marquez 2016). It describes the capacity of an entity or system to return to its normal state after facing disruptive events. Over the years, researchers from diverse fields have applied the concept of resilience in their work. Initially introduced in the field of ecology in the 1970s (Holling 1973), the concept has since evolved. Despite its development, there remains no universally accepted definition of resilience, leading researchers to define it according to their specific project goals and the type of infrastructure being examined (Gauthier, Furno, and El Faouzi 2018; Lhomme et al. 2013). In the realm 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). This definition highlights not only recovery but also preparation and adaptability as key components of resilience.

There have been five distinct approaches proposed for analyzing the resiliency of transportation networks (W. Liu and Song 2020; Serdar, Koç, and Al-Ghamdi 2022). These approaches include Big Data analysis (W. Liu and Song 2020), graph theory (Gauthier, Furno, and El Faouzi 2018; Sgambi et al. 2021; Zang et al. 2024), optimisation models (Kaviani, Thompson, and Rajabifard 2017; Omer, Mostashari, and Nilchiani 2013), simulation-based models (M. T. Aghababaei, Costello, and Ranjitkar 2020), and miscellaneous methods (Calvert and Snelder 2018). Each approach offers unique insights and tools for understanding resilience but also comes with its own set of limitations.

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 generally insensitive to demand and focus less on recovery simulation. They often assume the complete removal of nodes or links and typically do not account for different traffic modes or the specific characteristics of one system compared to another (Gauthier, Furno, and El Faouzi 2018; W. Liu and Song 2020; Wei and Xu 2024). This simplification can lead to inaccuracies when modelling complex, real-world transportation networks.

For example, in the study of Wei and Xu (2024), they assess the resilience of road networks in disaster-prone areas using a complex-network-based framework, focusing on the natural disasters (Wenchuan earthquake and the Taihu Lake Basin in China). The researchers employ complex network theory to model road networks, using metrics such as K-core, clustering coefficient, network density, average path length, maximum connectivity sub-graph, and network efficiency to evaluate resilience. These metrics assess different resilience aspects like vulnerability, survivability, adaptability, responsiveness, and recovery. Additionally, resilience curves are used to capture the dynamic changes in network performance over time. The study provides a detailed, quantitative analysis of road network resilience during disasters. Another study in which they have used graph network for evaluating road network resilience is the study of (Zang et al. 2024). Although they propose a novel approach for evaluating resilience during heavily rainfall events, the resilience evaluation metrics they use – node degree centrality, node betweenness centrality, and node reachability – are graph-based metrics and cannot capture the impact of functional performance changes in traffic flow or speed.

Optimisation models are utilised primarily during the design phase to ensure the best possible outcomes for resilience while adhering to budget constraints. These models aim to maximise efficiency and effectiveness in enhancing the resilience of transportation networks within the given financial limitations. While useful for planning, they may not account for real-time network dynamics and user behaviours.

Simulation models of resiliency analyze road traffic and simulate partial or total malfunctions in one or more roads, making them effective in analyzing the behaviour of a specific network. Additionally, simulation models of resiliency can evaluate specific driving and routing behaviour of road users, such as CAVs (W. Liu and Song 2020; Sun, Bocchini, and Davison 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 behaviour 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 behaviour of one vehicle affects the behaviour of others, and this can be modelled accurately. For example, CAVs may influence traffic flow patterns, which in turn affect HDVs. 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. Factors such as lane widths, signal timings, and road grades can be included in the simulation. 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. This flexibility makes simulation-based methods highly valuable for scenario analysis and planning. 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.

However, when investigating the impact of CAVs on road network resilience, it is important to acknowledge that while some studies have evaluated the impact of CAVs on road network resilience, there is currently no comprehensive research that has assessed the full range of potential impacts of CAVs on resilience. For instance, Ahmed, Dey, and Fries (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 behaviour. Similarly, Zou and Chen (2021) proposed an optimisation model for post-disaster recovery scheduling that accounts for CAVs but only considered the difference in route choice and driving behaviour between CAVs and HDVs, without incorporating features such as CAV rerouting behaviour. These limitations highlight the need for more comprehensive studies that include all functionalities of CAVs.

