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STUDYING THE SAFETY IMPACT OF SHARING DIFFERENT LEVELS OF CONNECTED AND AUTOMATED VEHICLES USING SIMULATION-BASED SURROGATE SAFETY MEASURES

- ESTUDIO DEL IMPACTO EN LA SEGURIDAD DE COMPARTIR DIFERENTES NIVELES DE VEHÍCULOS CONECTADOS Y AUTOMATIZADOS UTILIZANDO MEDIDAS DE SEGURIDAD SUBROGADAS BASADAS EN SIMULACIÓN -

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El doctorando Tasneem Falah Mohammad Miqdady y los directores de la tesis "STUDYING THE SAFETY IMPACT OF SHARING DIFFERENT LEVELS OF CONNECTED AND AUTOMATED VEHICLES USING SIMULATION-BASED SURROGATE SAFETY MEASURES" garantizamos, al firmar esta tesis doctoral, que el trabajo ha sido realizado por el doctorando bajo la dirección de los directores de la tesis y hasta donde nuestro conocimiento alcanza. En la realización del trabajo, se han respetado los derechos de otros autores a ser citados, cuando se han utilizado sus resultados o publicaciones.

Granada, Abril 2023

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"Are those who know equal to those who do not know?" None will be mindful ˹of this˺ except people of reason "

The Qur'an 39:9

"Dile: "¿Acaso son iguales los que tienen conocimiento y los que no tienen conocimiento?", Sólo reflexionan los dotados de entendimiento"

Capítulo 39 "Los Grupos", El Corán

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RESUMEN

Los CAV (vehículos conectados y autónomos) se están convirtiendo en una realidad y se están infiltrando en los mercados de forma gradual pero constante. Los CAV prometen mejorar la seguridad del tráfico y se prevé que eliminen los errores cometidos por los conductores humanos.

En consecuencia, el número de estudios de seguridad vial que involucran CAV ha aumentado recientemente. Debido a que existe una falta de información sobre el comportamiento real de los CAV en flujos de tráfico mixto, las plataformas de simulación de tráfico se utilizan para proporcionar un enfoque razonable para probar varios escenarios y flotas. Varias plataformas de microsimulación de tráfico con distintos modelos de flujo de tráfico (por ejemplo, Aimsun, VISSIM, PARAMICS y SUMO) se han utilizado en la literatura, donde los estudios han determinado que los CAV pueden mejorar la seguridad vial, particularmente en escenarios donde su porcentaje de penetración es alto.

Sin embargo, la investigación existente se ha limitado a incluir uno o dos niveles de automatización, y/o no analiza los resultados en términos del efecto de incluir cada nivel de automatización. Además, el término de severidad no ha sido claramente establecido y discutido en estas investigaciones, ni se abordó antes una comprobación de la sensibilidad que presenta la seguridad vial frente a la variación de los parámetros que normalmente se utilizan para la calibración de los CAV.

Esta tesis doctoral tiene como objetivo evaluar el impacto en la seguridad vial de la introducción progresiva de los CAV en el flujo de tráfico con diferentes niveles de automatización (desde el nivel 1 hasta el nivel 4), teniendo en cuenta que los vehículos de nivel 4 no circularán por las carreteras de inmediato. Este impacto se evalúa tanto en términos de frecuencia como en términos de severidad. La tesis también tiene como objetivo evaluar el impacto en la seguridad vial si se establece una configuración operacional determinada en la carretera, es decir, operar los CAV en carriles exclusivos. Por último, la tesis trata de resaltar los factores más influyentes en la dinámica de conducción desde la perspectiva de la seguridad vial. La investigación comienza con la modelización de varios niveles de CAV utilizando la calibración del modelo de Gipps, seguida de la simulación de nueve flotas mixtas de vehículos con diferentes niveles de CAV (nueve escenarios diferentes que representan la introducción progresiva de estos vehículos) en un segmento de carretera simulado. A continuación, a partir de las trayectorias de los vehículos, se realiza un análisis de seguridad utilizando medidas subrogadas.

Según los hallazgos, la penetración gradual de los niveles de CAV resultó en una reducción progresiva de los conflictos de tráfico. Esta reducción va desde el 18,9% cuando

el 5% de los vehículos en el flujo de tráfico tienen niveles altos de automatización (vehículos de nivel 3 y nivel 4) hasta el 94,1% cuando todos los vehículos en el flujo de tráfico son de nivel 4. Además, los vehículos de conducción humana y los vehículos con bajos niveles de automatización (vehículos de nivel 1 y nivel 2) están más frecuentemente involucrados en conflictos (como posibles inductores de situaciones de riesgo; como vehículos seguidores) que los vehículos con altos niveles de automatización (nivel 3 y nivel 4). De hecho, dependiendo de la combinación de diferentes tipos de vehículos en el flujo de tráfico, los vehículos de conducción manual están involucrados en conflictos entre el 8% y el 122% más que su porcentaje de flota compartida, mientras que los vehículos con altos niveles de automatización están involucrados en conflictos entre el 80% y el 18% menos que su porcentaje de flota compartida.

Por otro lado, en general, ante condiciones de tráfico ligero, no usar un carril dedicado para la circulación de los CAV cuando la tasa de penetración de los mismos es inferior al 55% (de vehículos nivel 3 y nivel 4) proporciona mejores resultados de seguridad que usar un carril dedicado, mientras que en condiciones de alta densidad de tráfico siempre es mejor utilizar un carril dedicado, independientemente del porcentaje de penetración de los vehículos de nivel 3 y nivel 4.

Finalmente, a partir del estudio de sensibilidad, los parámetros que se identificaron como clave, por tener una mayor influencia en la seguridad vial, incluyen el tiempo de reacción, el espacio libre entre los vehículos, la aceleración máxima, la desaceleración normal y el factor de sensibilidad. Además, cuando estos parámetros se estudiaron dos a la vez, se descubrió que una aceleración máxima baja, aunque se combine con diferentes valores de otros parámetros, siempre produce el mayor número de conflictos, mientras que un tiempo de reacción corto, al combinarse con diferentes valores de otros parámetros, siempre produce los mejores resultados de seguridad vial.

Esta tesis confirma la teoría y las conclusiones de la literatura previa que indican una mejora en seguridad debido a la penetración de los CAV. Por otro lado, ofrece una perspectiva más amplia y apoyo para la introducción progresiva de los CAV. Además, este estudio arroja luz sobre la cantidad de conflictos potencialmente graves que surgen durante el período de transición de un escenario de operación de vehículo totalmente manual a un escenario de operación de CAV completo. Como resultado, esta tesis amplía las perspectivas tanto de los fabricantes como de los investigadores sobre el comportamiento de los CAV para futuras implementaciones.

ABSTRACT

CAV (connected and autonomous vehicles) are becoming a reality and are gradually but steadily infiltrating the markets. CAV have promised improving traffic safety and are anticipated to do away with mistakes made by human drivers.

Accordingly, the number of traffic safety studies involving connected and autonomous vehicles (CAV) has recently increased. Because there is a lack of information about the real behaviour of CAV in mixed traffic flows, traffic simulation platforms are used to provide a reasonable approach for testing various scenarios and fleets. Various traffic microsimulation platforms with distinct traffic flow models (e.g. Aimsun, VISSIM, PARAMICS, and SUMO) have been used in the literature, where studies have reported that CAV may improve traffic safety, particularly in high sharing percentage scenarios.

Nevertheless, the exist research was either limited for including a calibration of one or two levels of automation, or do not analyse and present the results in term of the effect of including each level of CAV. Moreover, the severity term was not clearly stated and discussed in these investigations. Further, a check of the sensitivity of the usual parameters used for CAV calibration on traffic safety has not been addressed before.

This doctoral thesis aims to assess the impact of near-real-time introduction of CAV into the traffic flow with varying levels of automation (from Level 1 to Level 4) on traffic safety in terms of quantity and severity, taking into account the fact that Level 4 vehicles won't be introduced into the traffic right away. The thesis also aims to evaluate the safety impact of a proposed scenario for CAV introduction; operating the CAV on dedicated lanes. Lastly, the thesis endeavors to highlight the most influential factors of driving dynamics from a traffic safety perspective. The investigation began with the modelling of various CAV levels using Gipps' model calibration, followed by the simulation of nine mixed fleets of CAV levels on a simulated highway segment. Following that, the Surrogate Safety Assessment Model has been used for vehicle trajectory safety analysis.

According to the findings, gradual penetration of CAV levels resulted in a progressive reduction in traffic conflicts. This reduction ranges from 18.9% when 5% of the vehicles on the traffic flow have high levels of automation (Level 3 and Level 4 vehicles) to 94.1% when all vehicles on the traffic flow are Level 4. Furthermore, human-driven vehicles and vehicles with low levels of automation (Level 1 and Level 2 vehicles) are more frequently involved in conflicts (as potential inductors of risky situations; as follower vehicles) than vehicles with high levels of automation (Level 3 and Level 4 vehicles). In fact, depending on the combination of different types of vehicles in the traffic flow, human-driven vehicles are involved in conflicts from 8% to 122% more than their fleet sharing percentage, whereas vehicles with high automation levels are involved in conflicts from 80% to 18% less than their fleet sharing percentage.

Increasing interaction with CAV on roads reduces the severity of conflicts, especially for vehicles with high levels of automation (Level 3 and Level 4 vehicles). Level 4 vehicles operation result in conflicts with the lowest severity.

Afterwards, in general, in relation to investigating the effect of using a dedication lane during the CAV introduction period, it is found that not using a dedicated lane for a penetration rate up to 55% (Level 3 and Level 4 vehicles) provides better safety outcomes than using a dedicated lane for light traffic condition, whereas, using a dedicated lane is better always in congestion conditions.

Finally, by exploring the influence of driving parameters in calibration on traffic safety, the main key parameters that show significant influence on traffic conflicts are reaction time, clearance, maximum acceleration, normal deceleration, and sensitivity factor. Further, by exploring the influence of the interaction between each two of these key parameters, the results show that, a low maximum acceleration when combined with other parameters' values, always generate the highest number of conflicts, whereas short reaction time combinations always produce the best traffic safety results.

On one hand, this thesis confirms the theory and previous literature conclusions that indicate a safety gain due to CAV penetration. On the other hand, it offers a broader perspective and support for the implementation of CAV levels. Furthermore, this study sheds light on how many potential conflicts could arise as serious conflicts during the transition period from a fully manual vehicle operation scenario to a fully CAV operation scenario. As a result, this thesis broadens both manufacturers' and researchers' perspectives on CAV behaviour for future implementation.

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LIST OF ABBREVIATIONS

Advanced Driver Assistance Systems	ADAS
Application Programming Interface	API
Artificial Intelligence	AI
Automated Vehicle	AV
Average Daily Traffic	ADT
Connected and Autonomous Vehicle	CAV
Connected Vehicle	CV
Co-operative Adaptive Cruise Control	CACC
Deceleration Rate to Avoid the Crash	DRAC
Dedicated Lane	DL
Difference in vehicle Speeds as observed at conflict	DeltaS
Dirección General de Tráfico	DGT
Federal Highway Administration	FHWA
Human-Driven Vehicle	HDV
Level 0 to Level 5 of automation	L0 - L5
Maximum Speed of either vehicle throughout the conflict	MaxS
Modified Time-To-Collision	MTTC
On-bord Unit	OBU
Peak Hour Volume	PHV
Post-Encroachment Time	PET
Rear-end Collision Risk Index	RCRI
Software Development Kit	SDK
Surrogate Safety Assessment Model	SSAM
Surrogate Safety Measure	SSM
Time Exposed Rear-end Crash Risk Index	TERCRI
Time-Exposed-Time-to-collision	TET
Time-Integrated-Time-to-collision	TIT
Time-to-accident	TA
Time-To-Collision	TTC
Traffic Management Center	TMC
Vehicle to Everything connectivity	V2X
Vehicle to Infrastructure connectivity	V2I
Vehicle to Vehicle connectivity	V2V

I INTRODUCTION

CHAPTER I: INTRODUCTION

This chapter presents the introduction to the thesis and the motivation that drives the research. Then, it describes the structure of the thesis. Finally, the main contributions of this thesis are mentioned.

1.1. Problem statement

Connected and Automated Vehicles (CAV) are the developing summit of the integration between artificial intelligence (AI), robotics, automotive design and information technologies. CAV have good potential to be a useful intervention for smart mobility by enabling the car to take control, make decisions and interact with the environment and traffic flow. Autonomous driving includes the control of vehicle motion in both the longitudinal and lateral direction. It is equipping vehicles with Advanced Driver Assistance Systems (ADAS) with higher computational power, improved safety features, and navigation systems.

In terms of potential road safety of CAV, they are supposed to contribute in significant reduction of road accidents (Fagnant & Kockelman, 2015). Since CAV do not make human errors and do not intentionally violate traffic regulations, they are assumed to outperform the human driver and enhance the safety on the road. Sivak & Schoettle (2015) support that the first analysis of accidents with CAV indicates lower accident rates than those of manually human-driven vehicles (HDV). However, some studies express certain reservations about these expectations. ATKINS (2016) indicated that the actual impact of automated driving on road safety is largely unknown.

Meanwhile, road safety experts discussed the prospected risk as an issue to be considered when CAV systems are completely applied. For example, soon after cruise control will be introduced, driving convenience will increase; that will allow drivers to pay less attention to the road, which may increase the number of incidents (ATKINS, 2016) at this level of automation. Nevertheless, with a promising future, CAV may reduce the 94% of all crashes that refer to driver (NHTSA, 2016) (i.e. in the case of fully automation level). The apparent question, what will be the safety state during that change, while different levels of CAV are sharing roads with other users?

Owing to the unfeasibility of obtaining CAV behaviour in fleet as real-data for study at present, most research has turned to CAV simulation. Traffic simulation provides valuable initial insight into the implementation of CAV (Gettman et al., 2008; Wang et al., 2021).

As a consequence of the likely transition period where fully-CAV, partially-CAV, and HDV will be sharing our roads, this research is trying to understand the impact of the gradually entry of CAV on traffic safety by modelling the behaviour of each level of automation using a traffic microsimulation program (Aimsun). Aimsun software provides Internal and External Driver Model Application Programming Interface (API), and an external Software Development Kit (SDK) that are all designed to model vehicle controlling and behaviour in simulation process.

The proposed modelling will be assigned to each vehicle type in different scenarios. It will be also tested in a calibrated motorway model. The corridor-level safety impact of CAV will be finally evaluated using the Surrogate Safety Assessment Model (SSAM). SSAM is a program that utilizes surrogate safety measures in analyzing vehicle trajectories (from microsimulation outputs) to identify and assess potential traffic conflicts (Gettman et al., 2008).

Predominantly, microsimulation has been efficiently used in solving real-traffic problems. It provides an advanced method of analysis, verification, and calibration. In addition, simulation and modelling provides inherent understanding by giving clear insights into complex systems. Several previous studies (El-Hansali et al., 2021; Guériau & Dusparic, 2020; Morando et al., 2018; Papadoulis et al., 2019; Rahman et al., 2019; Sinha et al., 2020; Virdi et al., 2019; Weijermars et al., 2021; Zhang et al., 2020) presented adequate and integrated work to understand the safety impact of CAV with different penetration rates at motorways and intersections using several microsimulation platforms (e.g. VISSIM, Aimsun, SUMO). They also used several surrogate safety measures (SSM) to discuss the traffic safety consequences. Results in these studies showed that CAV improve traffic safety significantly, especially at high penetration rates, although they operate with shorter headways.

However, the results of the mentioned studies are restricted to only quantifying the safety impact while others have recommended going through other evaluation processes of safety performance at the CAV introduction stage. For example, Zheng et al. (2014) and Whang et al. (2021) recommended to provide a traffic conflict technique for severity analysis and to generate global adequate SSM for CAV. Further, other studies more focussed on traffic efficiency (Chen et al., 2017; Hamad and Alozi, 2022; He et al., 2022; Zhong et al., 2020) investigated the possibility of using dedicated lanes for CAV, and they encouraged the modellers to explore its impact from a traffic safety perspective. Afterall, a calling question is floaten regarding the CAV behaviour calibration: which are the driving behaviour parameters that may reflect the highest influence on traffic safety?

This thesis will use a two-stage procedure with Aimsun traffic microsimulation platform. The proper traffic dynamic representation in Aimsun simulation process will end up with better understanding of CAV behaviour and their impact along the transition period from totally manual to fully autonomous driving. In comparison with previous research works, this study will provide for the first time safety results for varying all automation levels penetration rates (not only for one or two levels). It will also introduce certainly reasonable results because of the careful parameters' modelling and the application of wide-range of fleet mixes that could be faced in the real world.

Moreover, in order to reach a further step than previous studies, this thesis presents other aspects of traffic safety regarding the CAV introduction. Precisely, it discusses the severity extent related to the potential conflicts, the safety impact of using a dedicated lane at the introduction stages, as well as it explores the driving parameters that exert a significant influence on traffic safety while converting to the autonomous driving.

1.2. Thesis structure

The thesis is organized into the following seven chapters.

Chapter I includes the introduction to the thesis, giving an overview of the topic and the motivation regarding this investigation represented by a problem statement section. It is followed by a section that describes the thesis structure, and ends with a section that browses the main contributions of this investigation.

Chapter II consists of the state of the art, which presents the sufficient background related to CAV, exhibits the benefits of CAV discussed in the literature, and highlights the results of traffic safety of studies including CAV in their investigation. Finally, as it demonstrates the research questions extracted from the limitations of the previous studies.

Chapter III highlights the general and the specific objectives of the current dissertation, and shows the drawn expected hypotheses after achieveing the objectives.

Chapter IV presents the study area calibrated in the simulation model, and describes in detail the modelling process (modelling the study area, model calibration and validation).

Chapter V describes the methodology followed in detail. Starts with an overview of the methodological approach. Continues demonstrating the details of CAV levels calibration framework. Finally, it illustrates the procedure followed to evaluate traffic safety of CAV levels among various perspectives.

Chapter VI includes the results of safety evaluation from the perspectives studied at this investigation and lays the major findings beside the outcomes found in other studies.

Chapter VII points out the main conclusions stated in this investigation, and highlights the limitations, followed by the suggested future research to address those limitations.

1.3. Main contributions

The main related research activities (see the Appendix) that are generated after the proposed work to address the research questions are classified into four conference papers and three journal articles:

Note: The first two conference papers are considered as a preliminary analysis of CAV introduction by studying the penetration of only one level of automation (the fully automation).

Conference article 1. Miqdady, T., De Oña, R., De Oña, J. (2021). “Quantifying the safety impact of connected and autonomous vehicles in motorways: A simulation-based study”. Procedia 14th CIT, 2021, pp. 2654–2671.

Conference article 2. Miqdady, T., De Oña, R., De Oña, J. (2021). “Estimating traffic conflict severity for Connected and Automated vehicles using simulation-based surrogate safety indicators”. 20th CCHIT, SOCHITRAN, 21/10/2021-93b.

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II STATE OF THE ART

CHAPTER II: STATE OF THE ART

The introduction of the Connected and Autonomous vehicles (CAV) is becoming a reality in the nearest future. Therefore, a huge research effort was directed in the recent years to study their employment and impact on traffic efficiency and safety. This chapter exhibits the background related to the technologies used in this type of vehicles, which result in different levels of CAV. It also demonstrates the theoretical expected behaviour according to the equipped technologies. The projected benefits of CAV among several aspects of transportation are also shown in this chapter.

Later, the chapter illustrates extensively the related investigation about traffic safety in parallel to CAV introduction stages. Firstly, it shows the incorporated safety behaviour regarding commercial CAV deployment studies and the limited traffic safety evaluation studies that used real-world safety data of CAV. Afterword, it shows the related work that tried to evaluate traffic safety in simulation-based studies and surrogate safety measures (SSM). Then, it discusses the calibration of CAV behaviour parameters, the different values used in literature, and the trials in literature to apply a sensitivity analysis of traffic safety regarding these parameters or those which brought out an optimization combination of the safety behaviour parameters. Finally, it presents the research questions arised according to the critical review of the previous studies and which highlights the lack on the topic.

This review will motivate and highlight the novelty of the methodological process proposed in this doctoral thesis, as well as its need to be applied to study traffic safety through the transition period between manual and fully autonomous vehicles, not only the first or the last stages as in other previous studies.

2.1. Automation and connectivity

2.1.1. Technological background

CAV are game-changing vehicles supported by technological advances that have the ability to alter the way people and goods move (CAV Readiness strategy, 2022). There are various quickly growing technological advances applied in a vehicle to call it automated vehicle (AV). These built-in or externally equipped systems are called Advance Driver Assistance Systems (ADAS). ADAS are devices designed to support drivers while they are on the road, such as Adaptive Cruise Control (ACC), intelligent speed adaptation, lane departure warning, traffic sign recognition, collision warning systems, object detection, pedestrian detection, potentially combined with automatic emergency braking. As a more advanced technology, it was important teaching ADAS to grasp driving intention. Thus, a human-machine interface based on neural networks models was recommended to be included in an ADAS design to promote vehicle comfort and safety.

In general, ADAS features can be divided into two categories: comfort features and safety features. The comfort features' main purpose is to alert the driver by causing an alert, such as a flashing light, sound, vibration, or even a light steering suggestion. When a driver fails to react to a potentially dangerous situation, safety features are designed to intervene on the vehicle itself. Potential responses include hood lifting, automatic braking, evasive steering, safety belt preparation, and brake pre-charging. One front stereovision camera is the basic technology for these ADAS features. Sometimes data from other sensors, such as radio detection and ranging (RADAR) or light detection and ranging (LIDAR), is added to the camera data. To keep the glass in front of the camera as spotless as possible, the ADAS camera field of view is situated in the wiper area. Even at night, camera systems in ADAS may project what is behind or alongside the vehicle on the screen. They can also look for automatic lane-departure warning systems and high/low-beam headlamp management in the video content.