According to Sun, Bocchini, and Davison (2020), resilience measures for transportation infrastructure can be broadly categorised 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. Conversely, topology-based measures employ graph theory to evaluate topological characteristics, primarily focusing on connectivity and centrality. However, these measures do not consider the dynamic impacts and driving behaviours affecting the network. Socioeconomic measures, another category, evaluate the resilience of transportation infrastructure based on socioeconomic benefits, such as reduced emissions and lower economic costs, which are highly dependent on available resources. This study, however, will focus on traffic-related measures. Several studies have investigated these measures to assess the resilience of road networks. One commonly used tool for evaluating resilience is the resilience triangle, which includes three key features: reducing failure probabilities, minimising the consequences of failures, and shortening recovery times. The original concept of the resilience triangle was introduced by (Bruneau et al. 2003) and has been further refined by various researchers. The resilience triangle provides a framework for quantifying the performance loss and recovery over time. For example, 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. (2018):

- Robustness: The capability to withstand or absorb disturbances, maintaining integrity when exposed to disruptions.
- Redundancy: The ability of certain system components to take over the functions of failed components without negatively impacting the system's overall performance.
- Resourcefulness: The availability of materials, supplies, and personnel necessary to restore functionality, particularly in studies of transportation resilience.
- Rapidity: Implies not just the ability to recover, but emphasises the speed at which recovery occurs.

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 illustrates the recovery period from t_0 to t_h, and the slope of the third edge indicates the speed of recovery (Sun, Bocchini, and Davison 2020). By utilising this figure, resilience can be mathematically quantified by integrating the area within the resilience triangle, providing an estimate of the resilience loss due to the disruptive event (as shown in Equation 1). A highly resilient system will exhibit a low value of resilience loss.

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

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

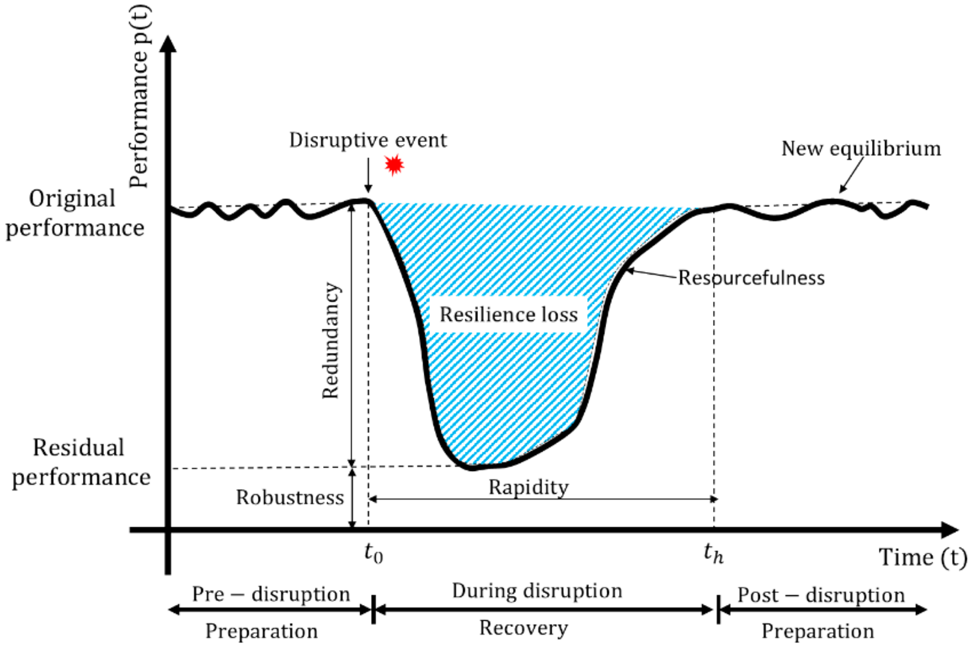

Figure 1. Schematic of performance of a resilient system (Wan et al. 2018).

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. (2019) utilised 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. A network-level approach is necessary to understand the interconnected impacts of disruptions across the entire system. 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, Costello, and Ranjitkar 2021). However, previous studies have emphasised that recovery and rapidity are critical components of road network resilience, particularly in the context of new technologies like CAVs (Ahmed, Dey, and Fries 2019). Ignoring these aspects can lead to incomplete assessments of a network's true resilience. The study of Z. Liu and Song (2020) is one of the few that employs a comprehensive resilience evaluation framework. While the resilience evaluation framework includes important metrics such as robustness, recovery, rapidity, and performance, the framework is not dynamic and fails to account for adaptive traffic management and variable recovery rates based on real-time conditions.

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, Costello, and Ranjitkar 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 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. A more comprehensive approach is needed to fully understand and enhance network resilience. This study aims to address these gaps by introducing a novel performance indicator based on simulation-based methods. Subsequently, this performance indicator is utilised 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. On top of that, this study provides significant societal value by addressing how CAVs can enhance road network resilience in response to incidents, a crucial aspect of modern urban planning. By simulating CAV impacts under various disruption scenarios, our research informs policymakers and urban planners on effective CAV integration strategies. Enhanced resilience leads to reduced travel times and fewer disruptions, ultimately resulting in lower emissions and improved safety and accessibility for all road users.

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 generalisable 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 approach facilitates a more comprehensive understanding of the network's resilience, enabling the resilience triangle to be plotted 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 measured by the number of completed trips within a unit of time, also known as the network outflow (Amini, Tilg, and Busch 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, Tilg, and Busch 2018b; 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.

$$A_t = V_t^i + V_t^o \tag{3}$$

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 min, 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 Y-axis represents the accumulation in the network, and the X-axis represents the time interval. The resilience loss formulation can be defined as follows:

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

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.

Using accumulation as the performance indicator to plot the resilience loss triangle allows for a comprehensive assessment of all aspects of resilience, including redundancy, robustness, and recovery. This method also facilitates the evaluation of the impact of CAVs

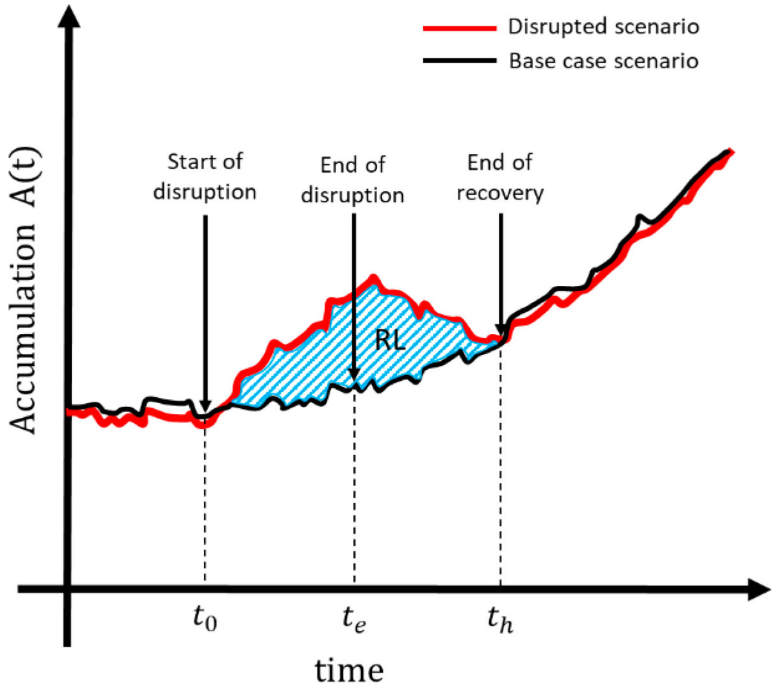

Figure 2. Road network resilience triangle using accumulation.

on the overall network resilience, especially considering their rerouting capabilities. CAVs can bypass congested and disrupted roads, leading to an increase in network outflow, as captured by the accumulation measure. This rise in outflow correlates with enhanced network performance, indicating a more resilient network. Thus, employing accumulation as a performance indicator effectively quantifies the benefits of CAVs in enhancing network resilience, particularly in the face of disruptive events. Figure 3 presents a flow chart outlining the methodological approach for evaluating road network resilience in this paper.