Other technology-based devices are the transmitter/receiver technologies. For example, a microcontroller-controlled 77 GHz transmitter in a collision-warning system sends out signals that are reflected off of things in front, behind, and to the sides of the vehicle. Several receivers built into the vehicle then pick up these signals. A single-or dual-core architecture optimized with extensions for image improvement filtering and edge or spot identification receives incoming video frames from an image sensor interface for processing.

A connected vehicle (CV) is equipped with data transmission technologies. CV have several systems that help in driving decisions; a central computer to processing the data with an user interface appeared to the driver, a GPS system as a standard application or an additional device to follow the route, standard or advanced sensors to gather, process and analyse the data transmitted to vehicle, and wireless connection to help the vehicle/driver communicate with other vehicles (V2V), infrastructure (V2I), or with everything (V2X) on the road network. Accordingly, the wireless connection could be short-range transition (Wi-Fi technology) or a long-range transition (Long Term Evolution, LTE) 4G or 5G cellular network.

Technologies for connection and autonomous devices are not necessarily dependent on each other. Nevertheless, integrating these technologies into vehicles enables for a mobility that is safer, faster, and more efficient. This is accomplished by giving machine-driven vehicles the ability to "know" the state of the road network up ahead, to reroute based on fresh information (like a lane closure), and to alert vehicles behind of incidents such as the need to avoid a hazard.

After all, a CAV is a vehicle that has the same data transfer and programming capabilities as CV systems, as well as the ability to make independent driving decisions and act correspondingly. For example, if the driver of a CAV is above the speed limit, the vehicle decides on its own to apply the brakes to ensure the driver's safety. Figure 1 illustrates in a simple way how ADAS technologies help in driving process.

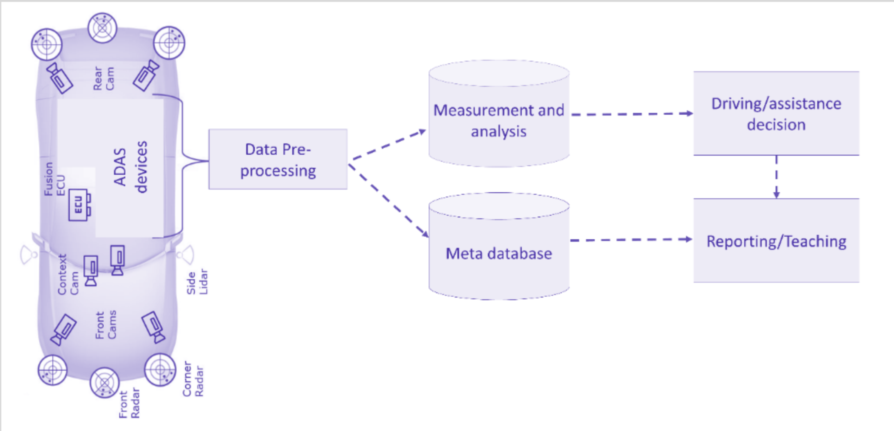


Figure 1: CAV driving process
Adapted from CANape (2022)

The gathered data by the aforementioned ADAS devices (cameras, sensors, and transmitter/receiver) are filtered and classified regarding their quality and type in the first step (data pre-processing) using several data mining techniques. The classified data are then saved in a Meta database describing the nature of the data. An appropriate measurement and analysis tool is used depending on the vehicle type and driving situation. The outputs of data analysis are used to help the driver in decision or take the decision totally in highly automated CAV. Both the Meta data and decision data are used in reporting and machine learning for future similar driving situations.

2.1.2. Levels of automation

Since the late 1950s, when cruise control first began to offer some degree of limited automation in vehicles, the idea of automation in vehicles has been in existence (CAV Readiness strategy, 2022). Partially autonomous vehicles, such as self-parking, improved driver assistance, lane control, and autonomous emergency braking technologies, are now becoming accessible on the market. In the upcoming ten years, higher degrees of automation, where humans will be removed from the driving process, are anticipated to be operated on the road networks. Both academics and business are now making investments in autonomous driving in addition to the incorporation of ADAS features in existing and future vehicles.

According to the Society of Automotive Engineers (SAE, 2014), they classified the autonomous driving into six levels ranging from Level 0 (completely manual) to Level 5 (totally autonomous). Table 1 reflects the automation levels according to (Martínez and Cao, 2019) tasks classification: (1) Steering, acceleration and deceleration; (2) Environment monitoring and (3) Fallback performance of dynamic driving task.

Table 1: SAE classification of the levels of driving automation

Automation level	Denomination	Steering, acceleration and deceleration	Environment monitoring	Fallback performance of dynamic driving task
L0	No automation	Human driver	Human driver	Human driver
L1	Driver assistance	Human driver	Human driver	Human driver
L2	Partial automation	Autonomous system	Human driver	Human driver
L3	Conditional automation	Autonomous System	Autonomous System	Human driver
L4	High automation	Autonomous System	Autonomous System	Autonomous System
L5	Full automation	Autonomous system	Autonomous System	Autonomous System

Adapted from Martínez and Cao (2019)

Conventional vehicles without any driver assistance technology and total reliance on a human driver to handle all aspects of driving were considered to have no automation or Level 0 (Human Driven Vehicles, HDV). Automation Level 1 (L1 vehicles) was defined as a vehicle which allows for specific help in certain instances that either requires steering or acceleration/deceleration, while the majority of the tasks are anticipated to be performed by the human driver. Information about the driving environment provided by particular sensor capabilities fitted for the features' purposes helps with these activities. Automation Level 2 (L2 vehicles) is often defined as partial automation; it allows for simultaneous steering and acceleration/deceleration only in certain circumstances and relies on the driver to do the other driving tasks. According to Martínez and Cao (2019), the first three levels were not technically considered autonomous driving; however Levels 3 (L3 vehicles), 4 (L4 vehicles), and 5 (L5 vehicles) were considered. All dynamic tasks are handled by autonomous driving at Level 3, although the driver is still expected to be able to take back control in emergency situations by making a request to intervention, which is called conditional automation. L4 and L5 vehicles would indeed be high and fully autonomous vehicles, respectively, which in any case do not require driver involvement. Particularly, if the human driver does not step in after the request has been issued, L4 vehicles can resolve issues even without their involvement. Whereas, L5 vehicles can handle all circumstances that human drivers might handle, and intervention is never required. The ability to resolve all driving modes is the primary distinction between L4 and L5 vehicles, though in all instances the vehicle can deal with the situation even without the driver's involvement, which needs a stable environment with a fully (well) learnt machines of all potential driving circumstances.

In parallel, the National Highway Traffic Safety Administration (NHTSA) defined the levels of automation with very close definitions. Table 2 compares the automation levels used by SAE and NHTSA. Even though the initial automation levels are similar, high automation levels are not easily distinguishable between SAE and NHTSA because they implemented a different automation levels. NHTSA classification did not distinguished clearly between the high automation levels (L3 and L4 vehicles), further, the case of fully connected and autonomous vehicle (L5 vehicles) was not clearly addressed as in SAE classification.

Table 2: Levels of driving automation according to SAE and NHTSA

Automated driving system	SAE automation level	NHTSA automation level
No automation	0	0
Driver assistance	1	1
Partial automation	2	2
Conditional automation	3	3
High automation	4	3/4
Full automation	5	

Adapted from Martínez and Cao (2019)

2.1.3. Theoretical background of CAV behaviour

Transport operators are preparing to face the challenge of CAV in the next years. Therefore, CAV prototypes are being tested in numerous large cities across the world. Within the next seven to eight years, predictions state that half of all automobiles will be "totally autonomous" (CAV Readiness strategy, 2022). Practically, several investigations (Ada, 2021; ATKINS, 2016; Beckers, 2020; Fagnant & Kockelman, 2015; Naujoks et al., 2016; Stanek et al., 2018) predicted that CAV will operate with a different behaviour from conventional vehicles. Because planning and managing current and future mobility requires understanding the interactions between fleets of CAV and conventional vehicles, transportation modelling came in to simulate all the thoughts of CAV behaviour and the facing challenges regarding their interactions.

One of the key questions around the introduction of sharing CAV on road networks was how will CAV be programmed to drive? (PTV, 2017) (i.e. focusing on the microscopic behaviour of traffic and the driver-vehicle unit movement and its effect on the traffic outputs). In other words, the ways that new technology, such as improvements in autonomy and connection, might affect how vehicles behave. ATKINS (2016) summarized the answer by three general statements: 1) vehicles' acceleration and deceleration patterns could be modified; 2) following different types of vehicles could cause that some vehicles change their longitudinal behaviour; and 3) when changing lanes, vehicles could display different lateral behaviours.

They also expected that a portion of the upcoming CAV vehicle fleet will be more cautious than the current fleet when user preference, comfort, and safety are taken into account (ATKINS, 2016). Early (i.e. limited penetration) CAV deployments would include a proportionally high percentage of cautious vehicles (ATKINS, 2016; Weijermars et al., 2021). This could have a negative impact on the performance of the network, especially in high-speed, heavily-flow scenarios. However, several studies highlighted the importance of CAV amount of penetration (e.g. ATKINS, 2016; Bierstedt et al, 2014; Stanek et al., 2018). They affirmed that before a significant penetration of CAV (>75%) with advanced technology, the benefits will be marginal. According to Arnaout et al. (2011), the benefits of the behavioural improvement will not be realized until at least 40% of vehicles are equipped.

Concretely, Evanson (2016) analysed thirteen projected behaviour aspects that CAV could perform. CAV could keep smaller standstill distances (clearance), smaller time gaps, accelerate faster and smoother, keep constant speed with no or smaller oscillation at free flow, form platoons of vehicles, following vehicles react on green signal at the same time as the first vehicle in the queue, communicate other vehicles, communicate with the infrastructure, perform more cooperative lane-changing at higher speeds, keep smaller lateral distances to vehicles or objects, operate on exclusive lanes with or without platoons, drive as a CAV on selected roads and as a conventional vehicle on others, and divert vehicles already on the road onto new routes and destinations (e.g. come from a parking to pick up a rideshare app passenger).

ATKINS (2016) established different categories of these potential behaviours of CAV based on driving condition as follows. In free flow driving conditions, whereas the vehicle is almost driving without any effect from other traffic around, CAV is expected to perform with no oscillation around a desired speed even with changing the acceleration and deceleration profiles. In vehicle following driving conditions, CAV will be able to move more quickly, safely, and over shorter gaps than conventional vehicles do now. Whereas, in lane changing condition, CAV may safely manoeuvre between traffic streams at a higher speed and accept narrower gaps in the road to change their lane.

Regarding the merging and joining the traffic stream, they assumed that CAV cooperation makes it possible for competing traffic streams to merge smoothly, more quickly, and with less gaps. Lastly, at planning and decision making (CAV reaction), they confirmed that CAV can provide better data supply, inter-entity communication results, and more efficient judgment and decision-making. However, they (ATKINS, 2016) affirmed that none of these behavioural aspects' are currently understood very well or measured in quantities. Therefore, they recommended to perform a range of scenarios in any attempt to assess the effects of these vehicles with different longitudinal behaviours on traffic output. They recommended also to consider different penetration rates of CAV as well as different CAV capabilities.

Stanek et al. (2018) addressed other perspectives of CAV behaviour among several issues. Firstly, they discussed that CAV is required to obey the local regulations in driving operations. However, they suggested that some driving rules and regulations could be reproduced and updated after CAV introduction. Secondly, they pointed out that CAV could act differently based on network design, geometrical configurations and traffic control operation priorities. For example, to promote their use, CAV could use privileged lanes, signal phasing, or other advantages. After that, compared to HDV, they highlighted that CAV could perform differently in terms of performance capability, such as acceleration, deceleration, turning radius, etc. Lastly, they discussed the "CAV driver behaviour capabilities" which were presented by calibrating the parameters of traffic car-following and lane-changing models regarding the Evanson (2016) recommendations within VISSIM microsimulation traffic models.

In Levitate project -performed on Aimsun microsimulation platform-, in one hand, Papazikou et al. (2020) discussed the expected driving behaviour for cautious driving as the first generation of CAV and for aggressive driving as the second generation of CAV. In the caution's behaviour, CAV always exhibit a safe behaviour, which was translated to longer headways and larger gaps at junctions in the car-following model. When changing lanes, wider anticipation zone and gaps are used. Whereas, enhanced perception and predicted capabilities were seen in aggressive CAV driving. Specifically, shorter spacing at junctions, shorter anticipation when changing lanes, and shorter clearance when following a car were all expected in the aggressive behaviour. Nevertheless, they assumed that cautious CAV driving could be still more aggressive than human driving. On the other hand, Weijermars et al. (2021) pointed out different highlights related to CAV behaviour: 1) in typical driving situations, CAV commit fewer driving errors, obey traffic laws more consistently, react to situations more quickly, and exhibit less variable driving behaviour; and 2) CAV are expected to bring out some additional risks, including the possibility of system failure, issues related with cyber security or hacking, and, in the event that CAV are not yet fully automated, the possibility of control transfer or mode confusion.

2.2. Quantifying the benefits of CAV

As discussed earlier, CAV operations will be different from those of HDV. CAV could be programmed to obey traffic laws. They will not ever drink and drive. Their reaction times will be faster, and they could be optimized to improve fuel economy, smoothen traffic flow, and reduce emissions. They could transport both freight and unlicensed passengers to their destinations. This subsection exhibits some of the most significant potential benefits identified in existing research although the precise extent of these benefits is currently unknown.

Numerous researches have looked into the possibility of CAV reducing congestion in various contexts (Fagnant & Kockelman, 2015). By attempting to reduce accelerations and braking in freeway traffic, different levels of CAV adoption could smooth traffic flow. Depending on V2V communication and how traffic-smoothing algorithms will be applied, this might improve fuel economy and congested vehicles speeds in the freeway travel stream by 23% to 39% and by 8% to 13%, respectively (Atiyeh, 2012).

Berry (2010) calculated that a 20% reduction in accelerations and decelerations could result in a 5% reduction in fuel consumption and related emissions. Smart parking choices made by CAV could result in further fuel savings and prevent cruising for parking (Bullis, 2011). For instance, in-vehicle technologies might interface with parking infrastructure to enable driverless drop-offs and pickups.

The system's fuel and congestion savings would grow if vehicles could move closer to one another, and a considerable boost in highway capacity on existing lanes is expected (Tientrakool, 2011). According to Shladover et al. (2012), cooperative adaptive cruise control (CACC) adopted at market penetration rates of 10%, 50%, and 90% will enhance lanes' effective capacity by approximately 1%, 21%, and 80%, respectively. More consistent trip times are generated combined with nearly constant velocity, which is a crucial consideration in trip planning, timing, and route considerations. Similar to this, lower start-up durations at traffic signals will allow for more CAV to exploit the green phase of the signal more efficiently, which greatly increases intersection capacity (Shladover et al., 2012).

Long-term applications of CAV's potent capabilities include new paradigms for signal control, like autonomous intersection management. There is some evidence that suggested cutting-edge technology might almost completely eliminate junction delays, but this idea is still purely theoretical and is still a long way off (Fagnant & Kockelman, 2015). Dresner and Stone (2008) predicted that it may take several years before such technologies are deployed since a 95% or higher CAV-market penetration may be necessary. Although CAV may boost road capacity with greater market penetration, the induced demand brought on by increased car use might need an extra capacity (Bose and Ioannou, 2003).

Furthermore, it was addressed that the effect of CAV on reducing traffic congestion could have the potential to significantly alter travel behaviour. For example, elderly drivers were observed to make an effort to manage driving difficulties by avoiding congested roads, unfamiliar routes, driving at night, and bad weather; while others give up driving completely (Wood, 2002). CAV could promote individual independence mobility while overcoming several types of driving difficulties of different passengers (elderly, minors, and disabled), which also might impact the growing of travel demand (Fagnant & Kockelman, 2015).

Due to more trips being taken, it was predicted that already-congested traffic patterns and other road infrastructure would worsen. Fagnant & Kockelman (2015) suggested that to mitigate growing demand, CAV might, however, offer smarter routing in combined with intelligent infrastructure, faster reaction times, and closer spacing between cars. In addition, they explained that the final outcome of the road congestion will depend on the amount of vehicle-miles travelled realized, the relative size of CAV advantages, and the application of demand control techniques, like road user fees and pricing.

Moreover, they discussed that technologies might expand CAV sharing and dynamic ride sharing by enabling real-time rentals of the near shared CAV on a per-minute or per-mile basis. According to the preliminary results of Fagnant & Kockelman (2015) (utilizing an agent-based model for allocating vehicles around a region), a single shared CAV is supposed to replace between nine and thirteen privately owned or household-owned vehicles.

The literature also addressed that the transport of freight will be affected also. For instance, the KPMG and CAR (2012) reported that Rio Tinto, a mining operator, employed 150 autonomous ore trucks and intends to increase that number more and more. They mentioned also that the trucking industry may utilize the same technology that applies to autonomous cars to improve fuel efficiency and reduce the need for truck drivers even for long-distance trips. However, they reported that workers would still need to load and unload freight. Aside from improved travel times on higher capacity networks, they pointed out that tight platoons can also result in higher fuel savings because of the reduced air resistance and enabling adaptive braking of shared slipstreams.

Regarding the platooning choices and the spacing between trucks, according to Bullis (2011), four-meter inter-truck spacing was found to bring out lower fuel consumption by 10 to 15 percent. A trial run with 10-meter headways between numerous trucks was successfully demonstrated by Kunze et al. (2009) on German highways, and various autonomously platooned spacing, Volvo vehicles travelled with good conditions 10,000 km along Spanish routes (Newcomb, 2012). In contrast, tight vehicle spacing was found to generate difficulties for other drivers to exit or enter highways, stimulating the construction of new or upgraded infrastructure with reserved platoon lanes and thicker pavements to handle heavy truck traffic (Fagnant & Kockelman, 2015).

Lastly, it has been highlighted in the literature that CAV are supposed to improve traffic safety on the roads. The number of crashes involving CAV could be reduced dramatically. Over 90% of crashes are considered to be caused primarily by driver errors (NHTSA, 2016). Moreover, alcohol, distraction, drug use, and/or exhaustion are concurrent factors in more than 40% of fatal crashes (NHTSA, 2016). Additional human variables, such as inattention, distraction, or speeding, are frequently identified to have contributed to the crash probability and/or injury severity, even when the primary cause of a crash is attributed to the vehicle, infrastructure, or environment. Therefore, machine-driving cars could be immune to human error, potentially resulting in a reduction of the total potential crashes by more than 90% and of fatal crash rate of at least 40%.

2.3. CAV and traffic safety

Because traffic safety of CAV is the primary objective benefit that is investigated in this thesis, a detailed literature review is demonstrated in a specific subsection. As declared before, CAV technologies have the potential to reduce the number of collisions in the road (NHTSA, 2016). Over the past ten years, research has begun focusing on the influence of CAV on traffic safety. Researchers used a variety of techniques to determine the extent of CAV effect on traffic safety, including studying historical crash data and working with open-source real CAV datasets, as well as using simulation and modelling techniques.

The initial strategy involved attempting to eliminate the impact of human error either by re-analysing historical collision data without the presence of human error factors (Fagnant & Kockelman, 2015) or by presuming that autonomous driving on roads will provide similar safety benefits to those seen in rail or aircraft driving environments (Hayes, 2011; Karjanto et al., 2017). After determining the preliminary degree of the safety advantages using these simplified techniques, the focus was shifted to CAV modelling and simulation in order to gain a more thorough understanding.

According to the RAND Corporation's report (Blumenthal et al., 2020), they classified safety evaluation into three categories: evaluating safety in process (traffic safety optimization), safety measurement (performance), and safety threshold. The first category was presented by CAV trajectory optimization and modelling; to optimize the movements of CAV during merging and crossing manoeuvre safely and the safe space between vehicles using distance and time gap constrains (e.g. Ding et al., 2020; Liu et al., 2020; H. Xu et al., 2019; X. Xu et al., 2018; Zhou et al., 2020).

The second category (Figueiredo et al., 2009; Pereira & Rossetti, 2012; Talebpour & Mahmassani, 2016; Ye & Yamamoto, 2018) was directed to measuring the safety performance of CAV on the road by investigating either: 1) real-world CAV data, obtained from the preliminary pilot CAV deployment, which is limited because there is a very small amount of data which are publicly accessible; or 2) simulation methods that concentrate on CAV simulation in calibrated traffic models regarding the technology advances of CAV, within microsimulation platforms, and then utilizing surrogate safety evaluation approaches and traffic operation dynamics to assess traffic safety.

The third category of CAV safety evaluation was supposed to discuss the change in surrogate safety measures thresholds that should be applied in safety evaluation of CAV (Rahman et al., 2019; Sinha et al., 2020).

Accordingly, several research works aimed to evaluate one or more of these categories in investigating the impact of CAV behaviour on traffic safety.

2.3.1. CAV's safety in process and real-world performance

Substantially, Reed (2020) underlined that studying the safety aspects of CAV in process (behaviour) is the guide to evaluate the other two CAV safety categories (CAV safety performance and thresholds). Thus, the focus was directed to this stage by manufacturers and policy makers.

Regarding the manufacturer's projects, as example, BSI (2021) aimed to provide confidence for CAV trials by developing an acceptable safety case by optimizing a definition of the safe operational design using collected data from CAV trials. They offered a lot of useful details on how CAV trialling organizations should behave to guarantee safety performance, with resonance over how same guiding principles might apply in CAV when they are widely deployed. Nevertheless, they were not able with their trial data to develop standards for CAV safety benchmarking.