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 km⊐2, 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 kilometres, five international airports, a usable rail network of 3,602 kilometres, and five seaports (Statista 2009; 2020). Among EU countries, Belgium ranks 7th in terms of passenger-kilometres, 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

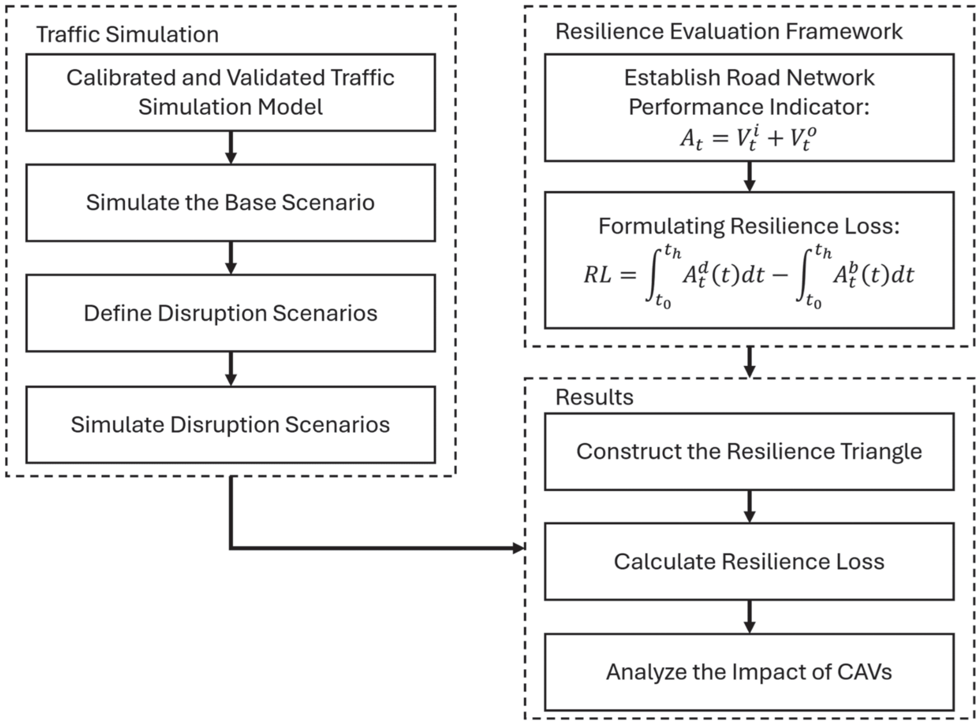

Figure 3. Road network resilience evaluation methodology.

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 4 shows the peak hour traffic volume simulated for Belgium.

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 behaviour and route choice.

In the context of driving behaviour, this study employs the traffic simulation software SUMO to model traffic flow at the mesoscopic scale. SUMO's mesoscopic model utilises a queue-based approach developed by (Eissfeldt 2004). This model calculates the travel time for a vehicle from the queue by considering the traffic state in both the current and

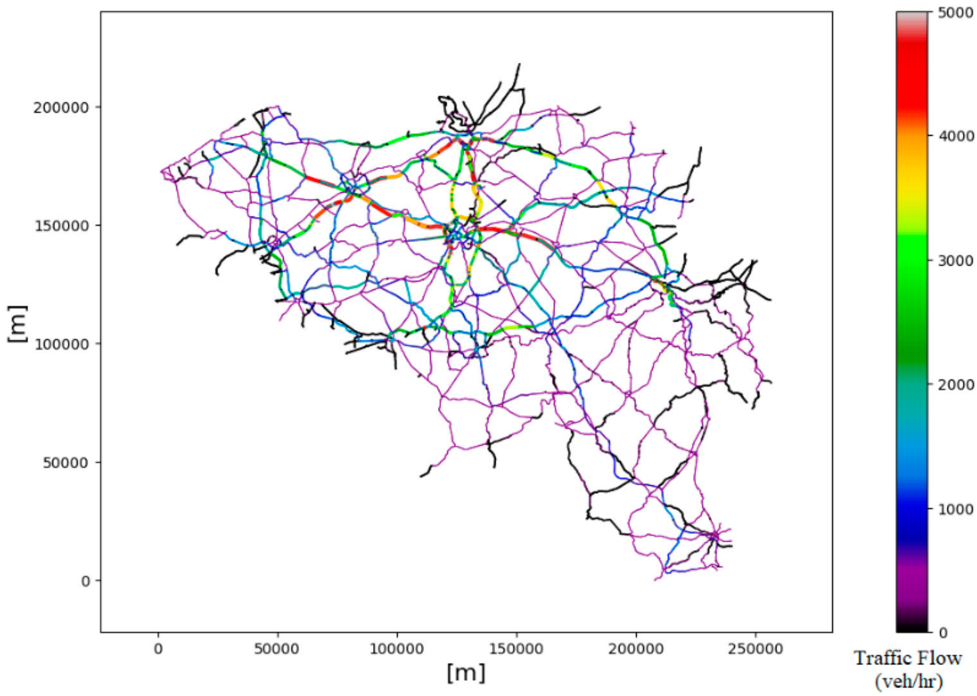

Figure 4. Simulated peak hour traffic flow of the Belgium road network.

subsequent queues, the minimum travel time, and the intersection stage (e.g. red, green, yellow). There are four possible traffic state combinations between consecutive segments (DLR 2023), each with a distinct minimum headway between vehicles:

1. Travelling from one congested segment to another congested segment (default minimum headway 1.4).
2. Travelling from a congested segment to a free-flowing segment (default minimum headway 1.73).
3. Travelling from a free-flowing segment to a congested segment (default minimum headway 1.13).
4. Travelling from a free-flowing segment to another free-flowing segment (default minimum headway 1.13).

The parameter τ is used to establish the minimum headways between vehicles, serving as a multiplier for each of these scenarios. Each of these headway values is multiplied by the τ value specified for the vehicle type (with the default τ set to 1).

The driving behaviour of CAVs centres around their fully autonomous capability (level 5), resulting in safer and more efficient driving. This automation technology enables CAVs to react more quickly, allowing them to maintain shorter following distances compared to HDVs. Consequently, CAVs are assumed to have reduced time headways (Karbasi et al. 2022). Distinctions between CAVs and HDVs are made based on their queuing model parameters, specifically the minimum headway (τ) values assigned to each vehicle category. The underlying assumption is that CAVs can follow preceding vehicles more efficiently across sequential segments than HDVs, leading to a reduced τ parameter for CAVs (Yu et al. 2021). While some studies have utilised cell transmission models or simplified car-following models to simulate CAVs at the mesoscopic level (Mansourianfar et al. 2021; Melson et al. 2018), to the best of the authors' knowledge, the only study that has calibrated the Eissfeldt model parameters for CAVs is the authors' previous research (Bamdad Mehrabani et al. 2023). Therefore, this study will employ the same parameters calibrated in the authors' prior work, with the τ value set at 1.06 for HDVs and 0.79 for CAVs. For further details on the calibration process of these parameters, please refer to the authors' previous work (Bamdad Mehrabani et al. 2023).

In the context of route choice behaviour, it is assumed that CAVs are under the control of a central traffic management system, which guides them to follow the route that minimises the overall travel time of the system, utilising 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 minimises 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 utilised by CAVs both prior to entering the network and during driving based on real-time information of traffic congestion. This can help in optimising 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 utilise mobile navigation applications (Yang et al. 2021).

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 behaviours. To tackle the multiclass TAP involving mixed traffic flow, the authors have utilised 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 behaviour 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 min 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 min 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 min. 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 behaviour 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.

5. Result and discussion

Table 2 provides an overview of the traffic metrics generated at various penetration rates of CAVs across all scenarios. As shown in the table, an increase in the percentage of CAVs corresponds to a reduction in the total travel time of the network. This improvement can be attributed to CAVs adhering to the System Optimum (SO), which aims to optimise the overall travel time of the entire network. Particularly in disrupted scenarios, the reduction in total travel time with a higher percentage of CAVs can be explained by their connectivity. When a sudden incident occurs, CAVs can communicate with each other, allowing vehicles that have not yet reached the incident to reroute and avoid the disruption.

Figure 5 displays the accumulation curves (resilience triangle) for a base scenario and the disrupted scenarios in which the 1–10 most critical links are closed, across 0%, 10%, 20%, 40%, 60%, 80% and 100% penetration rates of CAVs. Given that the accumulation

Table 1. Malfunction scenarios.

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

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

Table 2. Simulation Results-Total Travel Time (min).

	0%CAV	10%CAV	20%CAV	40%CAV	60%CAV	80%CAV	100%CAV
1 link Closure	13076523	12737497	12447666	12360555	11834474	11840927	11727832
2 Link Closure	13117268	12745272	12479101	12392351	11871907	11859870	11760581
3 Link Closure	13165122	12839657	12489484	12395149	11907132	11870081	11807367
4 link Closure	13260307	13010625	12494796	12498335	11911474	11875285	11874124
5 Link Closure	13316268	13064213	12592035	12502181	11976920	11926337	11892919
10 Link Closure	13463633	13236609	12834344	12571591	11986508	11954628	11900310

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.