In nVidia (2019) the researchers gave a thorough mathematical explanation of how autonomous vehicles could function in a dynamic environment without running into any other static or dynamics objects by mapping the road users and environment perception to the control restrictions. However, it made no attempt to define or ascertain how specific environmental characteristics or the behaviour of other objects might affect the driven vehicle. For instance, a CAV passing a motionless pedestrian at a certain distance would exhibit the same behaviour whatever the vehicle driving speed.

On the other side, Waymo (2020) is widely regarded as the industry leader in CAV operations on public roads. Their safety framework explained how they create, test, and deploy CAV in the real world using a variety of methodologies to incorporate safety into their hardware (to be effective, secure, and robust), behaviour (to be safe and responsible), and operations (which are safely deployed and operated). CAV driving behaviour decisions were evaluated based on "hazard analysis" and "scenario-based verification". Precisely, they incorporated collision avoidance testing on both closed track trials and simulation of millions of miles examined using the high-quality human driving as a base standard. In addition, they included analysis of situations where a human driver took over to determine whether autonomous system would have reacted appropriately.

Nevertheless, they did not show details about how they chose the acceptable driving behaviours that their CAV adopt inside their operational design domains. This may come with according this information as being commercially confidential.

Other projects which aimed to develop CAV traffic safety benchmarks commercially are also acknowledged in this work (e.g. Automated Vehicle Safety Consortium, Connected Places Catapult and Roadcraft).

Additionally, some studies used real-world data to evaluate traffic safety involving CAV on roads. For example, Sinha et al. (2021) conducted a detailed safety analysis using data from the California Department of Motor Vehicles, USA (2014-2019). The reported data were used to create a number of crash models that focused on injuries for all crash types. Machine learning classification techniques were applied to better comprehend the severity of CAV crashes. However, the factors that contributed to the severity of a CAV crash were not clearly characterized due to a lack of information on crashes involving CAV.

Similar methods were utilized by Chen et al. (2020) who showed that Xtreme gradient boosting, a decision tree classification model, outperformed all other investigated classifiers in identifying injuries that occur in CAV crashes. According to their research, the severity of a crash dramatically increased if two automated vehicles collide at an intersection or do so in bad weather conditions (such as snow or fog). Furthermore, areas with a variety of land use patterns have a higher risk of injury-causing crashes. Multiple land uses (such as residential, commercial, and public) lead to a variety of traffic behaviour and modifications in regional traffic flow, which showed a significant impact on traffic safety.

2.3.2. Safety evaluation using simulation-based surrogate safety measures

Although it sounds that the real-world data evaluation strategy might be the most effective one, the concern is how reliable it is, given that CAV deployment is still in its early stages and that CAV has only been tested in very few circumstances. Therefore, until now the main methodology used to investigate the effects of CAV has been by modelling a virtual environment of CAV to answer the operational questions. Simulation platforms provided several advantages which enable the investigation of such complex environments: they permit to test specific technologies by running a software and hardware in the loop (PTV, 2017); they are flexible and qualified enough to quickly take on and evaluate countless fleet scenarios (Wang et al., 2021); and, they even enable the identification of the acceptable CAV accompanying-configurations for deployment. As a result, simulation platforms provide a forum for roundtable discussions among vehicle manufacturers, technology suppliers, infrastructure designers, and transportation operators (PTV, 2017).

Some researchers have simulated CAV using multi-level simulation platforms or a customized simulation framework (e.g. Figueiredo et al., 2009; Pereira & Rossetti, 2012; Talebpour & Mahmassani, 2016; Ye & Yamamoto, 2018). However, the outcomes of these unique models are less sound and more challenging to compare (Li et al., 2013; Papadoulis et al., 2019). As an alternative, additional research (El-hansali et al., 2021; Genders & Razavi, 2016; Morando et al., 2018; Papadoulis et al., 2019; Rahman, 2019; Sinha et al., 2020; Virdi et al., 2019; Weijermars et al., 2021; Xie et al., 2019; Zhang et al., 2020) used traffic microsimulation software and its extensions. Owing to its viability and benefit of operating various future scenarios in a short amount of time, this method has become the most popular.

A summary of previous research that used simulation to gauge the effect of CAV on traffic safety is presented in Table 3. The table includes the following details: the simulation software platform, the calibrated network, the type of vehicle taken into consideration, penetration rates used during the simulation, thresholds for surrogate safety measures used to spot potential conflicts, safety evaluation indicators, and finally the levels of CAV examined.

In traffic safety studies, various microsimulation platforms were used to model CAV. Along with its Wiedemann 99 internal model calibration, the VISSIM interface was commonly used with various external car-following algorithms (e.g. Intelligent Driver Model, Newell's car-following model). Several studies, however, used other platforms (e.g. Aimsun, PARAMICS, SMART, SUMO). Aimsun's internal interface algorithms (both car-following and lane-change Gipps' models) and well-structured external interfaces to model connectivity (V2X extension, the External Agent Interface) have recently added more capability to CAV modelling. Yet, all of the mentioned platforms are suitable for CAV simulation. See Gettman et al. (2008) for more information and discussion about some comparisons connected to these platforms.

CAV traffic safety has been tested in a variety of networks and vehicle types. While many studies focused on freeways, two-lane highways, or intersections (e.g. roundabouts, signalized, unsignalized) (e.g. El-Hansali et al., 2021; Papadoulis et al., 2019; Sinha et al., 2020; Virdi et al., 2019; Zhang et al., 2020), others studied urban arterials and intersections (e.g. Guériau & Dusparic, 2020; M. S. Rahman et al., 2019). However, the results of traffic safety were comparable (i.e. high penetration rates of CAV enhance traffic safety).

Table 3: Summary of previous simulation-based studies for CAV effect on traffic safety

Reference	Simulation platform	Studied network	Vehicle type	Penetration rates	SSM thresholds	Evaluation indicators	Level of CAV
Genders & Razavi (2016)	PARAMICS	Network with work zone	PC	0,20,40,60,80,100	1.5s TTC	Conflict frequency	L2
Morando et al. (2018)	PTV-VISSIM	Signalized intersection, roundabout	PC, HV(5%)	0,25,50,75,100	1.5s TTC (HDV-HDV, AV-HDV) 1.0s 0.75s TTC (AV-AV) 5.0s PET	Conflict frequency, Involved vehicles	L4 (2 models)
Ye & Yamamoto (2019)	Costumized modelling	2-lane road (10 km)	PC	0,25,50,75,100	-	Distripution of TTC, acceleration, and velocity difference	L2
Papadoulis et al. (2019)	PTV-VISSIM	3-lane motorway (44.27 km)	PC	0,25,50,75,100	1.5s TTC 5.0s PET	Conflict frequency, Involved vehicles	L4
Rahman et al. (2019)	PTV-VISSIM	Arterial (61.15 km)	PC, HV (%real data)	30,40,60,80,100 (CV and L2 tested apartly)	1.5s TTC 5.0s PET	Conflict frequency, Severity (TET, TIT, TERCRI, LCC, and NCJ)	L1, L2
Xie et al. (2019)	SMARTS	Freeway, CBD, Campus	PC	0,20,40,60,80,100	1.5s TTC	Conflict frequency (sensitivity analysis)	L1,L2,L3,L4
Virdi et al. (2019)	PTV-VISSIM	Urban intersections	PC	0,10,20,…,90,100	1.5s TTC (?-HDV)* 0.5s TTC (?-CAV) 5.0s PET (?-HDV) 1.65s PET (?-CAV)	Conflict frequency, Involved vehicles	L4
Zhang et al. (2020)	PTV-VISSIM	4-lane freeway (7km)	PC, HV (0%-30%)	0,10,20,30	2.0s TTC	Severity (TET, TIT, TERCRI, and LCC)	L4
Guériau & Dusparic (2020)	SUMO	Motorway (7 km), National (5.3 km), Urban (3x3 km)	PC, HV (%real data)	0,2.5,7,20,40,70 (mix of L2 & L4)	1.5s TTC (?-HDV) 0.75s TTC (?-CAV) 5.0s PET (motorway & national) 0.75s PET (urban)	Conflict frequency, Involved vehicles	L2, L4
Sinha et al. (2020)	PTV-VISSIM	2-lane motorway	PC	0,10,20,…,90,100	1.5s TTC 5.0s PET (?-HDV only)	Crash rate (if PET=0), Severity (TTC, PET, Delta S)	L4
El-hansali et al. (2021)	PTV-VISSIM	6-lane freeway	PC	100	1.5s TTC 5.0s PET	Conflict frequency, Severity (MaxS, MaxD, MaxDeltaV)	L4
Sharma et al. (2021)	Costumized modelling	-	PC	Mixed fleet of CV levels	-	MTTC, DRAC	L2
Weijermars et al. (2021)	Aimsun	3 tested Networks	PC, HV	Mixed fleet	1.5s TTC (?-HDV) 1.0s (1st generation) 0.5s (2nd generation) 5.0s PET	Crash frequency	L4 (2 driving styles)

Where; PC: passenger car, HV: heavy vehicle, HDV:human driven vehicle, CAV: connected and automated
TTC: time-to-collision, PET: post encroachment time, TET: time-exposed-time-to-collision, TIT: time-integrated-time-to-collision, TERCRI: time exposed rear-end crash risk index, LCC: lane changing conflict, NCJ: number of critical jerks, DeltaS: difference in vehicle speeds as observed at tMinTTC, MaxS: maximum speed of either vehicle throughout the conflict, MaxD: maximum deceleration of the follower vehicle, MaxDeltaV: maximum DeltaV value of either vehicle in the conflict, MTTC: modified time-to-collision, DRAC: lower deceleration rate to avoid accident.
**(?-HDV) means the follower vehicle is HDV whatever the first vehicle*
(?-CAV) means the follower vehicle is CAV whatever the first vehicle
Adapted from Miqdady et al. (2023)

Similarly, some studies simulated only passenger cars, whereas others included a percentage of heavy vehicles in their simulated traffic flow to simulate more real traffic flow conditions (Guériau and Dusparic, 2020; Morando et al., 2018; Rahman et al., 2019; Weijermars et al., 2021; Zhang et al., 2020).

Simulating the pattern of CAV introduction is critical for reflecting the implementation process. Although most studies represented the introduction by increasing L2 or L4 vehicle penetration rates, Guériau and Dusparic (2020), Sharma, et al. (2021), and Weijermars et al. (2021) proposed a mixed fleet that included vehicles with varying levels of automation in the same scenario.

2.3.2.1. Surrogate safety measures (SSM) used in safety evaluation and thresholds

The frequency of crashes, crash rate, and crash severity are direct indicators of traffic safety performance. However, crashes data are not always statistically sufficient for studies. Traffic conflicts, on the other hand, are more frequent events. Traffic conflicts are observable non-crash incidents where there is a risk of accident due to interactions between various road users in space and time if these users do not alter their trajectories of movement (Amundsen and Hyden, 1977). Indeed, a conflict is considered to be connected to a crash, when a failure (e.g. human operator failure, road failure, or vehicle failure) that leads to the conflict cannot be properly corrected (Davis et al., 2011; Tarko, 2020). Therefore, several researchers (e.g. Laureshyn et al., 2010; Wu et al., 2018) derived and improved several Surrogate Safety Measures (SSM) from traffic conflicts and validated them by field data (i.e. motion tracking from recorded videos and sensors utilizing human observers or by computer vision) to be used as safety indicators instead of crashes frequency and severity.

Regarding simulation-based studies focusing on traffic safety, SSM were the only available criteria attached to this types of studies (Wang et al., 2021). According to previous studies (Gettman and Head, 2003; Huang et al., 2013; Ozbay et al., 2008; Zheng et al., 2019), simulated SSM were significantly compatible with field-observed SSM if the simulation models were properly calibrated. This demonstrates the validity and reliability of SSM based on traffic simulation. Further, in the case of CAV, where it is unfeasible to collect field data for mixed fleet scenarios, traffic simulation-based-SSM is the only criterion available to conduct traffic safety studies.

In other words, because researchers frequently used SSM to better understand the safety implications of new traffic designs and alternative safety solutions, determining the safety effects of CAV and their interactions with HDV was considered as a relevant application of SSM. Moreover, SSM are employed to get several attributes of traffic safety; the number of conflicts as well as the conflicts' severity by time-based, deceleration-based, and energy based indicators. By studying traffic trajectories and extracting the values of SSM, the Federal Highway Administration's (FHWA) Surrogate Safety Assessment Model

(SSAM) tool or other specially designed tools were frequently used in safety evaluation (Wang et al., 2021).

The following are some of the SSM used in safety evaluation in simulation-based studies:

Time-based SSM gauge the closeness interaction relation to how close it is to a collision in time. Time-to-collision (TTC), the most popular time-based SSM (Wang et al., 2021), was described as "the amount of time that is left before a crash between two vehicles would have occurred assuming the crash route and speed difference are maintained" (Hayward, 1972). Time-to-accident (TA), also a popular time-based SSM, was first presented by Perkins and Harris (1967). When the evasive action is first noted by a field observer, TA is computed using the estimated distance and speed. The primary distinction between TTC and TA is that TTC is estimated based on the observed evasive behaviour, whilst TA is measured at the start of the conflict occurrence. In order to establish if a conflict is high risk or not, it was suggested that both indicators use specific thresholds (Gettman et al., 2008).

Another time-based SSM often used in simulation-based studies is the Post Encroachment Time (PET). PET is the minimum time between when the first vehicle last occupied a position and the time when the second vehicle subsequently arrived to the same position (Gettman et al., 2008). A value of zero indicates a collision.

Several more intricate SSM were created based on TTC. Time-Integrated TTC (TIT) and Time-Exposed TTC (TET) were proposed by Minderhoud and Bovy (2001). TIT is the area between the TTC curve and the threshold level when the curve deviates below the threshold. TET is the period of time during a conflict when the TTC is below a specific threshold value. TET and TIT, as opposed to TTC and TA, concentrate on quantifying the risk connected to the length of time under hazardous driving conditions. TTC must be continuously calculated to derive TET and TIT.

Deceleration-based SSM, on the other hand, were supposed to concentrate on how vehicle deceleration can prevent crashes rather than measuring time proximity. For example, Cooper and Ferguson (1976) suggested DRAC (Deceleration Rate to Avoid the Crash) to gauge the severity of an interaction. It was defined exactly as the minimal braking rate necessary for a vehicle to avoid colliding with another one. It is calculated under the presumption that one vehicle makes evasive manoeuvres while the other keeps moving in the same direction and at the same speed. For DRAC, certain thresholds are also necessary in order to calculate the severity of a collision.

According to Oh et al. (2006), who assumed the lead vehicle executes an emergency braking manoeuvre with the maximum deceleration rate, the Rear-end Collision Risk Index (RCRI) was developed to identify hazardous conditions by comparing the stopping distance between the lead and trailing vehicles. Based on RCRI, the Time Exposed Rear-end Crash Risk Index (TERCRI) was proposed to measure the aggregated risk over time (Rahman and Abdel-Aty, 2018), which is only applicable for longitudinal car following cases. MaxS and DeltaS are also deceleration based SSM which were used to analyse the simulation-based studies (Wang et al., 2021). MaxS was defined as the Maximum Speed of either vehicle throughout the conflict (i.e. while the TTC is less than the specified threshold). Whereas, DeltaS was defined as the magnitude of the difference in vehicle velocities (Gettman et al., 2008).

Energy-based SSM added a new dimension to the definition of severity: the consequences of the risk brought on by an interaction (conflict). According to the theory, strong kinematic forces caused by vehicle interactions have a significant negative impact on road user's safety and almost certainly cause serious injuries and fatalities (Shelby, 2011). Researchers have shown high confidence in this type of indicators for predicting crash severity over the years. In order to anticipate injuries and fatalities, DeltaV was employed in Carlson's (1979) attempt to construct models for assessing the likelihood of injuries or fatalities in a crash based on factors like the velocity of the impact and vehicles masses. DeltaV is the change in pre-collision and post-collision velocities (Gettman et al., 2008). Later, Evan (1994) fitted a number of conflict-related injury and fatality prediction models using DeltaV. However, the creation of new equations was not significantly pursued because this indicator was not employed for traffic conflict analysis until its recent introduction into SSAM (Shelby, 2011). As a result, the traditional Evan's models (Evan, 1994) continued to be applied.

In CAV's traffic safety studies, time-based and deceleration-based SSM have been mainly used. In contrast, energy-based SSM were not used before in this context (Wang et al., 2021). The most popular SSM in CAV's traffic safety context is TTC (Rahman et al., 2018, 2019; Tiblja˘s et al., 2018; Li et al., 2018; Virdi et al., 2019; Morando et al., 2018; Papadoulis et al., 2019). TET and TIT have also been frequently used (e.g. Li et al., 2017; Rahman et al., 2019; Zhang et al., 2020). TA has also been implemented (Wu et al., 2018). The distributions of hard braking (Zhong et al., 2021), RCRI (Li et al., 2018; Rahman and Aty, 2018; Rahman et al., 2019), sideswipe crash risk (i.e. the number of lane-changing conflicts) (Rahman and Aty, 2018), and TERCRI are all applications of deceleration-based SSM (Rahman and Aty, 2018). Other safety indicators, such as standard deviation of speed (Rahman and Aty, 2018; Fu et al., 2019), MaxS (Tibljas et al., 2018), and DeltaS (El-Hansali et al., 2021; Sinha et al., 2021; Tibljas et al., 2018) have also been used to evaluate CAV safety effects.

In SSAM, TTC and PET thresholds were designed to serve as the starting point for determining risky interactions and the resulting SSM. SSAM's default values are 1.50 s and 5.00 s, respectively. Evidently, a sufficient threshold must be defined to distinguish between serious and non-serious conflicts. The determination of this value is an ongoing issue involving CAV conflicts that must be resolved. Those values, however, were assigned in SSAM with HDV crash validation. According to Table 3, some researchers used the default values after performing a sensitivity analysis with several values (Papadoulis et al., 2019; Zhang et al., 2020). Others, on the other hand, argue that it is critical to change the default TTC value when dealing with CAV due to their faster reaction times and shorter headways. Morando et al. (2018) tested the resulting conflicts of CAV vehicle penetration using three TTC thresholds: 1.50 s for any conflict involving HDV, and the other two lower values (1.00 s and 0.75 s) for CAV-CAV interactions that showed statistically significant differences. Furthermore, Guériau and Dusparic (2020) used the value 0.75 s for CAV conflicts, whereas Virdi et al. (2019) used a value equal to 0.50 s.

2.3.1.2. Safety evaluation regarding CAV levels

Among the research work that investigated the traffic safety of CAV, various levels of automation were calibrated. Table 3 shows that, in general, a large portion of previous studies focused only on the effect of high level of automation (L4 vehicles penetration) (e.g. El-Hansali et al., 2021; Morando et al., 2018; Papadoulis et al., 2019; Sinha et al., 2020b; Virdi et al., 2019; Weijermars et al., 2021; Zhang et al., 2020), as this is the most anticipated stage. Even though, many studies were conducted to deal with only low levels of automation and connectivity (L1 and L2 vehicles) (i.e. vehicles with one or two advanced systems) (Genders & Razavi, 2016; Rahman et al., 2019; Sharma et al., 2021) in order to reflect the near future traffic safety expectations.

In particular, Genders and Razavi (2016) analysed L2 vehicles with connectivity between vehicles (Vehicle-to-Vehicle, V2V), according to those who looked into the safety impact of L1 and/or L2 vehicles. Thereafter, they examined three behavioural models with various penetration rates while considering varying levels of driver compliance (high, moderate, and low compliance). Viably, they discovered that the level of driver compliance of the data collected by V2V at work zones is correlated to traffic safety: moderate and low levels of driver compliance are correlated with significant traffic safety drawbacks, whereas a high level of driver compliance of interaction with V2V-received data was correlated to good results in traffic safety. Additionally, this study revealed that while high penetration rates increase network safety, L2 vehicles penetration rates below 40% contributed to more traffic conflicts. As well, they recommended to analyse the impact of platoon spatial arrangement to assess the safety of mix fleets of HDV and L2 vehicles with high/low compliance drivers of the connected data.

Sharma et al. (2021) used their model also to evaluate traffic safety generated by L2 vehicles introduction under different levels of compliance and various platoons' arrangements. First, after looking into homogenous scenarios (scenarios with only one type of behaviour), they discovered that platoons of L2 vehicles with high compliant drivers achieve a higher level of safety than platoons of L2 vehicles with low compliant drivers (higher modified time-to-collision (MTTC) and lower deceleration rate to avoid accident (DRAC)). Yet, L2 platoons with low compliant drivers still showed more safety advantages than HDV. In contrast, for heterogeneous scenarios, it was noted that vehicle placement within a platoon—rather than penetration rate—was the crucial element in obtaining the safety gains. The ideal vehicle configuration for a platoon was for a L2 vehicle with poor compliance to follow a L2 vehicle with high compliance, with HDV in between.

Rahman et al. (2019) used evasive action indicators (e.g. number of critical jerks and time exposed rear-end crash risk index) along with TTC-derived measures (e.g. TET and TIT) to estimate the severity of traffic conflicts when L1 and L2 vehicles enter a traffic stream. The findings showed that when CAV penetration rates exceeded 60%, the intensity of conflicts at arterial segments and intersections was significantly reduced.

Papadoulis et al. (2019) assessed a highway safety outcome on road segments by introducing L4 vehicles that were calibrated by an external VISSIM interface and examined by the quantity of conflicts. For different days of the week, the number of conflicts showed reductions of 12–47%, 50–80%, 82–92%, and 90–94% for 25%, 50%, 75%, and 100% CAV penetration rates, respectively.