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 5, 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, 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. Given that the number of vehicles remains constant across all scenarios, with only the CAV penetration rate varying, it can be inferred that the completed trip rate increases as the CAV penetration rate rises. This leads to a reduction in the network accumulation value over a specific period. In other words, the overall network performance improves with a higher penetration rate of CAVs.

By comparing the curves in Figure 5, it can be observed that the introduction of CAVs at varying penetration rates significantly influences the network's ability to recover following disruptions. In scenarios with lower CAV penetration rates (Figure 5(a–c)), the accumulation curves for disrupted scenarios show a marked and sustained deviation from the baseline curve after an incident. This deviation highlights a slower recovery process, as the network struggles to return to its original state of functionality. Specifically, the distance between the accumulation curves in disrupted and baseline scenarios indicates substantial resilience loss, reflecting limited network recovery in these scenarios. Lower CAV penetration implies fewer vehicles are capable of rerouting effectively, leading to increased congestion and extended travel times. However, as CAV penetration rates increase (Figure 5(d–f)), the disrupted accumulation curves gradually return to align more closely with the baseline curve,

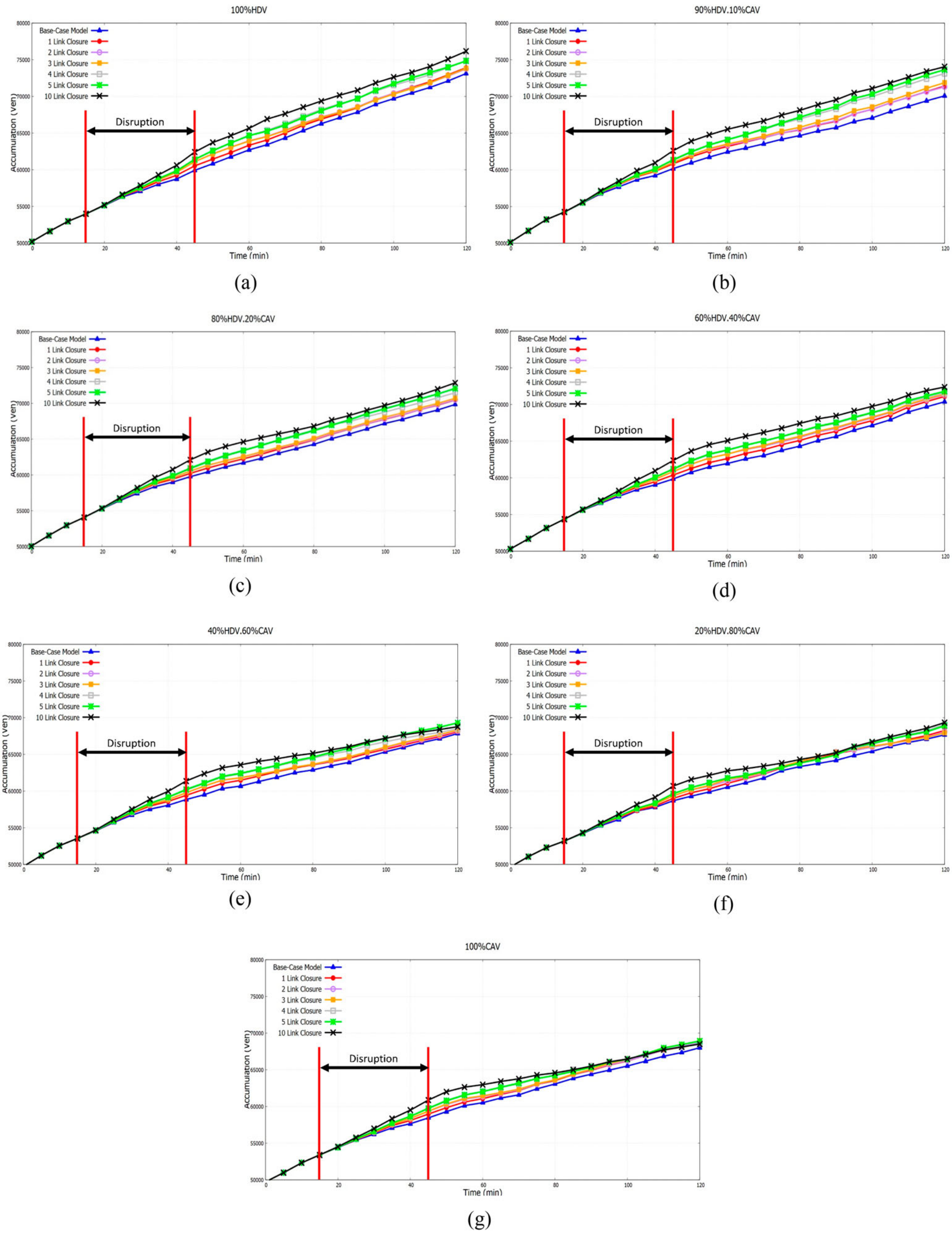

Figure 5. Accumulation Curve (resilience triangle) for all scenarios.

demonstrating improved resilience. This change reflects the enhanced recovery capabilities afforded by the higher proportion of CAVs, which are able to bypass congested routes and re-establish efficient traffic flow quickly. At higher CAV rates, the resilience of the network improves significantly, as shown by the reduced distance between disrupted and baseline accumulation curves. This behaviour suggests that with a larger presence of CAVs,

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

the network experiences less congestion impact and achieves a faster recovery, even under disruption.

In summary, after analyzing Figure 5, 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 6 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 behaviour 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.

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%.