El-Hansali et al. (2021) compared the traffic safety of HDV against L4 vehicles on a 6-lane motorway segment that was operated entirely by either of these two vehicle types (i.e. 100% HDV vs. 100% L4 vehicles). Only 8.6% fewer problems between autonomous and conventional traffic were found as a result of their study. They exhibited also the results of SSM (e.g. maximum speed of either vehicle throughout the conflict (MaxS) and maximum deceleration of the follower vehicle (MaxD)) for these two fleets. Their results showed higher MaxS and MaxD for L4 vehicles than those for HDV. However, they do not necessarily reflect reality.

Sinha et al. (2020)'s case study was to evaluate the severity of the introduction of L4 vehicles. They looked at the traffic flow efficiency, prospective conflicts, and predicted probable crash rates which estimated based on the resulted potential conflicts. Overall, the findings showed that CAV-HDV interaction is safer than HDV-HDV interaction.

Zhang et al. (2020) proposed a special study focused on road segment's configuration. They looked into the safety of L4 vehicles using exclusive lanes with various penetration rates. They emphasized how establishing even one exclusive lane would increase safety by reducing unsafe situations during both longitudinal and lateral movements. They also emphasized that creating two separate lanes is more suited for situations with heavy demand.

Other researchers examined L4 traffic safety at intersections. For instance, the reduction in conflicts caused by L4 vehicles in Morando et al. (2018) was predicted to range from 20% to 65% for signalized intersections and from 29% to 64% for roundabouts with penetration rates between 50% and 100%, respectively. Additionally, according to Virdi et al. (2019), L4 vehicles advantages will be felt at large penetration rates (especially for signalized and diverging diamond intersections). Conflict reductions were anticipated to be 48%, 100%, 98%, and 81% for the signalized, priority, roundabout, and diverging diamond intersections, respectively, assuming 90% of L4 vehicles penetration rate.

However, L4 vehicles will not be driving immediately; instead, they will be sharing the road with vehicles with lower levels of automation. More scenarios with lower levels should be examined in order to show more realism. In this aspect, only few earlier investigations simultaneously modelled multiple CAV levels.

For example, Xie et al. (2019) used SMARTS to conduct a sensitivity analysis of the effect of four levels of automation (L1, L2, L3 and L4 vehicles) on traffic safety using various parameters (e.g. maximum acceleration/deceleration, space/time headway, reaction time, etc.), traffic flow (1000, 3000, and 5000 vehicles per hour), and different areas (e.g. urban area, interurban freeway). They discovered that while an increase in automation level would improve traffic efficiency, it might also increase the likelihood of conflicts at low penetration rates of CAV. However, there were a number of points that could be connected to that conclusion: they considered the same TTC threshold for HDV and vehicles of any level of automation, despite the fact that CAV present higher capabilities; they considered scenarios that were not very realistic (such as penetration rates of 100% for L1 or L2 vehicles), that the drivers will not see during the transition to CAV; and finally, they did not consider the effect of connectivity that may lead to more adapting and harmony between vehicles and indeed improve traffic safety.

Guériau and Dusparic (2020) attempted to combine mixed fleets of HDV with more than one level of CAV (L2 and L4 vehicles). They carried out a thorough study that calibrated real traffic demand (with light and heavy trucks) in a variety of networks (motorway, national, and urban). Additionally, they used two kinds of connectivity (Vehicle-to-Vehicle, V2V, and Vehicle-to-Infrastructure, V2I). According to their research, low CAV penetration rates negatively impacted traffic safety and raised conflicts by 30% when compared to a human-driven scenario, but high CAV penetration improved safety by reducing conflicts by 50% to 80%. They underlined that traffic congestion contributes more in potential conflicts than the penetration rates of L2 and L4 vehicles. So, they highlighted the importance of assessing traffic efficiency and safety at the same time.

On the other hand, Weijermars et al. (2021) used traffic data calibrated from three city networks and eight mixed fleets to mimic two driving styles of CAV (i.e. cautious, forceful). However, the primary omission in the last two studies (Guériau and Dusparic, 2020; Weijermars et al., 2021) is that CAV driving behaviours were not illustrated or covered in the findings. They only exhibited the total decrease of conflicts by CAV as one unit instead of demonstrating them by vehicle type (i.e. the role of each vehicle type: HDV, cautious CAV, and aggressive CAV in the conflicts).

In reality, CAV will be implemented throughout a phase of transition with a variety of mixed fleets and levels. Consequently, it is crucial to discuss these two issues simultaneously by highlighting the safety implications of increasing the penetration rates of CAV levels across scenarios, as well as by addressing how each level participates in both the total number of resulting conflicts as involved vehicles and their role as a fault vehicle in any potential conflicts or crashes.

2.3.3. Dedicated lane configurations for CAV

The impending arrival of CAV emphasizes the necessity of preparing the road network for traffic that includes both CAV and HDV. One of the feasible and probable approaches to improve the road infrastructure for mixed traffic is to designate a dedicated lane (DL) for CAV and test various configurations that could maximise traffic efficiency and safety.

Accordingly, several studies have started to test this option recently. Among two-lane segment, Chen et al. (2017) tested the impact of three configurations of DL on the capacity of the road at different penetration rates of CAV: zero DL, one DL mandatory for HDV, and one DL mandatory for CAV. Their results showed that zero DL, in general, generated better capacity. As well, traffic volumes on the road beside the penetration rate of CAV are critical factors in giving back the benefit of DL. Mohajerpoor and Ramezani (2019) tested the impact on traffic delay also at different penetration rates of CAV. They applied four DL configurations: zero DL, one DL mandatory for HDV, one DL optional for CAV, and one DL mandatory for CAV. Their findings were summarised as follows. Zero DL performed better than DL across the entire transition period to CAV. The optimum strategy to use a DL was: below 50% CAV penetration rate on the road, it is better to use a DL for HDV; between 50 and 65% CAV penetration rate, a DL for both CAV and HDV (optional DL) is appropiate; and finally above 65% CAV, it is better using a DL for CAV.

On the other hand, the majority of studies tested the DL configurations on more than two-lane highways. For instance, two consecutive studies (Zhong et al., 2020; Zhong and Lee, 2019) examined the impact of one DL and two DLs for CAV on road capacity and performance at different CAV penetration rates on a four-lane highway. Their research determined that when CAV penetration rate was 40% or higher, road capacity and performance were better with both one or two DLs.

Hamad and Alozi (2022), on five-lane highway, applied various percentages of DLs at each penetration rate of CAV to get the optimum capacity. Afterwards, these optimum percentages of DLs were tested at different traffic volumes. Their results demonstrated that zero DL performed better at light traffic volumes, whereas using DLs improved the performance at congested traffic conditions. Specifically, delay and throughputs were decreased with DLs if the penetration of CAV was above 30%, while the emissions (gCO_2) started to decrease at 40% CAV.

He et al. (2022) studied the impact of zero DL, one DL for CAV (optional and mandatory), and two DLs for CAV (optional and mandatory) configurations at two-, three-, and four-lane highways on both capacity and throughputs at different CAV levels and penetration rates. By operating L3 to L5 vehicles on the DLs, they found that if the penetration rate of CAV is below 50%, the implementation of DLs for CAV does not have a significant positive impact on traffic efficiency. In such case, if a DL policy was chosen, the “mandatory use” was recommended compared with the “optional use”. However, the “optional use” of DLs is recommended when CAVpenetration rate is above 80%.

Regarding the safety impact of DLs, Zhang et al. (2020) tested the zero, one, and two DLs configurations for CAV on a four-lane highway. They evaluated the longitudinal and lateral traffic safety at different CAV penetration rates (0%-30%) and percentage of trucks. Two major findings were highlighted from this study: (1) one DL was capable to improve traffic safety at light traffic volumes, yet two DLs were needed for congestion conditions; and (2) low penetration rates CAV’s scenarios had adverse effect on longitudinal safety.

2.3.4. Parameters values used in CAV calibration

Platforms for traffic simulation provide a useful approach to assess various circumstances and fleets including CAV. The literature has used a range of traffic microsimulation platforms with various traffic flow models, including Aimsun, VISSIM, PARAMICS, SUMO, etc. Previous findings agreed in that CAV may improve traffic safety, particularly in situations where there is a high penetration rate of this vehicle type. However, based on their projections of CAV future behaviour, each study employed different calibration parameters and values. Whereas, in order to get effective simulation results, it is always necessary to take into account the dynamic as well as the stochastic nature of traffic simulation models and the calibration factors inherent to these models (Schultz and Rilett, 2004).

To increase traffic safety knowledge and to obtain a robust calibration of the models, some researchers attempted to optimize the dynamics of CAV when examining the system behaviour. In fact, the ability to accurately and effectively describe the interaction that occurs between drivers, vehicles, and the environment is essential for both operational and planning applications. However, due to improved computer power, recent years have shown an increasing trend toward model-based optimization strategies for trajectory planning and vehicle control (Nolte et al., 2020).

For instance, in order to overcome the difficulty of figuring out how to calibrate the car-following sensitivity parameter in CORSIM microscopic traffic simulation model, Schultz and Rilett (2004) attempted to utilize the computer capabilities. In order to enter the car-following model, they used a genetic algorithm to compare the values of eleven sensitivity parameters (as various types of drivers) across several distributions (e.g.

lognormal distribution and normal distribution). Their findings highlighted genetic algorithms' capacity to calibrate sensitivity parameter distributions; also, the mean absolute error between observed and simulated traffic volume and journey data was minimized within the two studied distributions.

Batsch et al. (2021) tested CAV in a scenario-based environment using the Gaussian Process. They used a number of vehicle simulation situations and developed probabilistic (Gaussian) prediction models to gauge the outcomes of the scenarios. They demonstrated that the Gaussian Process could accurately predict the results. A sensitivity analysis of the optimized data, taking into account two scenarios (a pedestrian crossing the road in front of the ego car and a traffic jam approach), revealed that the geometric layout of the scenario and the combinations of the road users' speeds had the greatest impact on the outcome of the scenario. They also found that changes in the sensor's parameters had a less significant impact.

Xie et al. (2019) is the most pertinent to the current investigation. They looked at the relationship between automation levels, traffic efficiency (travel time), and road safety (traffic conflicts) by adjusting their chosen criteria, such as maximum acceleration, maximum deceleration, clearance, minimum headway, aggressiveness factor, reaction time, etc. They have demonstrated that raising the level of automation might enhance traffic efficiency but may also increase the likelihood of vehicle conflicts, which should not be disregarded if human-drivers are still required to participate in the driving process.

In fact, without a thorough grasp of the parameters that dominate a model at particular operations, the adoption of model-based algorithms in this field may be unfeasible (Nolte et al., 2020). The main parameters for CAV calibration are highlighted in the following paragraphs, along with discussions of the suggested values in the literature.

CAV parameters could be divided into three categories: technology advancement parameters (e.g. reaction time, gaps for follower and leader), longitudinal movement parameters (e.g. acceleration, deceleration, speed oscillation, platoon size), and lateral movement parameters (e.g. lateral clearance, look ahead distance, and overtaking speed). Typically, each study used three to five parameters to calibrate the CAV’s behaviour. The most widely used parameters are those related to the longitudinal behaviour, showing their sensitivity to change traffic efficiency and safety.

According to the three discussed categories in the previous paragraph, nine examination parameters were noted to be significant in literature, either as the most frequently used in CAV calibration or less frequently utilized yet crucial from a safety standpoint. All the studied parameters are depicted in Figure 2. This figure also displays the ranges of values used in the literature to calibrate these parameters.

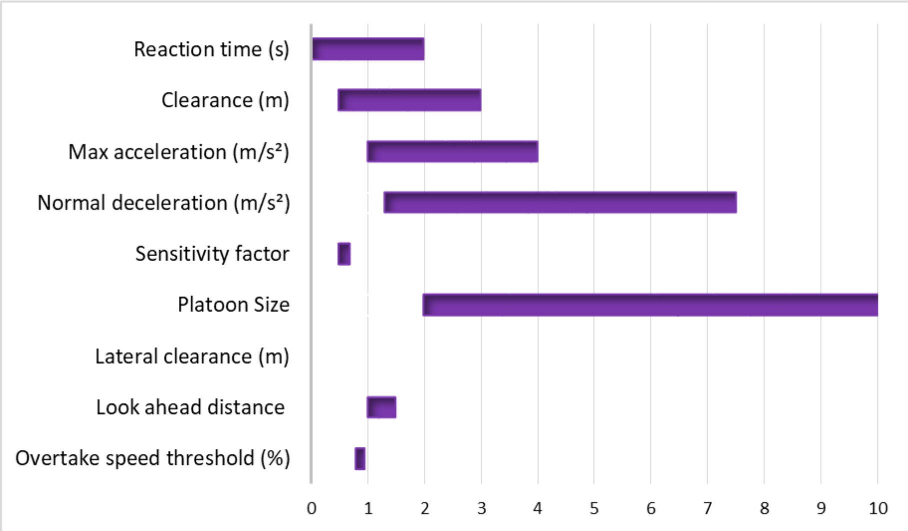


Figure 2: Parameters values used in CAV calibration

One of the most frequently suggested technological advancements in autonomous driving is the reaction time (the amount of time it takes a vehicle to react to the vehicle in front of it) (ATKINS, 2016; Stanek et al., 2018; Weijermars et al., 2021). Previously, reaction time was regarded as a global characteristic (parameter) in the simulation platforms' API that could not be altered throughout the experiment. As a result, this parameter was rarely calibrated. However, when simulating CAV with external driver model extension with VISSIM platform, Zhang et al. (2020) assumed a value of 0.5 s. Aimsun, in their most recent editions, focused on CAV modelling and developed extensions to model its behaviour (Aimsun, 2020). Consequently, studies that used Aimsun changed the reaction time directly in the internal model depending on their assumptions. Specifically, they predicted that the CAV could respond in 0.1 s (Mesionis et al., 2020; Weijermars et al., 2021). Different values were considered in a sensitivity analysis performed by Xie et al. (2019) (2.0, 1.5, 1.0, 0.5, 0.0 s for different CAV levels from L0 to L4, consecutively).

Another crucial parameter for safety consideration is the distance between two vehicles when they are at a standstill (Stanek et al., 2018), often known as the minimum standstill spacing headway, minimal gap, or clearance. CAV are generally expected to maintain closer spacing than HDV (ATKINS, 2016; Stanek et al., 2018). In studies that employed VISSIM platform to simulate CAV, Stanek et al. (2018) and Sinha et al. (2018) used 1.2 and 0.5 m, respectively, as alternatives to the default value (1.5 m) in VISSIM model for HDV. The clearance values indicated by Morando et al. (2018), who employed two models (ATKIN, PTV), were 0.5 and 0.75 m. According to Guériau et al. (2016), calibrating the SUMO model, the clearance for HDV was 2.5 m on average, compared to 1.5 m for L2 vehicles and 1.0 m for L4 vehicles. For various levels of automation, 1.0, 1.5, 2.0, 2.5, and 3.0 m were proposed by Xie et al. (2019) (for L4 to L0 vehicles consecutively).

Maximum acceleration is considered as the most common and controversial measure used in CAV calibration. Some studies (Guériau and Dusparic, 2020; Weijermars et al., 2021; Zhang et al., 2020) proposed lower values for CAV than for HDV, but others proposed greater values (ATKINS, 2016; Sinha et al., 2020; Xie et al., 2019). In addition, other studies continued to use the same values for both CAV and HDV (e.g. Makridis et al., 2018; Stanek et al., 2018; Zhong et al., 2021). On the one hand, Karjanto et al. (2016) argued that the correspondent value ought to be correlated with the chosen driving style. They claimed that an aggressive driving style recommended a greater value than human driving, and a cautious driving style should be represented by low values that may reach the value of a light rail transit (1 m/s^2). Guériau and Dusparic (2020), on the other hand, proposed that maximum acceleration will decrease with the amount of automation; they proposed values of 2.5, 1.5, and 1.0 m/s^2 for L0, L2, and L4 vehicles, respectively. As opposed to Xie et al. (2019), that asserted that this value should rise from L0 to L4 vehicles from 1.4, 1.6, 1.8, 2.0, to 2.2 m/s^2, consecutively.

Another parameter taken into account in CAV traffic safety research is speed oscillation. However, this parameter presents a strong correlation with acceleration, which causes that one parameter reflects the other.

The same pattern of assumptions is related to the anticipated deceleration of CAV. In particular, normal deceleration has been presented within a wide range of values in literature: between 1.3 and 7.5 m/s^2 (Figure 2). While Guériau and Dusparic (2020) and Stanek et al. (2018) did not suggested any differences between human behaviour and autonomous behaviour, ATKINS (2016) predicted an increase in deceleration for autonomous vehicles. The value for CAV, according to Zhang et al. (2020), was assumed to be lower than for human drivers.

Regarding the maximum deceleration, it was believed to remain constant between human and autonomous driving in various studies (e.g. ATKINS, 2016; Guériau and Dusparic, 2020; Mesionis et al., 2020; Papadoulis et al., 2019; Stanek et al., 2018; Weijermars et al., 2021; Zhang et al., 2020). They argued that it should not be impacted by technology because it is the vehicle's capacity, which is an extreme value applied in both types of vehicles with the same magnitude (Stanek et al., 2018).

Another useful indication for assessing traffic safety is the effect of overestimating or underestimating the leading vehicle deceleration (i.e. the sensitivity factor). A value below 1.0 denotes an underestimate situation, whereas a value above 1.0 denotes an overestimation of the leader's deceleration by the vehicle. Only one study that calibrated CAV using the Aimsun platform attempted to alter this parameter in the Levitate project (Papazikou et al., 2020). Two values were proposed: 0.7 for cautious driving and 0.5 for aggressive driving. They made the assumption that even while driving cautiously, CAV are perceived as being more aggressive than HDV from a safety perspective.

The maximum number of vehicles that can belong to a platoon (also known as platoon size) was also tested in relation to traffic safety (Aramrattana et al., 2021; Faber et al., 2020). Aramrattana et al. (2021) considered 2, 3, 4, and 5 vehicles in their research, while Faber et al. (2020) considered 5, 7, and 10 vehicles. They found that more vehicles in a platoon generated more braking actions, worsening traffic safety in general.

Regarding vehicle's lateral movement, Stanek et al. (2018) talked about how CAV should do more cooperative lane changes given that lane changes may happen at a higher speed. Additionally, it can be occurred at shorter lateral clearance. However, the simulation-based studies on this topic did not sufficiently study lateral movement. Delpiano (2021) recommended a study of the lateral dimension according to CAV behaviour.

Aimsun (2020) demonstrated the feasibility of calibrating these parameters in their traffic model. Indeed, the effect of modifying the distance zones used in the lane-changing model and looking-ahead distances was analysed. To adjust where lane changes start to be considered; regarding CAV behaviour, a factor of minimum and maximum look ahead distances is defined. For instance, if the look-ahead distance is defined as 200 m, the minimum look-ahead factor is 0.9, and the maximum look-ahead factor is 1.2, then the perception of the distance will range from 180 m (calculated as 0.9 × 200) to 240 m (calculated as 1.2 × 200). All vehicles selected distances in the range of 180–240 m using a uniform random distribution. The values are given as a range in the Aimsun model to randomise the behaviour (Aimsun, 2020). Different values were assumed in the Aimsun calibration of CAV studies (1.25, 1.5 (Mesionis et al., 2020), 1–1.25, and 1.1–1.3 (Papazikou et al., 2020)). Because CAV are projected to perform with high cooperation during lane-changing, the values in both studies are higher than the human driving range for both cautious and aggressive driving styles.

Other parameter that was calibrated in Aimsun's lateral movement model is the speed threshold that prevents an overtaking (overtaking speed threshold). The vehicle will attempt to pass the leading vehicle whenever it is moving more slowly than the overtaking speed threshold (%) of its intended speed. Previous studies using Aimsun platform (Mesionis et al., 2020; Papazikou et al., 2020) revealed lower values for both cautious and aggressive driving (80% and 85%, respectively), than the human driving value (90%).

2.4. Research questions

After reviewing the literature presented in the previous sections, and as an outgrowth of the international attention to the feasibility of connected and autonomous vehicles (CAV) as new mobility on our roads in the following years, regarding traffic safety, the following research questions have been extracted:

(1) The majority of the research studies that conducted a safety evaluation of the introduction of CAV mainly considered one definition and calibration of the autonomous vehicle (i.e. one level of automation, either the near future definition (L2 vehicles) or the furthest definition (L4 vehicles)) and mixing them with the human-driven vehicles (HDV) with various penetration rates. However, studying the safety related to sharing the road of different levels of automation and connectivity might reflect better the real effect of CAV introduction. In addition, the involving of CAV levels in traffic safety events needs more understanding and analysis.

> The actual calibration of one or two levels of automation that are supposed to share the road with HDV resulted in improvement of traffic safety.
>
> **RQ1** – Will the calibration of all levels of CAV in various mixed fleets scenarios representing CAV introduction can reflect different traffic safety impact than previous studies calibrating just one or two levels of automation?

(2) The majority of traffic safety evaluation studies for CAV introduction used few surrogate safety indicators to quantify the traffic safety events (i.e. conflicts or the time under risk). A thorough investigation of the safety dimensions (e.g. proximity, consequences, and level of severity) could help to indicate and assess another dimension of safety (severity) regarding CAV introduction.

> The actual safety evaluation depends on safety-event quantification using limited surrogate safety measures.
>
> **RQ2** – Could the employment of different safety measures reflect more understanding of the safety dimensions regarding CAV introduction?

(3) There is in literature a wide talk about the possibility of using dedicated lanes for CAV introduction. However, the existing research works sought to study their impact on traffic efficiency and, therefore, there is a lack of studying the safety impact of this choice.