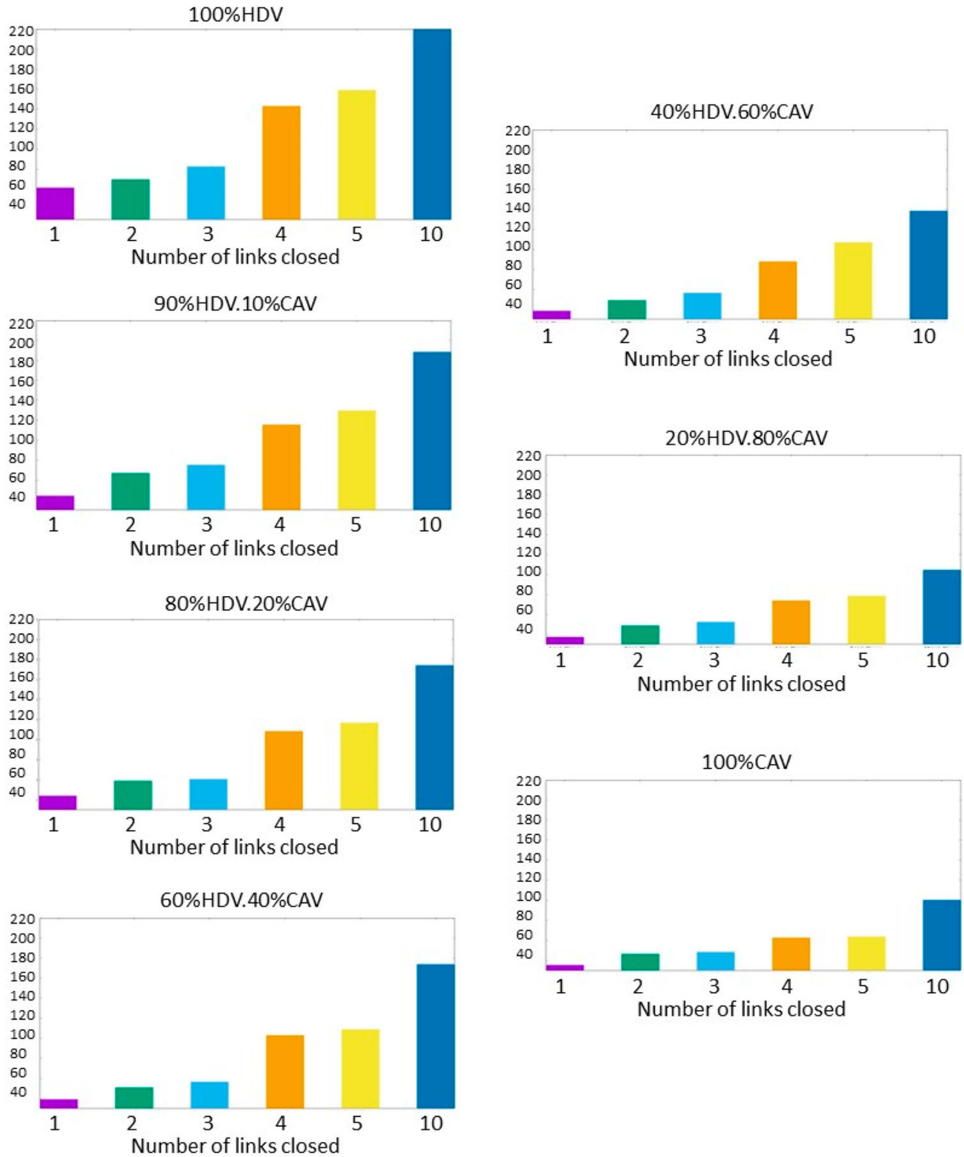

Figure 6. Resilience Loss for all scenarios (Veh. Min x1000).

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.

We also observe that in the 10-link closure scenario, the percentage improvement in network resilience is 20.7% at 20% CAV penetration and only slightly increases to 20.8% at 40% CAV penetration. This minimal change is due to the severe disruption caused by closing multiple critical links, which significantly strains the network's capacity. At these lower CAV penetration rates, the benefits of CAVs – such as improved driving behaviour and rerouting capabilities – are not sufficient to substantially alleviate the congestion resulting from such extensive disruptions. The remaining open routes are heavily congested, and the presence of HDVs still dominates traffic conditions, limiting the potential gains from additional CAVs. Only at higher penetration rates (above 40%) do we see a more significant improvement in resilience. This is because a greater proportion of CAVs can better utilise the available infrastructure through enhanced coordination and optimised routing. Therefore, the relatively small difference between 20% and 40% CAV penetration reflects the network's limited ability to benefit from CAVs under severe disruption until a higher threshold of CAV presence is reached.

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 utilised 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 CAVs offer numerous advantages, it is crucial to consider their features that can impact the resilience of road networks. One significant benefit of CAVs is their capability to have their routes managed by a traffic management centre, which sets them apart from HDVs. This could lead to a scenario where diverse road users with varying preferences coexist. Additionally, CAVs can adapt their routes in response to disruptions within the road network, influencing its overall resilience. Moreover, CAVs can communicate with each other, enabling optimised route choices, reduced congestion, and improved network resilience. Therefore, it is essential to assess whether the presence of CAVs genuinely enhances the resilience of road networks. The primary objective of our 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 used which were previously calibrated and validated in authors previous work (Mehrabani et al. 2023). In this study, it is assumed that the driving behaviour and route choice behaviour of CAVs are different from those of