The actual evaluation of using dedicated lanes for CAV introduction is oriented to traffic efficiency.

RQ3 – How will the employment of dedicated lanes for CAV introduction affect traffic safety?

(4) The CAV behaviour in traffic flow (in both car following and lane-change) was calibrated in the literature using stochastic modelling (within simulation tools). Moreover, different sets of parameters were utilized and several values were assumed for those parameters in calibrating the CAV behaviour in literature. A stop-and-investigate step is needed to rationalise the effect of changing these parameters on traffic safety and to identify the key parameters untill we will obtain real data of CAV behaviour.

The actual simulation of CAV is conducted by assumption of different parameters of traffic behaviour.

RQ4 – How will the change of the values of traffic behaviour parameters affect traffic safety? What are the key traffic parameters that affect traffic safety?

III RESEARCH OBJECTIVES AND HYPPOTHESES

CHAPTER III: RESEARCH OBJECTIVES AND HYPOTHESES

Because of the research questions discussed previously and according to the state of the art displayed in Chapter 2, the general and the specific objectives of this investigation are identified in this chapter.

3.1. General objective

The potential of the capability of CAV is continually growing with a particular emphasis on technological performance and much associated work centred on traffic safety. Indeed, as in any other developed design, engineering process (phases) requires the auditing (evaluation-planning) at each phase. In CAV case, the actual phase is the pre-implementation phase, thus, traffic pre-safety-evaluation research is conducted worldwide to audit this phase shown in **Error! Reference source not found.** . Therefore, the general objective of this doctoral thesis is to investigate the likely traffic safety among the transition period between human-driving and autonomous driving. As a necessary planning step to start addressing the new problems that CAV can raise, and perhaps even to help stakeholders and policemakers to introduce some changes in design and policies in the meantime to achieve safe enough roads with the introduction of CAV.

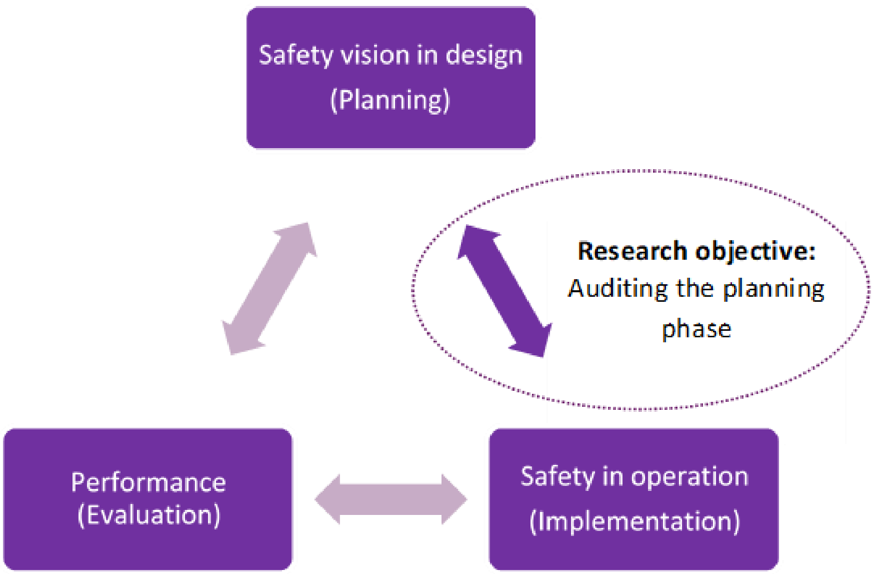


Figure 3: The general objective of the thesis

The goal is to quantify the potential safety impact of CAV comprehensively; regarding: the levels of automation, establishing safety indicators, the infrastructure configuration, and finally the behaviour calibration until we have real-data of CAV behaviour.The thesis also allows to understand where we are in research from real evaluation of CAV's impact by putting in hand the compatibility sides and the missing sides to assess CAV behaviour and impact.

3.2. Specific objectives

According to the general objective and the identified research questions, the specific objectives of this thesis are summarised out as follows:

Linked to RQ1:

- To calibrate the behaviour of CAV levels in a simulation model.
- To quantify the traffic safety impact of CAV penetration among some possible real-world introduction scenarios.
- To estimate the involvement of CAV levels in traffic conflicts and their likely responsibilities.

Linked to RQ1 and RQ2:

- To estimate the traffic conflict severity among the different scenarios based on some severity dimensions (proximity, consequences, and proximity/consequences) and a traffic conflict technique concerning CAV levels.

Linked to RQ1 and RQ3

- To estimate the traffic safety impact of using a dedicated lane for CAV introduction, allowing to set an optimal strategy of deploying a dedicated lane.

Linked to RQ4

- To explore the sensitivity of traffic safety to changes in the parameters that define the CAV behaviour (CAV calibration parameters), and to identify which are the key parameters affecting traffic safety.

3.3. Research hypotheses

Related to the previous research objectives, we adopt seven main hypotheses, which are to be tested using the methodological approaches set out in this thesis.

Hypothesis 1: calibrating all the CAV levels will generate wider knowledge about the safety impact of CAV introduction.

Hypothesis 2: the increase in the penetration rate of CAV in general will enhance traffic safety.

Hypothesis 3: HDV and vehicles with low level of automation will be more involved in conflicts than vehicles with high level of automation at mixed traffic fleets.

Hypothesis 4: the penetration of low levels of automation will provide no significant improvement in traffic safety, while high automation levels will do.

Hypothesis 5: increasing the level of automation and its penetration in the traffic stream will generate less serious conflicts.

Hypothesis 6: roads configured with dedicated lanes will satisfy good traffic safety results at high CAV's penetration rates.

Hypothesis 7: reaction time and car following parameters are key parameters in enhancing traffic safety on roads.

IV STUDY AREA

CHAPTER IV: STUDY AREA

This chapter provides a corresponding background for the study area chosen for modelling and analysis work in this thesis, then presents the modelling criteria used to set the study area into the microsimulation process.

4.1. Description of the study area

This section provides a brief description of the analysed motorway segment; the road geometry and traffic data collected by the general directorate of traffic (Dirección General de Tráfico, DGT).

4.1.1. An overview

The selected segment for our investigation (shown in Figure 4) is an urban motorway segment of Granada (Spain). This segment corresponds to part of the GR-30 highway, and it has 20.27 km of length (PK-111 to PK-132). The GR-30, also known as the “Circunvalación de Granada” or “Variante Interior de Granada”, encircles Granada from the west as well as many municipalities in the first belt of Granada city. It consists of the A-44's initial ring road, which was opened in 1990. The original portion closest to the city was given the new name GR-30 with the launching of the second ring road (“Segunda Circunvalación de Granada”) in 2020, which was constructed to solve the congestion problem in the first ring), which was heavily utilized according to its importance as one of the major routes in Spain, with 120,000 to 150,000 cars passing through each day, 5% of which are heavy vehicles (The Granada Independent, 2016).

In fact, the GR-30 includes the two main entry points to Granada city, providing a strategic alignment and access to its most important locations (i.e. city centre, hospitals, schools, university, etc.). Moreover, the segment includes sixteen ramp junction (entry/exit) points.

Figure 4: Study area (GR-30) illustration
Wikipedia (GR-30, 2022)

4.1.2. Road characteristics

GR-30 is a combination-type (i.e. of elevated and ground-level) highway, mostly accessed by straight ramps with acceleration/deceleration lanes or it is connected with weaving segments of two successive entrance and exit. The GR-30 provides north- and southbound routes, and it consists of several link types; of two-, three-, and four-lane two-way. However, the selected segment is three-lanes two-way (i.e. six-lane divided highway). The details of the roadway cross section are obtained from the Dirección General de Tráfico (DGT) as shown in Figure 5. The cross section of the road segment consists of three lanes at each direction, lane width of 3.0 m, paved left shoulders width equals to 2.2 m, and a median part. The median part which meters in total 5.0 m, contains the right shoulders of each direction (right shoulder width of 1.0 m) and a rised dick median.

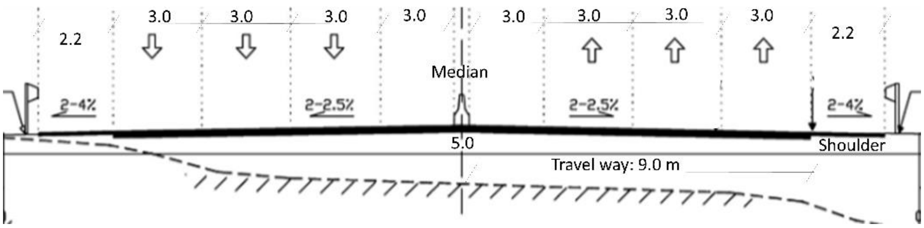


Figure 5: Cross section of the GR-30 (m)

4.1.3. Traffic volume characteristics

As explained in the overview of the current section, GR-30 is an important highway in Spain and especially in the south of the country. This section provides some traffic information regarding GR-30 highway. Firstly, it presents a summary of traffic volume data for the highway segment, afterwards, it provides time-based distribution charts that describe the hourly and daily variations in traffic volumes.

The data collected by DGT of traffic volume at 10 continuous count stations were used to extract the mentioned characteristics. DGT data were taken in February of 2020. Before analysis, a check of the minimum number of count stations needed was applied following the student's t-distribution criteria (Garber and Hoel, 2014) for a 95% level of accuracy for the representative data. In our case, the 10 stations were enough, given thatthe mean of traffic volumes achieved the 95% at 8.06 stations.

The collected data during the specified time period, in groups of 15 minutes intervals, were analysed and the main traffic characteristics are summarized in Table 4. The average of 24-hour counts that collected over the 29 days of February of 2020 (Average Daily Traffic, ADT) was 85,191 veh/day. In addition, maximum number of vehicles that pass the highway during 60 consecutive minutes (Peak Hour Volume, PHV) was 8.409 veh/hr. Whereas, over the count period (29 days), traffic sensors at count stations provided a vehicle classification in two-types: 87.55% of the passed vehicles recorded as passenger cars and 12.45% recorded as heavy vehicles in general.

Table 4: Summary of Traffic Volume Data for GR-30 segment

ADT (veh/day)	85191
PHV (veh/h)	8409
Vehicle classification (%)	
Passenger car	87.55
Heavy vehicles	12.45

As well, traffic counts at the segment show that traffic volume varies from hour to hour and from day to day. Hourly and daily traffic variations during the collection time period is shown in Figure 6 and Figure 7. Traffic volumes in the figures are related to the first week of the collection period (1-7 February 2020), which are collected at an average link (section) of traffic characteristics.

A closer look to Figure 6 (the hourly variations) reflects that there is limited traffic between 1:00-6:00 am. The rush hours related to weekdays generally lies between three time periods: morning peak (7:30-9:30 am), noon peak (13:00-15:00 pm for Monday, Thursday and Friday, and 14:00-16:00 pm for Tuesday and Wednesday), and evening peak (18:00-20:00 pm). It can be indicated that the peaks are mostly caused by work trips according to the variation of peak hours in weekend days, where the morning peaks moves to be at late morning that is connected with noon peak. Likewise, the evening peak moves to be between 19:30-21:30 pm.

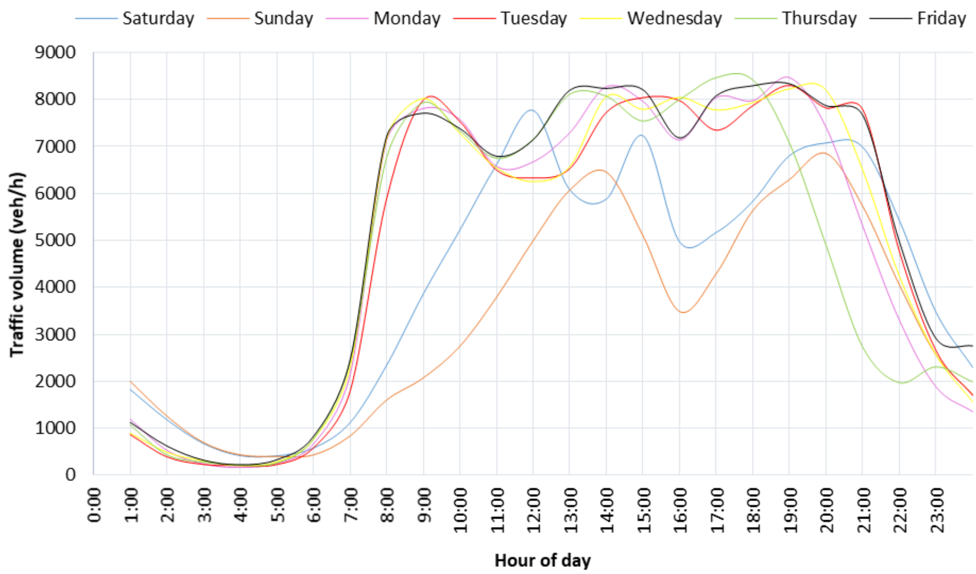


Figure 6: Hourly traffic volume variation on the GR-30 segment by day

Figure 7 shows that traffic volumes on Tuesday, Wednesday, and Thursday are similar, whereas a peak was observed on Monday and Friday. This suggests that when short counts are being considered for further analysis, it is helpful to schedule the collection of weekday counts for Tuesday, Wednesday, or Thursday, and, if required, to schedule the collection of weekend counts, it is better to do it separately for Friday and Saturday.

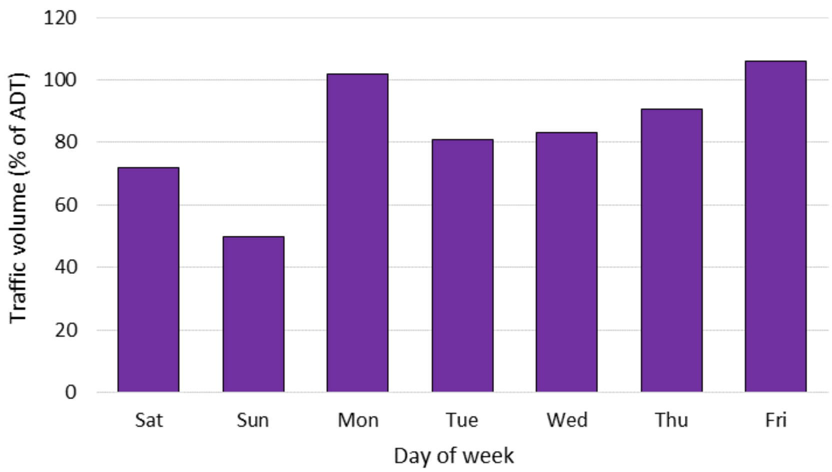


Figure 7: Daily traffic variation on the GR-30 segment

4.2. Modelling the study area

Following the traffic modelling guidelines provided by the Roads and Maritime Services (2013) for applying a microsimulation model, three steps are mandatory to obtain a useful and stable model (i.e. to achieve models that can provide accurate outputs that minimise risk in the forecasting process). As shown in Figure 8, the microsimulation modelling process starts by defining a study area to be built in the simulation platform. Afterwards, the network and traffic demand are calibrated. Finally, the operations on the calibrated model are validated by observed operations of the real network.

Figure 8: Microsimulation modeling phases

Regarding the microsimulation platform selected to apply this process in our research work, practically, we meant to select a platform that could highly serve in the calibration of CAV behaviour. Basically, we were able to get the following observation from a critical look at various microsimulation platforms utilized to calibrate both longitudinal and lateral movements (Pereira and Rossetti, 2012): Aimsun has enhanced their most recent editions (Aimsun next 8.4.3 to 20) to offer more specialized tools to calibrate CAV behaviour as a vehicle type, despite the fact that PTV-VISSIM has long been a popular choice for this kind of analysis. In addition, Aimsun is regarded as user-friendly platform, and it has various developed external API extensions to accurately depict the CAV, including the connectivity (V2X extension). Furthermore, drawing tools and an imported Open Street Map are used in the Aimsun platform to generate the segment's geometry details with substantial level of accuracy. Therefore, Aimsun next 20 API is considered as an appropriate platform for our microsimulation work.

4.2.1. Modelling phase

To build a model (a study area) with a sufficient complexity that could be compatible with our objectives (Roads and Maritime Services, 2013), a case study of 20.27 km segment of the GR-30 motorway, displayed in Figure 9, is modelled in Aimsun platform.

An Open Street Map was imported in the platform to be utilized in creating the geometry as well as the detailing of the segment (i.e. curves of the road segment, lane width, the length of sections, and merging and diverging areas) using various drawing tools provided by the platform and overlapping the sections created with the imported map. Many types of intersections belong to this property. However, only the links are considered and the intersections were modelled as access points.

In addition, as mentioned previously, 10 detectors were used for data collection along this segment, installed by the Dirección General de Tráfico (DGT); six on the northbound route and four on the southbound one. The placement of the detectors along the real motorway segment was established also in the model using Aimsun tools for getting the modelled traffic counts later.

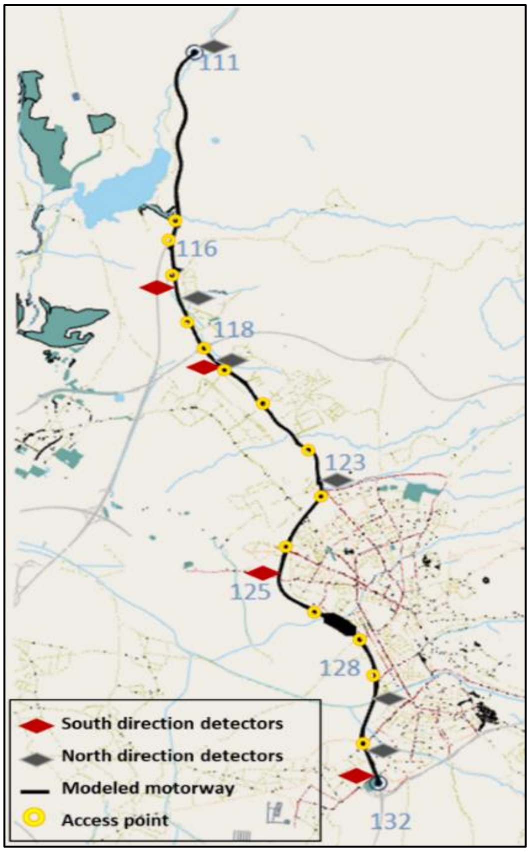


Figure 9: Modelled study area (GR-30 motorway section)
Adapted from Miqdady et al. (2023a)

4.2.2. Model calibration

Based on Roads and Maritime Services (2013) modelling guidelines, model calibration is splitted into three steps: network verification, demand calibration, and route choice calibration. After the verification of the details of the modelled network (including number of lanes, lane widths, slopes and the basic geometry), data collected from different detectors throughout the segment by DGT on a weekday – Tuesday, 11 February 2020 (10:00-11:00 am as off-peak hour, and 7:45-8:45 am as peak hour) – were used to calibrate the traffic demand and connections in term of turns and route choice. The speed limit, the average instantaneous speed of vehicles traversing the section during intervals of 15 minutes, the amount of traffic per lane (veh/hr/ln), and the distribution of traffic were all included in the DGT data (for passenger cars and heavy vehicles) (see Table 5) and used for data calibration.

Table 5: Descriptive observed traffic data on the segment

	Off-peak	Peak
Speed limit (Km/hr)	80, 90, 100, and 120	80, 90, 100, and 120
Average instantaneous speed (Km/hr)	83 to 118	39 to 98
Volume (veh/hr)	547-3570 pc/hr, 89-499 hv/hr	869-5556 pc/hr, 58-621 pc/hr

Accordingly, the data from detectors were calibrated as traffic states of volumes with distribution of movements and route choice at the access points to achieve the actual traffic demand collected at detectors. Regarding the behaviour calibration, this step used the default behavioural parameters' values recommended in Aimsun (2020) for both passenger cars and heavy vehicles (trucks).

The preparation for simulation was also handled after calibration process, according to previous studies (e.g. Papazikou et al., 2020; Morando et al., 2018; Papadoulis et al., 2019). The calibrated demand in this work was simulated for one hour with 0.1 s time steps, and an 18 minute warming-up period, calculated in accordance with Wunderlich et al. (2019), taking into account the length of the freeway segment and the average speeds within the segment. Shahdah et al. (2015) define the statistically sufficient number of simulations runs (N) to reach a 90% confidence interval level as (Eq. 1):

$$N = \left(\frac{t_{(1-\alpha/2),N-1} * \sigma}{E}\right)^2 \tag{1}$$

Where σ equals the sample standard deviation of the simulation output, *t* is the student's t-statistic for two-sided error of a α/2 with *N−1* degree of freedom and *E* equals the allowed error range, where $E=\varepsilon*\mu$; μ is the mean of the number of simulated conflicts based on the initial set of simulations runs and ε is the allowable error specified as a fraction of the mean. Accordingly, it was found that 15 runs of simulation are statistically sufficient for further analysis.

4.2.3. Model validation

Model validation refers to the independent verification process that is used to prove that a model has been calibrated sufficiently to accurately reproduce on-street circumstances. Particularly, it is necessary to deliver a statistical comparison of model performance to observed operations. The decision to accept or reject a model depends on their verification of the guidelines criteria (Roads and Maritime Services, 2013).

Applying the criteria of the modelling guidelines of the Roads and Maritime Services (2013), four measures were checked:

(1) the Geoffrey E. Havers (GEH) statistic function (see Eq. 2), which measures traffic volume deviation between the modelled and the on-street networks, where 85% and 100% of traffic volumes should render GEH statistics of less than 5 and 10, respectively,

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

Where M is the hourly traffic volume from a link or a point of the modelled network, and C is the real-world hourly traffic.

GEH volumes during the one-hour simulation period at 15-min intervals are shown in Table 6 for each traffic count location. Results in Table 6 satisfy both conditions, which suggests that the modeled network adequately reflects the real network and it is ready to perform the microsimulation.

Table 6: Traffic 15 minutes volume validation using GEH statistic

Northbound direction						
Detector	Observed (veh/15minutes)		Modelled (veh/15minutes)		**GEH**	
	PC	HV	PC	HV	**PC**	**HV**
PK-131	577 - 671	21 - 37	494 - 552	19 - 36	**3.59 – 5.42**	**0.17 – 0.86**
PK-129	872 - 941	59 - 68	834 - 890	54 - 62	**0.03 – 1.69**	**0.67 – 1.00**
PK-123	566 - 675	17 - 29	523 - 606	18 - 31	**0.53 – 2.73**	**0.22 – 0.37**
PK-119	250 - 285	21 - 29	195 - 261	19 - 28	**1.09 – 4.49**	**0.40 – 0.80**
PK-117	164 - 212	18 - 27	165 - 209	17 - 27	**0.07 – 0.22**	**0.00 – 0.39**
PK-111	117 - 151	18 - 28	112 - 159	15 - 30	**0.47 – 0.79**	**0.20 – 0.74**
Southbound direction						
Detector	Observed (veh/15minutes)		Modelled (veh/15minutes)		**GEH**	
	PC	HV	PC	HV	**PC**	**HV**
PK-117	176 - 231	20 - 28	168 – 227	21 - 29	**0.26 – 0.77**	**0.19 – 0.58**
PK-119	339 - 386	26 - 32	326 – 390	26 - 30	**0.11 – 0.71**	**0.19 – 0.57**
PK-125	759 - 874	112 - 132	756 – 869	90 - 121	**0.11 – 0.44**	**0.98 – 2.19**
PK-132	262 - 371	83 - 116	271 – 376	86 - 119	**0.22 – 0.55**	**0.28 – 0.88**

Adapted from Miqdady et al. (2023a)

(2) R^2 of the observed vs. modeled volumes plot: the modelling guidelines also address that if we plot the observed volumes vs. the modelled generated volumes, they should be enough correlated, which should be presented by R^2 above 0.90. This criterion is also achieved in our work with R^2 equal to 0.98 and 0.99 for the northbound and southbound directions respectively (Figure 10).

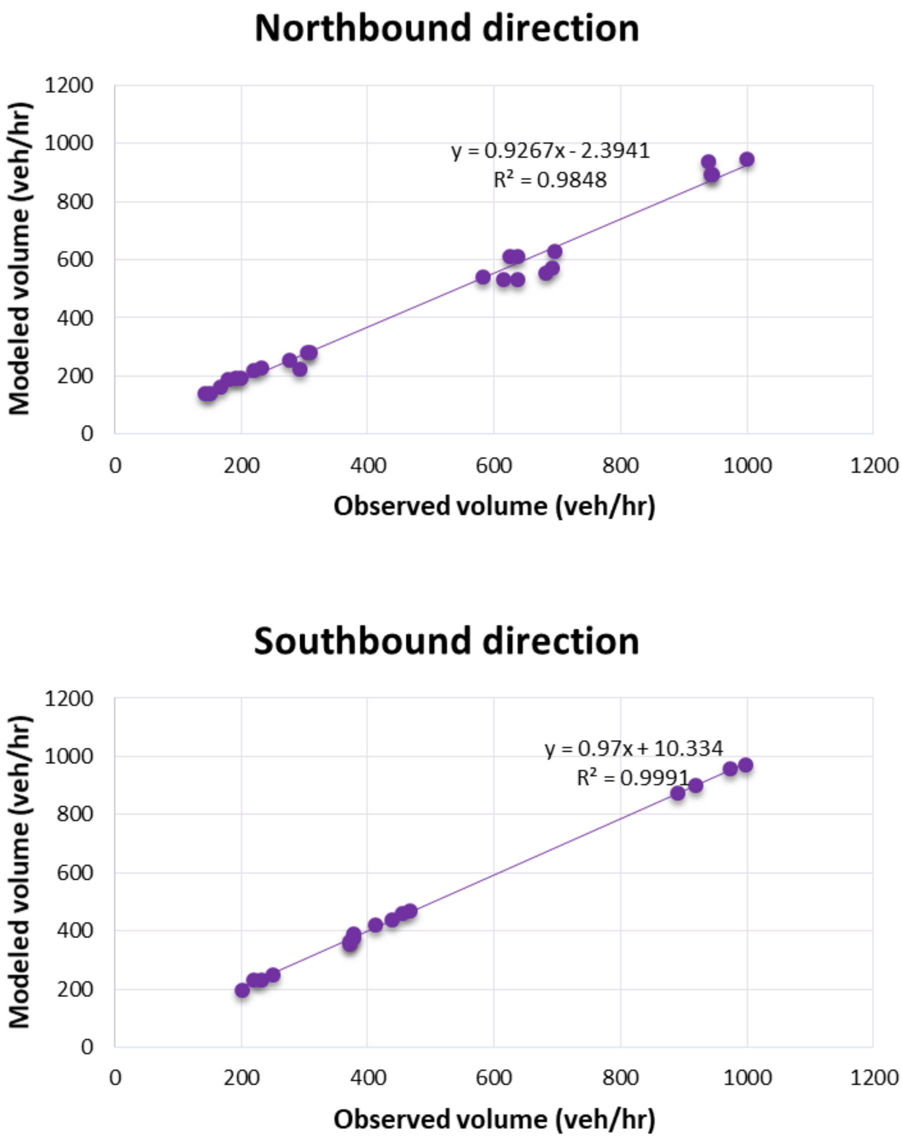
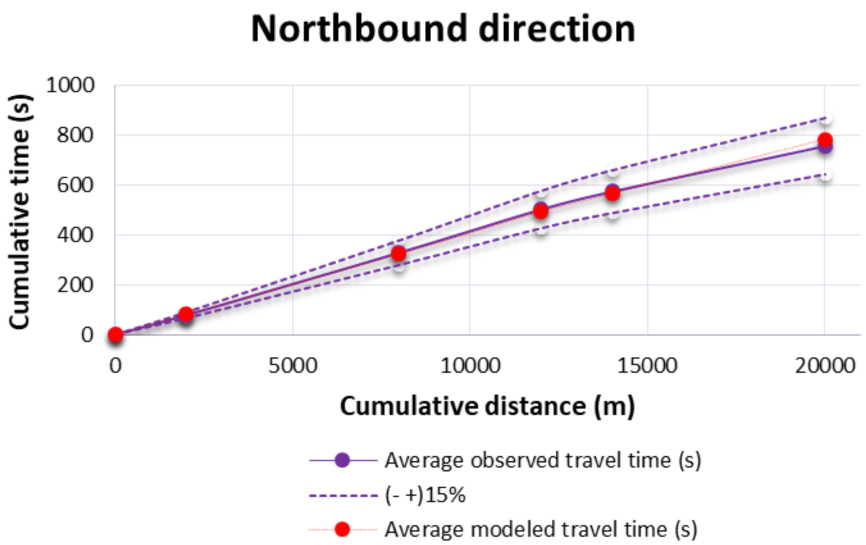


Figure 10: Observed volumes vs modeled volumes in northbound route, southbound route

Adapted from Miqdady et al. (2023a)

(3) In addition, these guidelines recommend to check the modelled travel times along the segment by cumulative graphing of average travel time by section (between detectors).It should be within 15% or one minute (whichever greater) of the observed travel time. According to the results shown in Figure 11, the average travel times are within 15% of the observed cumulative plot for both directions.



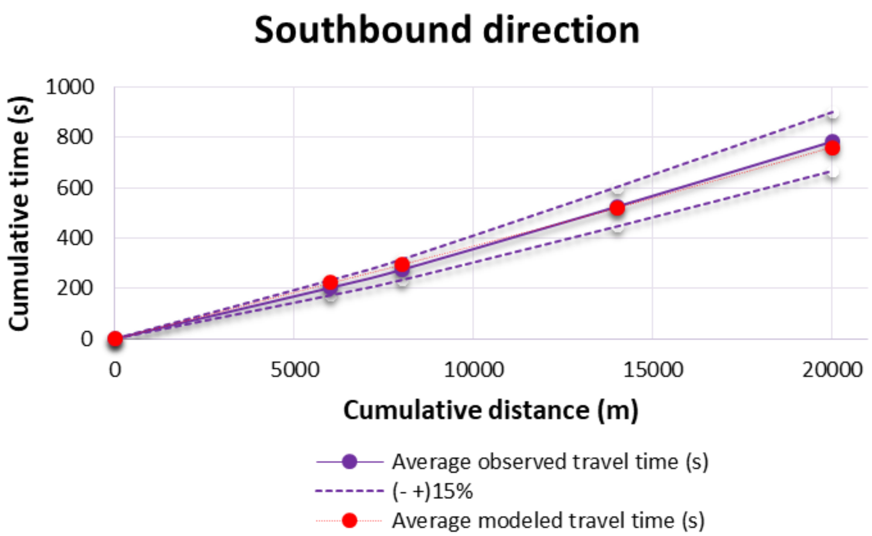


Figure 11: Travel time comparison for the northbound route, southbound route
Adapted from Miqdady et al. (2023a)

(4) The modelled average travel speed was also validated. It was ranging between 86.44% and 90.36% of the speeds registered by the DGT. The mentioned variations in speed (-9.64% and -13.56%) are considered acceptable, because they are below the 15% variation threshold recommended by the Roads and Maritime Services (2013) modelling guidelines.

V METHODOLOGY

CHAPTER V: METHODOLOGY

This thesis investigates traffic safety of CAV introduction among various dimensions. To address the research questions proposed at this thesis, this chapter displays the methodological approach used to calibrate the behaviour of CAV levels and the approaches and indicators used to gage traffic safety extents. Subsection 5.1 presents an overview of the methodology, and the other subsections comprehensively exhibit each of its parts.

5.1. Overview of the methodology

The methodological framework developed to fulfill the research objectives and to address the research questions established in Subsection 2.4 has been structured in two main blocks: measuring the traffic safety impact of sharing CAV levels on the road, and a traffic safety sensitivity analysis of changing the CAV behaviour on the road. **Error! Reference source not found.** shows the mentioned framework followed in this research.

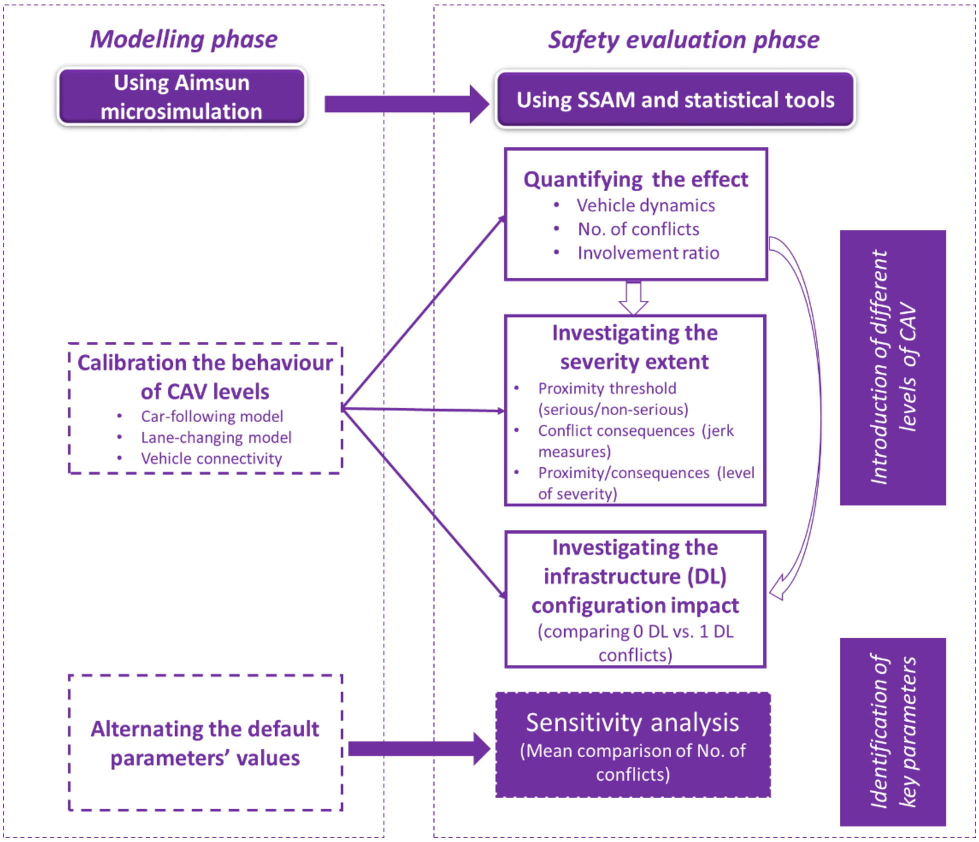


Figure 12: Overview of the methodological framework of the thesis

First, as the fully connected and autonomous vehicles will not enter the roads totally once at a time, a close approach to the on-street condition is to model the expected real introduction of the different levels of automation and connectivity. For that, **the first step was a try to calibrate these CAV levels in a data mining approach depending on literature, design, and operation expectations.** After the calibration of the behaviour of CAV levels, a comprehensive safety evaluation of three axes was conducted to thoroughly investigate the safety on the road regarding the transition period between human-driving and autonomous driving. Particularly, the safety evaluation includes: **(1) quantifying the safety effect** based on vehicle dynamics harmony, the number of identified conflicts and the involvement of CAV with different levels of autonomy in conflicts, **(2) investigate the severity extent** of the identified conflicts within several dimensions (proximity in time threshold to identify serious vs. non-serious conflicts, conflict consequences (using maximum speed and the difference between vehicles' speeds at conflict as jerk measures) and proximity/consequences indicator as reflexive measure of the level of severity, and **(3) investigate the safety impact of using different infrastructure configuration (a dedicated lane) for CAV introduction** and try to find the best strategy in deploying this configuration.

Afterwards, in an exploratory and critical view, **a traffic safety sensitivity analysis of the most commonly parameters used in science for calibrating the CAV behaviour** is applied to highlight the key parameters that modellers should consider until we will have the real validated values for these parameters.

5.2. CAV levels calibration in simulation models

This section illustrates the calibration of driving behaviour regarding CAV levels as different vehicles in the microsimulation platform (Aimsun next 20 API (Aimsun, 2020)), as specified by the SAE (2014). Given that a specific motorway segment is studied under specified conditions, L5 vehicles are not taken into consideration in this study. L4 vehicles therefore indicate completely autonomous vehicles in the tested setting.

CAV calibration is carried out by proposing some differences in driving behaviour among different CAV levels (i.e. how these vehicles will flow and interact throughout the transition phase) based on literature and manufactural interpretations (e.g. ATKINS, 2016; Papazikou et al., 2020; Guériau & Dusparic, 2020; Xie et al., 2019). These behavioural variations are implemented in Aimsun while considering specific parameters for both car-following and lane-changing traffic models.

Gipps' model's default values represent the HDV's behaviour. However, according to subsection 2.1.3, it is expected that CAV will maintain different standstill distances, accelerate and decelerate more quickly and smoothly, maintain a constant speed with fewer oscillations in free flow, form platoons of vehicles that follow the leader, and perform more cooperative lane changes because they may occur at a higher speed cooperatively. However, since CAV will be interacting with HDV during their initial introduction to the traffic stream, Levitate research project (Papazikou et al., 2020; Weijermars et al., 2021) predicts that CAV will have a cautious behaviour, while a second generation of CAV could to be more aggressive. Our work is based on the cautious driving style in an effort to project the most accurate portrayal of the introduction of CAV in the near future.

A data analysis technique is used as a type of data mining to simulate the behaviour of each level of automation. To identify the crucial parameters to calibrate our models, all the parameters used in empirical and simulation research are previously investigated and analysed (subsection 2.3.4). The important variables are those that have received the most attention from researchers who affirmed their impact on CAV behaviour. After that, the following approach is used to compare the values of important parameters across automation levels:

- If the parameter is examined in empirical research (for L1 or L2 vehicles), the value is taken from these studies (e.g. normal deceleration and maximum acceleration (Karjanto et al., 2016)), and occasionally, the empirical data is utilized to determine the direction of parameter values among automation levels (Naujoks et al., 2016).
- If we assign values for parameters at particular levels (L2 and L4 vehicles, for example) based on the previous two conditions, the choice for intermediate automation levels (i.e. values related to L1 and L3 vehicles) is made based on technology advances interpretation for that parameter (e.g. reaction time is kept constant in L1 and L2 vehicles because the driver is still reacting in both vehicles, whereas speed limit acceptance is represented with some improvement in L2 if compared to L1 vehicles).
- If the parameter is not thoroughly calibrated (e.g. sensitivity factor, aggressiveness level), a sensitivity analysis is carried out in order to determine an appropriate value.

In general, as a vehicle equipped with a driver assistance system is defined as L1 vehicle, modest changes are anticipated to perform its behaviour, reflected by improved acceptance of the speed limit and higher acceptance of the guidance of the leader. In contrast, L2 vehicles are provided by more sophisticated technologies (such as Cooperative Adaptive Cruise Control, CACC), and they behave with more controlled acceleration and deceleration and less aggression while lane-changing. Even though the CACC algorithm could occasionally take control of driving, the driver is always in control because he/she is the one reacting. Lower reaction times and more careful driving are displayed by L3 vehicles, which reflect greater autonomous advancements when changing lanes and in car-following (e.g. cooperating in creating gaps without imprudent lane change). Finally, L4 vehicles represent fully autonomous vehicles with a high degree of regulation in both longitudinal and lateral directions, very short reaction time and low level of aggression.

The parameters considered for Gipps' car-following and lane-change models at each level of automation are detailed in Table 7. The estimates are based on prior research and are influenced by the anticipated benefits of incorporating cutting-edge technologies as discussed in previous paragraphs. The mean, standard deviation, lowest and maximum values serve to establish the parameter distribution for both trucks and passenger cars (see Figure 13**Error! Reference source not found.** and Table 7). In the meaning of reliance on technology, standard deviation values typically decrease as automation levels rise (Stanek et al., 2018). The Gipps modelling default distribution is the one that is used (normal distribution).

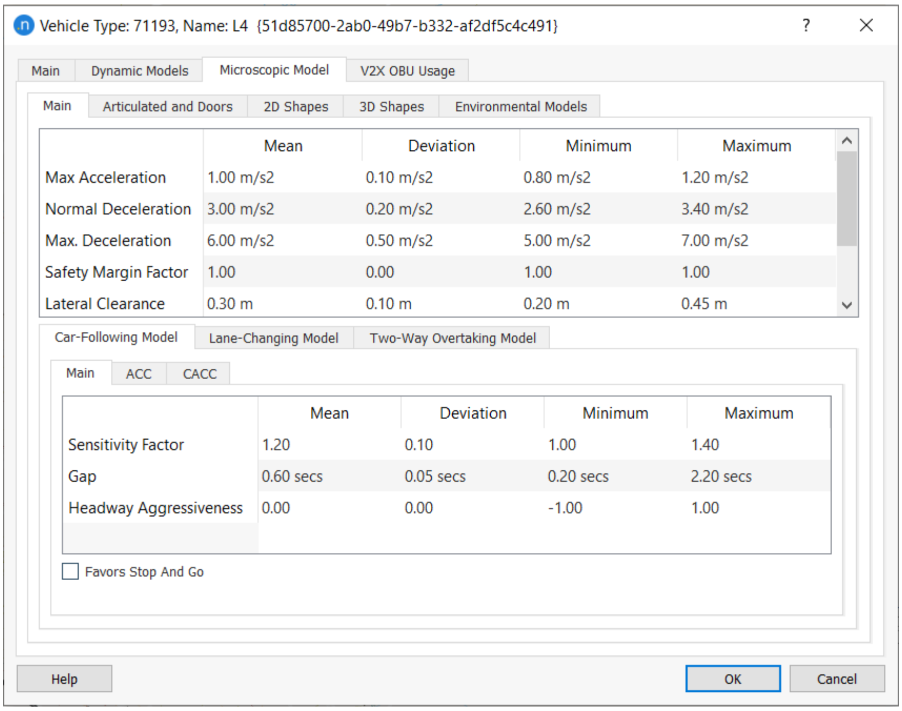


Figure 13: Parameters calibration in Aimsun platform

The definitions for the calibrated parameters as they are presented in the Aimsun user manual (Aimsun, 2020) and previous research that serve as a guide for the calibration of the parameters used in the current work are as follows:

Speed acceptance: How much vehicles could take a speed greater than speed limit (ATKINS, 2016; Guériau & Dusparic, 2020; Mesionis et al., 2020; Ye & Yamamoto, 2019).

Clearance (m): Distance that vehicle keeps with the preceding one when stopped (ATKINS, 2016; Guériau & Dusparic, 2020a; Morando et al., 2018; Stanek et al., 2018; Weijermars et al., 2021; Xie et al., 2019).

Guidance acceptance (%): The probability that a vehicle will follow the recommendations (Stanek et al., 2018).

Reaction time (s): The time to react in generla (Mesionis et al., 2020; Xie et al., 2019).

Reaction time at stop (s): This is the time it takes for a stopped vehicle to react to the acceleration of the vehicle in front (Mesionis et al., 2020; Weijermars et al., 2021).

Max acceleration (m/s²): The highest value that the vehicle can achieve under any circumstances (Guériau & Dusparic, 2020; Stanek et al., 2018; Zhang et al., 2020).

Normal deceleration. (m/s²): The maximum deceleration that the vehicle can use under normal conditions (Karjanto et al., 2017; Zhang et al., 2020).

Sensitivity factor: How much the vehicle could be sensitive to the deceleration of the leader (Papazikou et al., 2020).