HDV, resulting in a mixed traffic flow. Thus, the multiclass traffic assignment for mixed traffic 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 centre data, the proposed method can be utilised 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 behaviour and have different route selection behaviour 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 centre 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 utilise 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 behaviour 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 behaviour 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 realised.

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 emphasises 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 maximise 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.

Future studies should also examine the resilience of CAVs following critical operational disruptions, like communication disruptions or power losses disruptions. Communication disruptions and power losses can compromise their operation, so developing effective strategies, such as fail-safe systems and backup power, is essential to restore functionality.

Acknowledgements

The corresponding author would like to thank UC Louvain and Louvain Research Institute for Landscape, Architecture, Built Environment for providing 'FSR' and 'Erasmus+' funds during conduction of the research.

Author contributions

Behzad Bamdad Mehrabani was responsible for conceptualising the study, developing the methodology, conducting the investigation, curating the data, drafting the original manuscript, and creating visualisations. Luca Sgambi played a key role in validating the results, reviewing and editing the manuscript, providing supervision, managing project administration, and securing funding. Adam Pel contributed to the methodology, result validation, formal analysis, data curation, and manuscript review and editing. Simeon Calvert also assisted with the methodology, validated the results, and reviewed and edited the manuscript. Maaike Snelder contributed to the conceptualisation of the study, methodology development, result validation, data analysis and interpretation, and manuscript review and editing. All authors reviewed the results and approved the final version of the manuscript.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by UC Louvain FSR [grant number FSR].

ORCID

Behzad Bamdad Mehrabani http://orcid.org/0000-0001-8585-7879

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