Gap (sec.): How much override the headway calculated by car following model (Guériau & Dusparic, 2020; Mesionis et al., 2020; Zhong et al., 2021).

Overtake speed threshold (%): The threshold that delaminates an overtaking maneuver (Papazikou, et al., 2020; Mesionis et al., 2020; Weijermars et al., 2021).

Imprudent lane change: Defines whether a vehicle will still change lane after assessing an unsafe gap (Papazikou et al., 2020).

Cooperate in creating a gap: Vehicles can cooperate in creating a gap for a lane changing vehicle (Bakhshi & Ahmed, 2021; Guériau & Dusparic, 2020).

Aggressiveness Level: The higher the level, the smaller the gap the vehicle will accept, being a level of 1 is the vehicle's own length (Papazikou, et al., 2020; Mesionis et al., 2020).

Distance Zone Factor (Look ahead distance factor): To modify the distance zones used in the Lane Changing Model to adjust where lane changes start to be considered and, if a range is given, to randomize behavior (Papazikou, et al., 2020; Mesionis et al., 2020).

Additionally, the connectivity of the simulated vehicles is introduced in the following way: HDV and L1 vehicles are assumed to be modelled without connectivity; L2 vehicles are connected only with the CACC assistance system; L3 vehicles are connected with both

CACC and V2V connectivity (100% and 65%, respectively); and all L4 vehicles (100%) are assumed to be completely connected with V2V connectivity.

The next three subsections provide more information regarding the theory and connectivity calibration of the Gipps' models:

Table 7: CAV levels driving parameters modeled (Aimsun next, Gipps' model)

	HDV				L1				L2				L3				L4			
Parameters	Mean	dev	Min.	Max	Mean	dev	Min.	Max	Mean	dev	Min.	Max	Me an	dev	Mi n.	Ma x	Me an	dev	Min.	Max
Speed acceptance	1.1 1.05*	0.1 0.1	0.9 0.85	1.3 1.25	1.1 1.05	0.05 0.1	1.0 0.85	1.2 1.25	1.05 1.05	0.05 0.05	0.95 0.95	1.15 1.15	1.0 1.0	0.05 0.05	0.9 0.9	1.1 1.1	1 (1)	0.05 0.05	0.9 0.9	1.1 1.1
Clearance (m)	1.0 1.5	0.3 0.5	0.5 1.0	1.5 2.5	1.0 1.5	0.2 0.5	0.6 1.0	1.4 2.5	1.0 1.2	0.2 0.3	0.6 1.2	1.4 2.1	1.5 2.0	0.1 0.1	1.3 1.9	1.7 2.2	1.5 2.0	0.1 0.05	1.3 1.95	1.7 2.1
Guidance acceptance (%)	70 100	10 10	50 80	90 100	80 100	10 10	60 80	100 100	80 100	10 10	60 80	100 100	90 100	5 5	80 90	10 0 10 0	100 100	0.0 0.0	100 100	100 100
Reaction time (sec)	0.8 0.8	-	-	-	0.8 0.8	-	-	-	0.8 0.8	-	-	-	0.5 0.5	-	-	-	0.1 0.1	-	-	-
Reaction time at stop (sec)	1.2 1.3	-	-	-	1.2 1.3	-	-	-	1.1 1.2	-	-	-	1.0 1.0	-	-	-	0.1 0.1	-	-	-
Max acceleration (m/s^2)	3.0 1.0	0.2 0.5	2.6 0.6	3.4 1.8	3.0 1.0	0.2 0.5	2.6 0.6	3.4 1.8	2.0 1.0	0.2 0.5	1.6 0.6	2.4 1.8	1.0 0.8	0.1 0.3	0.8 0.6	1.2 1.2	1 0.8	0.1 0.3	0.8 0.6	1.2 1.2
Normal deceleration. (m/s^2)	4.0 3.5	0.25 1.0	3.5 2.5	4.5 4.8	4.0 3.5	0.25 1.0	3.5 2.5	4.5 4.8	3.5 3.0	0.2 1.0	3.1 2.0	3.9 4.3	3 2.5	0.2 1	2.6 1.5	3.4 3.8	3 2.5	0.2 1.0	2.6 1.5	3.4 3.8
Sensitivity factor	1.0 1.0	0.0 0.0	1.0 1.0	1.0 1.0	1.0 1.0	0.0 0.0	1.0 1.0	1.0 1.0	1.0 1.0	0.1 0.1	0.8 0.8	1.2 1.2	1.1 1.1	0.1 0.1	0.9 0.9	1.3 1.3	1.2 1.2	0.1 0.1	1.0 1.0	1.4 1.4
Gap (sec.)	1.2 1.5	0.2 0.2	0.8 1.1	1.6 1.9	1 1.5	0.2 0.2	0.6 1.1	1.4 1.9	0.8 1.0	0.1 0.1	0.6 0.8	1 1.2	0.8 1.0	0.05 0.05	0.7 0.9	0.9 1.1	0.6 0.8	0.05 0.05	0.5 0.7	0.7 0.9
Overtake speed threshold (%)	90 90	-	-	-	90 90	-	-	-	90 90	-	-	-	85 85	-	-	-	85 85	-	-	-
Imprudent lane change	Yes Yes	-	-	-	Yes Yes	-	-	-	Yes Yes	-	-	-	No No	-	-	-	No No	-	-	-
Cooperate in creating a gap	No No	-	-	-	No No	-	-	-	No No	-	-	-	Yes Yes	-	-	-	Yes Yes	-	-	-
Aggressivenes s Level	0-1 0-1	-	-	-	0-1 0-1	-	-	-	0-0.5 0-0.5	-	-	-	0.0 0.0	-	-	-	0.0 0.0	-	-	-
Distance Zone Factor (Look ahead distance factor)	0.8 - 1.2 0.8 - 1.2	-	-	-	0.8 - 1.2 0.8 - 1.2	-	-	-	0.8 - 1.2 0.8 - 1.2	-	-	-	1 - 1.2 5 1- 1.2 5	-	-	-	1.1 -1.3 1.1- 1.3	-	-	-

the first value in a row is related to passenger car, while the second *value is related to heavy vehicles (HV) calibration
Adapted from Miqdady et al. (2023a)

5.2.1. Car following model

The Aimsun next API Gipps' models are used to change the way that vehicles drive in relation to each CAV level. Gipps (1981) car-following model is used to calibrate the parameters to control car-following decisions in the algorithm according to each level of automation. The "type of driver" (i.e. acceptance of the speed limit by the vehicle), the geometry of the section (i.e. speed limits on the section, speed limits on turns, etc.), or the impact of vehicles on adjacent lanes can all be calibrated locally inside the microsimulation to achieve this control (Aimsun, 2020). However, acceleration and deceleration are the two main elements of Gipps' model. The first reflects a vehicle's willingness to reach a certain desired speed, while the second simulates the restrictions imposed by the preceding vehicle when attempting to travel at that speed. The maximum speed that a vehicle *(n)* can attain during a time period *(t,t+T)* is provided by Eq. 3:

$$V_a\,(n,t+T) = V(n,t) + 2.5a(n)T\left(1-\frac{V(n,t)}{V*(n)}\right)\sqrt{0.025+\frac{V(n,t)}{V*(n)}} \tag{3}$$

Where: $V_a(n,t)$ is the speed of vehicle n at time t; $V^*(n)$ is the desired speed of the vehicle n for the current section; $a(n)$ is the maximum acceleration for vehicle n; and T is the reaction time. At the same time, the maximum speed that vehicle n can reach during the same time interval *(t, t+T)*, according to its own characteristics and the limitations imposed by the presence of the lead vehicle (vehicle *n-1*) is provided by Eq. 4:

$$V_b\,(n,t+T) = d(n)\,T + \sqrt{d(n)^2T^2 - d(n)\left[2(x(n-1),t) - s(n-1) - x(n,t)) - V(n,t)T - \frac{V(n-1,t)^2}{d'(n-1)}\right]} \tag{4}$$

Where $d(n)$ (<0) is the maximum deceleration desired by vehicle n; $x(n,t)$ is the position of vehicle n at time t; $x(n-1,t)$ is the position of the preceding vehicle ($n-1$) at time t; $s(n-1)$ is the effective length of vehicle $n-1$; and $d'(n-1)$ is an estimation of vehicle $n-1$ desired deceleration.

The minimum of these two speeds is the speed of vehicle n during time interval *(t, t+dt)* (Eq. 5):

$$V(n,t+dt)= min\{V_a(n,t+dt),\ V_b(n,t+dt)\} \tag{5}$$

The integration of the speed is then used to update the position of vehicle n in the current lane. Different methods are used to integrate the acceleration and deceleration phases. The rectangle method is used to integrate the acceleration phase, which corresponds to the following equation (Eq. 6):

$$x(n,t+dt) = x(n,t) + V(n,t+dt)dt \tag{6}$$

While the trapezoid method is used for deceleration phase integration as follows (Eq. 7):

$$x(n,t+dt) = x(n,t) + 0.5(V(n,t) + V(n,t+dt)) \times dt \qquad (7)$$

The estimated deceleration of the leader is a function of the "Sensitivity Factor (α)" parameter, which is defined per vehicle type (Eq. 8):

$$d'(n-1) = d(n-1) \times \alpha \qquad (8)$$

When α is < *1*, the vehicle underestimates the leader's deceleration, which causes it to become more aggressive and close the distance between itself and the leader. While, when α is greater than *1*, the vehicle overestimates the leader's deceleration, and as a result, the vehicle becomes more cautious, increasing the gap ahead of it. As a constraint of the deceleration component, the model also includes the minimum headway between leader and follower.

Before updating the position *x(n,t+T)*, this constraint is applied. The minimum headway constraint is expressed as follows (Eq. 9):

If $x(n-1, t+T) - [x(n,t) + V(n, t+T)T] < V(n, t+T) \cdot MinHW(n)$

Then

$$V(n, t+T) = \frac{x(n-1,t+T) - x(n,t)}{MinHW(n) + T} \qquad (9)$$

Where: *x(n,t)* is the position of vehicle n at time *t*; *x(n-1,t)* is position of preceding vehicle *(n-1)* at time t; and *MinHW(n)* is the minimum headway of vehicle *(n)* between it and vehicle *(n+1).*

Accordingly, the car-following parameters are adjusted in the model as follows:

- **Speed acceptance:** With higher CAV levels, it is anticipated that CAV will operate with greater speed uniformity and less oscillating. In other words, they will show more acceptance of speed limits on the road (ATKINS, 2016; Stanek et al., 2018, Ye and Yamamoto, 2019). The default value for HDV is 1.1 for passengers cars (PC) and 1.05 for heavy vehicles (HV) (both operate with speed greater than the speed limit). Mesionis et al. (2020) use the value 1.0 for L4 vehicles, whereas Guériau & Dusparic (2020) use 1.05 for L2 vehicles and 1.0 for L4 vehicles. Therefore, the same values are used in this work, while in the cases of L1 and L3 vehicles, we are keeping the HDV’s value with lower deviation for L1 vehicles, and the same values of L4 vehicles for L3 vehicles as they operate approximately with the same advanced systems.

- **Clearance (m):** the clearance that a vehicle keeps with the preceding one in the traffic stream is adopted mainly from ATKINS (2016) report and other studies (Guériau & Dusparic, 2020a; Morando et al., 2018; Stanek et al., 2018; Weijermars et al., 2021; Xie et al., 2019) based on minimum space headway values. In addition, following the cautious driving behaviour, the clearance increases as the automation level increases.

- **Guidance acceptance (%):** increases as the CAV level increases from 70% for HDV to 100% for L4 vehicles following Stanek et al. (2018) assumption that L4 vehicles could have about 25% better detection system. In the case of trucks, driving operations in general are more homogenous and following the leaders as it must adhere to other restrictions (other laws and speed limits) (Law, 2020). So, the 100% guidance acceptance is kept for all levels.

- **Reaction time (s):** the default value for HDV is 0.8 s. Most of previous research that used other software in calibration did not consider this parameter. Even though, Zhang et al. (2020) address a value extracted from Adaptive Cruise Control real data (i.e. L1 or L2 vehicles) to be 0.50 s. Other authors (Mesionis et al., 2020; Xie et al., 2019) suggested that this value should be lower in L2 and L3 vehicles and around zero for L4 vehicles to reflect the effect of connection-automation technologies. However, as L1 and L2 vehicles operate under the human driver control, they are kept with the same value as for HDV. The same behaviour will be on unexpected stops, that requires a higher connection technology or referring to the driver.

- **Acceleration and deceleration (m/s^2)**: their values are discussed in abundance in CAV calibration as detailed in subsection 2.3.4. In fact, as this study considers the cautious CAV driving hypothesis, it follows Guériau and Dusparic (2020) and Zhang et al. (2020) values in decreasing both maximum acceleration and normal deceleration with increasing the CAV level. On the other hand, it also follows previous studies (Guériau and Dusparic, 2020; Stanek et al., 2018; Zhang et al., 2020) in keeping the same value of maximum deceleration for all levels, indicating that this parameter is used at emergence situations and it could be reflected by the same magnitude whichever the driving style as it is related more to the vehicle motor capacity, and not to the driving behaviour .

- **Sensitivity factor:** in cautious driving, CAV are supposed to be more sensitive to the leader deceleration to keep the safety distance (clearance higher than that kept in HDV-HDV interaction). Thus, the value of sensitivity factor is assumed to be higher than 1.00 (the vehicle overestimates the leader deceleration) for high level of automation (L3 and L4 vehicles) and 1.0 for levels that are still under human control all the time (L1 and L2 vehicles). Practically, a sensitivity analysis for the potential conflicts resulting of applying the values 0.5, 0.75, 1.0, 1.25, 1.5 in L4 vehicles is applied-with applying the values of other assumed parameters' values in L4 case- to analyse this factor. The values 0.5 and 0.75 (if the follower underestimated the leader deceleration) have shown 31.5% and 33.7% more potential conflicts than the default value (1.0) without significant difference between them but with significant differences with the other values (1.0, 1.25, and 1.5). The values 1.25 and 1.5 (if the follower overestimated the leader deceleration) showed a decrease in the potential conflicts by about 21.2% and 24.1% respectively, indicating the safety benefit of CAV. Again, these values (1.25 and 1.5) have not shown significant differences between them. Our decision for this value was to increase the value above 1.0 for high automation CAV levels, as the considered driving style is cautious.

- **Gap (s):** different studies (Guériau and Dusparic, 2020; Mesionis et al., 2020; Zhong et al., 2021) propose the values of 1.2 s and 1.5 s for HDV (for PC and HV, respectively), 0.8 s for L2 vehicles, and 0.6 s for L4 vehicles. These values are used directly in this work and in-between values are adopted for L1 and L3 vehicles.

5.2.2. Lane-changing model

Lane-change is modelled as a decision process in Gipps (1986)' algorithm, which analyses the necessity of lane change (such as for turn manoeuvres determined by the route), the desirability of lane change (to reach the desired speed when the leader vehicle is slower, for example), and the feasibility of lane change (using forward, backward, and adjacent gap evaluation) depending on the position of the vehicle in the road network with respect to the lane geometry and adjacency.

As a result, there are five aspects to simulate for vehicles lane change at sections:

- Computation of the lane-changing zone's distance,
- Calculation of the target lanes,
- Consideration of the target lanes by vehicles,
- Acceptance of lane-changing gap sizes, and
- Cooperation with the target gap.

The essential look-ahead distances provide limits on lane-changing zones (Stanek et al., 2018). The look-ahead distance is the distance upstream from the target lane that the vehicle is aware of, where it searches for a gap (downstream or adjacent) and tries to adjust speed. The upstream distance before the start of lane-changing is the vital look-ahead, where vehicles are scrambling to get to their valid lane, searching upstream for gaps and slowing down as needed.

According to Liu et al. (2018), the parameters are determined by multiplying the time needed for each zone by the section's posted speed restriction. The perception of the look-ahead and the critical look-ahead is given as a factor range in the Aimsun API. For instance, if a look-ahead distance is specified as 200 m, the minimum look-ahead factor is 0.9, and the maximum look-ahead factor is 1.2, then a uniform random distribution would predict that the perceived distance would range from 180 m (calculated as 0.9 x 200) to 240 m (calculated as 1.2 x 200).

When generating two sets of acceptable lanes, the microscopic model considers the "Visibility distance" of all obstacles as a result of look-ahead and critical look-ahead distances. The following technique defines the driving behaviour of those vehicles as they attempt to enter the set of target lanes:

- The critical look-ahead zone controls the behaviour of the vehicle if its present lane is not one of the subset of valid lanes that it has identified.
- The look-ahead distance zone governs the behaviour of the vehicle if its present lane is inside the subset of valid lanes specified by the critical look-ahead zone but outside the subset of legal lanes determined by the look-ahead distance.
- The "overtaking manoeuvre model" is applied to the traffic circumstances in the vehicle's present lane if it is one of the subsets of valid lanes in both zones.

The gap acceptance model is then utilized while maintaining the consistency of the car-following model. Gipps has imposed two key limitations to accomplish this objective to prevent the occurrence of contrived breakdown scenarios: (1) Gipps car-following model is steady (needs no decelerations greater than the maximum required deceleration); (2) To avoid collisions and to follow a new leader in the target lane, the gap and speed must remain positive during the slowing phase and at its conclusion. The two constraints can be met with the following condition at time t, which must be met for both the upstream and downstream gaps, according to the Gipps Gap acceptance model (Eq. 10, 11):

$$Gap_{\ Up} \geq max\,\{0, \frac{V^2\,k(t)}{2b\ k} + 0.5\ Vup(t)Tup + \max\left[0, (-\frac{V^2 up(t)}{2b\ up} + \alpha\ up\ (1-0.5\alpha\ up)b\ up\ T^2 up + (1-\alpha\ up)Vup(t)Tup)\right]\} \tag{10}$$

And

$$Gap_{\ Dw} \geq max\ \{0, \frac{V^2\ Dw(t)}{2b\ Dw} + 0.5\ Vk(t)Tk + \max\left[0, (-\frac{V^2 k(t)}{2b\ k} + \alpha\ Dw\ (1-0.5\alpha\ Dw)b\ k\ T^2 k + (1-\alpha\ Dw)Vk(t)Tk)\right]\} \tag{11}$$

Where, $Gap_{\ up}$ is the gap calculated for the upstream, $Gap_{\ Dw}$ is the gap calculated for the downstream, v_k is the speed of the subject vehicle, $v_{\ Up,}\ v_{\ Dw}$ are the speeds of the vehicles preceding and following, α is the sensitivity factor, b is the vehicle leader desired deceleration, and T is the reaction time.

By specifying the following parameters in Aimsun API (Aimsun, 2020), the gap acceptance in the lane-changing model can be changed: aggressiveness (enabling vehicles to approach lesser gaps without requiring the back vehicle to brake), and imprudent lane changing (vehicles can enter gaps that do not ensure car-following stability). The lane-changing cooperation parameter is used to define the percentage of upstream vehicles that collaborate in the lane-changing model for each automation level. If a vehicle is in its set of legal lanes when it switches lanes to pass another vehicle that is also considered an overtaking move. The overtake speed threshold parameter is assessed to encourage or discourage overtaking. This indicates that a vehicle will attempt to overtake anytime it is forced to drive slower than Overtake Speed Threshold of its desired speed. 90% is the default setting. All the parameters that have been considered in relation to automation levels are shown in Table 7.

The values among CAV levels are adjusted as follows:

- **Overtake speed threshold (%):** is the percentage of the desired speed of a vehicle below which the vehicle may decide to overtake. This means that whenever the leading vehicle is driving slower than the overtake speed threshold (in percentage) of its desired speed, the vehicle will try to overtake (Mesionis et al., 2020). Papazikou, et al. (2020), Mesionis et al.(2020) and Weijermars et al. (2021) (using Aimsun API) propose lower values for L4 vehicles (80% or 85%) than for HDV. In our calibration, we use the proposed value 85% for L3 and L4 vehicles and keep the 90% for other levels of automation that are still under human control (HDV, L1, and L2 vehicles) as this parameter is related to driver decision basically.

- **Imprudent lane changing:** this research follows Papazikou et al. (2020)'s argument in that HDV could be still changing lane even after assessing an unsafe gap (the same for L1 and L2 vehicles that are still under human control) while high automation levels (L3 and L4 vehicles) will not show this imprudent behaviour, especially in cautious mode.

- **Cooperate in creating a gap**: multiple assumptions have been drawn for this parameter. Stanek et al. (2018) tick the choice just for L4 vehicles, indicating that vehicles of this type can cooperate in creating a gap for lane-changing. Guériau and Dusparic (2020) propose a value of 0.5 (50% of cooperation) for HDV and L2 vehicles and a value of 1.0 (always cooperate) for L4 vehicles (for both PC and HV). On the other hand, for the studies that used Aimsun API, Mesionis et al. (2020) tick the parameter for HDV and both L4 vehicles driving styles (cautious and aggressive), whereas Papazikou et al. (2020) supposed that the cooperation will be present in HDV but not in L4 vehicles driving styles. In our calibration, we see that one of the technology benefits could be addressed by the ability of CAV to be more cooperative in creating gaps (Bakhshi and Ahmed, 2021; Guériau and

Dusparic, 2020). Thus, the followed logic is considering the cooperation behaviour for L3 and L4 vehicles.

- **Aggressiveness level** in gap acceptance to make a lane-change. Papazikou et al. (2020) suggest the values 0.00-0.25 for L4 assertive driving vehicles and the value 0.00 (without any aggressiveness level) for cautious driving. Mesionis et al. (2020) assume that L4 vehicles should show 0.00 aggressiveness level whatever the driving style. We assume that aggressiveness level will still oscilate between 0.00-1.00 for L1 vehicles, and it will decrease with more assistance advance systems (L2 vehicles) to 0.00-0.50. Afterward, it should show 0.00 aggressiveness level for high technologies in L3 and L4 vehicles, especially as we are modelling the cautious driving style.

- **Distance zone factor (look ahead distance factor):** As CAV are supposed to cooperate in creating gaps, they are leading to improve their manoeuvres (Papazikou et al., 2020; Mesionis et al., 2020). Therefore, the zones that are considered while lane-change are modified to larger zones following Papazikou et al. (2020) values for L4 cautious driving, and in-between values for L3 vehicles. Whereas, for HDV, L1 and L2 vehicles the value is kept the same as default because the main controller in the driving process is human.

5.2.3. Vehicle connectivity

By creating a Vehicle Ad-hoc Network (VANet) using the V2X Aimsun next extension (V2X Software Development Kit (SDK)) in addition to the CACC built-in Aimsun API, the connectivity of vehicles is modelled in the current research. Since V2I is expected to cover networks in the long future and our work aims to capture the most recent reality, only V2V connectivity is taken into consideration.

When platooning, the simulated cars have a dynamic "Cruise Control Status" employing the forward collision warning algorithm that the Federal Highway Administration (FHWA) proposed in Liu et al. (2018) (Eq. 12- 15):

- Acceleration: $a_{sv}(t) = (v_{sv}(t) - v_{sv}(t-\Delta t))/ \Delta t)$ (12)

- Current speed: $v_{sv}(t) = v_{sv}(t-\Delta t)+ k_p e_k(t)\ k_d e'_k(t)$ (13)

- Time gap error: $e_k(t)=d(t- \Delta t)-t_g{*}\ v_{sv}(t- \Delta t)-L$ (14)

- Speed error: $e'_k(t)=v_l(t- \Delta t)- v_{sv}(t- \Delta t)-t_g{*}\ a_{sv}(t- \Delta t)$. (15)

Where: a_{sv}: acceleration recommended by the CACC controller to the subject vehicle (m/s²); v_{sv}: current speed of the subject vehicle (m/s); Δt: time step for each update *(s)*; k_p and k_d: gains for adjusting the time gap between the subject vehicle and preceding vehicle (k_p in s^{-1} and k_d have no units); k_p corresponds to the parameter called Distance Gain in the CACC tab of the vehicle type editor and k_d corresponds to the parameter called Speed Gain in the CACC tab of the vehicle type editor; e_k: time gap error; t_g: is the constant time gap between the last vehicle of the preceding CACC string and the subject vehicle (s); L: length of the preceding vehicle; v_l: is the current speed of the preceding vehicle (m/s); and d: is the distance between the subject vehicle's front bumper and the preceding vehicle's front bumper (m).

The CACC gap regulation mode specifically compares the gap-to-leader at each time step to lower/upper gap criteria, allowing the vehicles to switch between CACC and manual driving modes if the algorithm predicts a potential accident. Additionally, Platooning is accomplished by using the follower and leader iterations of the Gap Regulation mode. The Time Gap that is employed in the formula varies between those variations. If a platoon is full when a vehicle tries to join it, the vehicle will take control of its own platoon instead.

CACC is applied by defining the percentage of vehicles equipped with this system (as highlighted in Figure 14), keeping the default gap thresholds defined in the FHWA algorithm the same (Weijermars et al., 2021): speed gain = 0.0125, distance gain = 0.45/s, time gap for leader = 1.5 s, time gap for follower = 0.6 s, the lower gap threshold = 1.5 s and the upper gap threshold = 2.0 s (Figure 15).

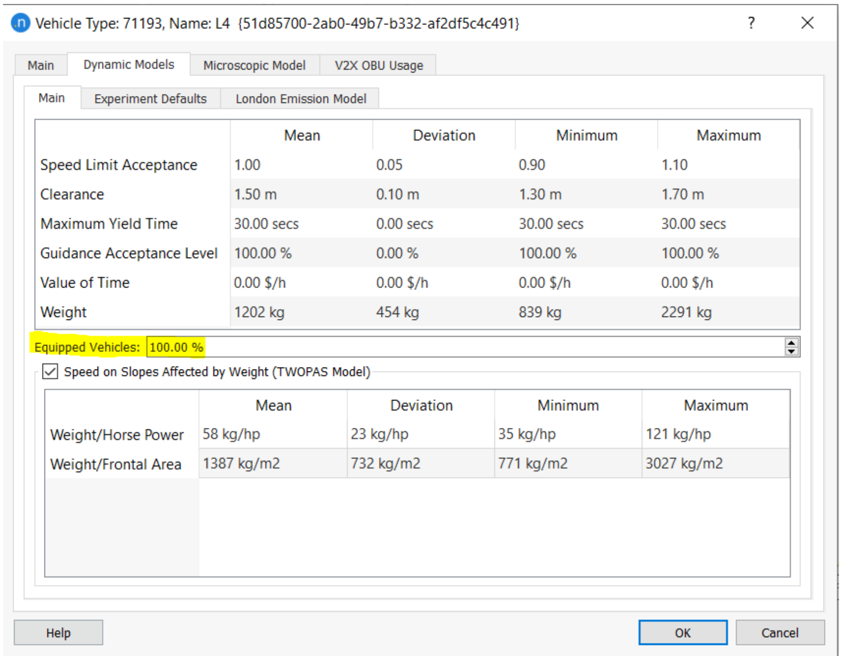


Figure 14: CACC % in Aimsun API

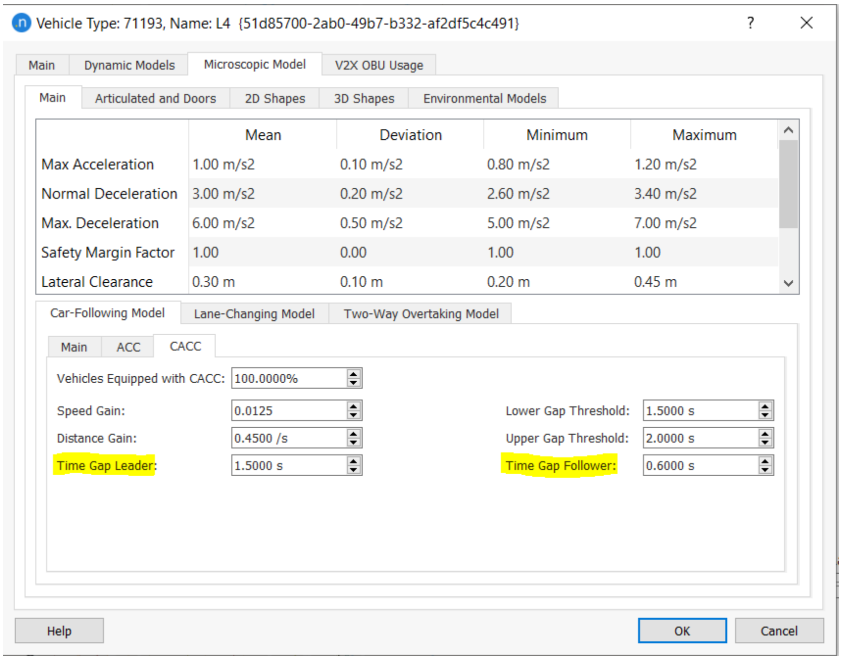


Figure 15: CACC calibration in Aimsun API

Making automobiles more aware of the presence and intents of other vehicles around is one of the services provided by Aimsun (2020) in their V2X extension.

A group of connected vehicles that are close to one another constitute the ephemeral network known as VANet (Figure 16).

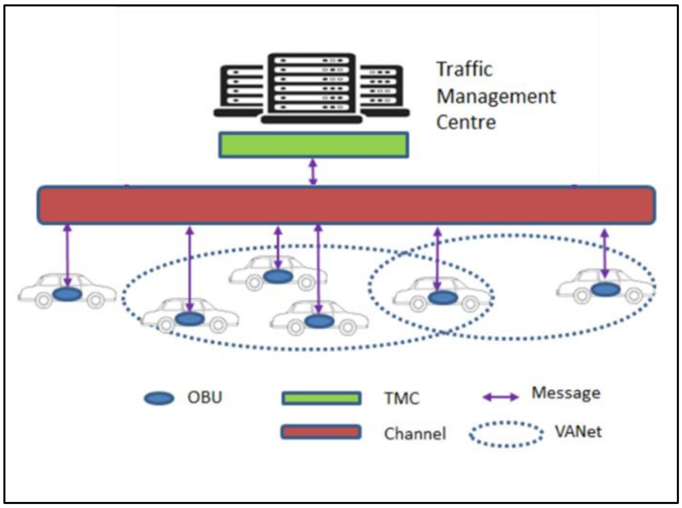


Figure 16: V2V connectivity network components and process
Aimsun (2020)

V2V network consists of (Figure 16): (1) On-Board Unit (OBU) equipped in CAV, representing the receiver and transmitter in the vehicle; (2) Channels, simulating the radio hardware and protocols which provide communication among vehicles; (3) Cooperative Awareness Messages, providing information about the presence, activity and position of CAV; and (4) the Traffic Management Centre (TMC), which joins the previous protocols, and controls all the connectivity process.

Vehicles use a communication channel connected to their OBU to communicate data over a specific set of messages inside a defined space. The TMC, which is devoted to communication management, receives messages from the vehicle-oriented communication channel in its local area. The equipped vehicles in the traffic network are informed of the TMC's decisions via channel signals after the TMC has evaluated the information. The "Vehicle Rules Engine" adds the V2X data from other vehicles to the vehicle's already-existing understanding of the traffic in the space. This class of rules is utilized in simulation to evaluate (before the time step) and perform action (after the time step). The Rules Engine then influences vehicle behaviour and decision making in terms of changing its longitudinal and lateral clearance, speed, acceleration, deceleration, and lane-change process.

Primarily, channel design is recognized as an important phase in designing the V2V connectivity network (Chen et al., 2019; Mir and Filali, 2014; Stibor et al., 2007; Teixeira et al., 2014). Channels are a sort of communication protocol that are used to convey data between vehicles, therefore their significance in this process is clear. Channels often perform using a long-range LTE cell-based transmission channel or a short-range Wi-Fi technology channel such as IEEE 802.11p (Mir and Filali, 2014). A network member, such as a vehicle in a VANet, must adhere to certain protocols for each type of channel that deal with entering and exiting a data network as well as handling channel congestion.

V2X SDK, the Aimsun extension, provides a default objected coded channel, simplifying the protocol when designing the important channel characteristics of reliability and the range of communication, which are expressed by packet loss (the percentage of packets not received), range of transmission, and latency (which reflects the delay in packet transmission).

Accordingly, especially in light of Chen et al. (2019) and Mir and Filali (2014), we apply IEEE 802.11p characteristics in our design VANets because implementing the V2V connection requires a short-range connection channel. The range of 250 m is chosen for this investigation because this sort of channel has demonstrated experimentally (Stibor et al., 2007) its great efficiency up to 250-300 m. Furthermore, various experimental studies (Chen et al., 2019; Mir and Filali, 2014; Stibor et al., 2007; Teixeira et al., 2014) have demonstrated that the number and speed of probable connected vehicles in the channel range have a significant impact on channel efficiency (latency and packet loss). The range in our case study could accomplish the largest studied category of connected vehicles

(125 vehicles), and the registered speeds were between 83-118 km/hr. Thus, as exhibited in Figure 17, the selected channel (IEEE 802.11p /250 m) was suggested to allow a 2100 ms latency and 0.75% packet loss following the experimented data in the aforementioned studies.

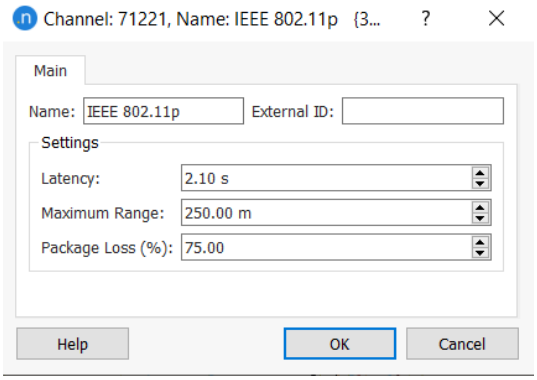


Figure 17: V2V channel calibration

5.3. Evaluating traffic safety among CAV levels

Microsimulation doesn't offer quantitative measurements for assessing traffic safety. The process that is typically used for CAV safety evaluation falls into two categories (Gettman et al., 2008; Wang et al., 2021): (1) analysing traffic dynamics and behaviour among its trajectory, showing the aggressiveness and jerk interactions during the simulation; and (2) analysing the microsimulation outputs (vehicle trajectories) with the SSAM to extract the potential traffic conflicts. While processing a trajectory file, SSAM tracks the position of the vehicles in a series of time steps. Vehicles are reported as having an overlap situation (a conflict) if they maintain the same speed and projection up to the TTC and PET thresholds (Gettman et al., 2008).

Gettman et al. (2008) gave the following definitions of the TTC and PET:

"TTC is the minimum time-to-collision value observed during the conflict. This estimate is based on the current location, speed, and future trajectory of two vehicles at a given instant. A TTC value is defined for each time step during the conflict event. A conflict event is concluded after the TTC value rises back above the critical threshold value. This value is recorded in seconds."

"PET is the minimum post-encroachment time observed during the conflict. Post-encroachment time is the time between when the first vehicle last occupied a position and the time when the second vehicle subsequently arrived at the same position. A value of zero indicates a collision. A post-encroachment time is associated with each time step during a conflict. A conflict event is concluded when the final PET value is recorded at the last location where a time-to-collision value was still below the critical threshold value.”

Mathematically, TTC indication is defined in Hayward (1972) as follows (Eq. 18):

$$TTC_i(t) = \begin{cases} \frac{xi-1\,(t) - xi\,(t) - li-1}{vi(t)-vi-1(t)}, if\ vi(t) > vi-1(t) \\ \infty, if\ vi(t) \le vi-1(t) \end{cases}, \tag{18}$$

Where *TTCi(t)* denotes the TTC value of the following vehicle *i*, at a time instant; *t, x,* and *v* denote the time, position, and velocity of the vehicles, respectively; and *li−1* represents the length of the leading vehicle.

Whereas, Allen (1978) defines PET as the time gap between one vehicle leaving and another vehicle entering a designated conflict area (Eq. 19):

$$PET\ (veh1, veh2\ at\ conflict\ area\ CA) = t_{entry}\ (veh2, CA) - t_{exit}\ (veh1, CA) \tag{19}$$

Assuming that the first vehicle (veh1) passes the conflict area CA before the second vehicle (veh2).

In order to determine the macroscopy safety effect of CAV's gradual introduction, we propose different scenarious that represent different mixed fleets, and employ two methods: (1) the analysis of trajectory dynamics by illustrating acceleration and velocity-difference distributions among the studied fleet mixes; and (2) the analysis of vehicle trajectories using SSAM to first identify the potential conflicts registered in each scenario and then to visualize the potential conflicts classification by each vehicle type interacting at them.

A two-steps process was used for identifying conflicts based on TTC thresholds and vehicle type: (1) the vehicle trajectory file was obtained from Aimsun next 20 (with GetAllInfVeh API extension), improved by Python code to extract vehicle type information that it is not a regular output; and (2) the trajectory file, containing proper vehicles information, was concatenated with SSAM output file to end up with a file that contains both conflicts data (i.e. SSM, conflict type, the leader and the follower vehicle involved in a conflict) and vehicles data (i.e. vehicle type, speed, acceleration, and position). StataMP 16 is used for that concatenation and afterward, it is used for a pro-filtration criterion for identifying the conflicts, given that different TTC thresholds are used depending on the vehicle types involved.

The default value for TTC is 1.50 s, and the default value for PET is 5.00 s. TTC is the indicator most frequently used in HDV and CAV conflict analysis and for examining traffic safety (Wang et al., 2021).

Consequently, following the concept in the literature that faster reaction times of CAV could increase their capability to significantly decrease TTC threshold (Guériau and Dusparic, 2020; Morando et al., 2018; Virdi et al., 2019), and taking into account a previously conducted sensitivity analysis (Miqdady et al., 2021) that revealed a statistically significant difference when comparing the change in conflict frequency evolved by L4 vehicles comparing several TTC values (0.50, 1.00, 1.50, 2.00, and 2.50 s), in this work the TTC thresholds used are:

- TTC=1.50 s for identifying conflicts between human driven vehicles (HDV-HDV) or between human driven and autonomous vehicles when the follower is the human driven one (CAV-HDV) (Sinha et al., 2020).

- TTC=0.75 s for conflicts between autonomous vehicles (CAV-CAV) or between autonomous and human driven vehicles when the autonomous vehicle is the follower (HDV-CAV).

The first group (TTC=1.50 s) includes L1 and L2 vehicles because both require human intervention while driving and reflect modest levels of automation, whereas the CAV is associated with higher levels of automation (L3 and L4 vehicles). The recommended value of 0.75s is consistent with two previous research studies (Guériau and Dusparic, 2020; Morando et al., 2018). Despite that Morando et al. (2018) tested two TTC criteria (1.00 and 0.75 s) for the identification of CAV conflicts and found that the results for 0.75 s had higher consistency. Virdi et al. (2019) utilized a smaller value (0.50 s), and even with a very low CAV penetration on traffic (only 10%), their results showed significantly reduction in conflicts. Whereas, Levitate project (Papazikou et al., 2020) analysed two values: 0.50 s for the second generation (aggressive driving) and 1.00 s for the first generation (cautious driving). These presumptions suit their modelled excessive driving behaviours. Therefore, the value used in this investigation (0.75 s) might be a representative value of all previously suggested values in the literature.

As a result, the potential conflicts among the examined scenarios are discussed in this study and described in terms of conflict type (rear-end, lane-change) and conflict reduction to the base scenario (scenario where all vehicles are HDV). To assess potential substantial changes in safety by comparing the outcomes of various scenarios, an analysis of variance using one-way ANOVA test respect the number of conflicts among the proposed scenarios is also presented.

As mentioned before, the information about the vehicle type (HDV or L1 to L4 vehicles) involved in the conflicts is available as the pro-filtration conflicts file contains the details of conflict data per vehicle. These data are utilized to analyze the conflicts by the involved vehicles and the interactions between them to broaden the understanding of how the different levels of CAV affect traffic safety. To follow that aim, three measures are represented as follows:

1. Involving ratio is a ratio computed for each type of vehicle among the scenarios, as follows (Eq. 20):

$$\text{Involving ratio}_{\ vt\ (i)} = \left[\frac{No.conflicts\ including\ vt\ (i)}{No.conflicts\ (i)}\right] . \frac{1}{\%\ penetration\ vt(i)} \quad (20)$$

Where, v_t is vehicle type (HDV, L1-L4 vehicles), and i is the scenario. Therefore, involving ratio of v_t in i is calculated by dividing the number of conflicts which include v_t whatever as a first or a second vehicle by the total number of conflicts in that scenario; later, the ratio is divided by the penetration rate of v_t in the scenario for standardization to consider its presence in the studied fleet mix. Then, if this value is higher than one, it means that this type of vehicle takes part in a higher number of conflicts than those proportional to its penetration rate at that scenario. On the contrary, if the ratio is below one, this implies that the participation of this type of vehicle in the conflicts is lower than its presence in the traffic fleet.

2. Interaction involvement ratio. Picturing the most repeated interactions of vehicles involved in the potential conflicts of each scenario (the leader and the follower vehicle of each conflict) represents a key analysis for illustrating traffic safety effect of CAV levels penetration at the transition period. Conflict proportion by vehicle interaction is represented in Eq. 21:

$$\text{Interaction involving ratio}_{vc\ (i)} = \left[\frac{No.conflicts\ including\ vc\ (i)}{No.conflicts\ (i)}\right] \frac{1}{\%\ penetration\ vt1(i)\ .\ \%\ penetration\ vt2(i)} \quad (21)$$

   Where, v_c is the vehicle interaction (e.g. HDV-HDV, HDV-L1) in a conflict, and i is the scenario. Conflict proportion by vehicle interaction (v_c) in i is calculated by dividing the number of conflicts which include v_c by the total number of conflicts in that scenario. Later, the interaction proportion is normalized by dividing it on the sharing percentages of both types of vehicles in that interaction.

3. Finally, as the follower vehicle in a conflict is considered as the main responsible of a conflict, the involving ratio for the follower vehicle at potential conflicts was calculated (Eq. 20) to highlight the type of vehicle that mostly could induce conflicts. The involving ratio of the follower in a scenario is calculated by dividing the number of conflicts where the corresponding vehicle type is the follower vehicle by the total number of conflicts in that scenario; then, the ratio is divided by the penetration rate of the follower vehicle type in the scenario for standardization purposes to consider its presence in the studied fleet mix.

A further step in traffic safety evaluation is to investigate traffic conflict severity rather than only its frequency. The next subsection presents this investigation to understand more the safety impact of CAV introduction on our roads.

5.4. Assessing conflict severity related to the levels of CAV

The three issues posed by Laureshyn et al. (2017a) are taken into account in our work to assess the severity of traffic conflicts in different simulated scenarios: (i) How can the proximity to a collision be determined?; (ii) How can the severity of a prospective crash's consequences be gauged?; and (iii) How may the two dimensions be combined?

Limited studies have examined how severe the conflicts are in the CAV context (Rahman et al., 2019; Sinha et al., 2020). But neither the totality of severity dimensions nor the totality of automation levels have been examined. Several SSAM indicators are used to establish the proximity and consequence dimensions for each conflict for the scenarios that have been considered.

5.4.1. Proximity threshold

According to the literature, the most common indicator used to represent the severity of a traffic conlict is regarded to its proximity in time or space. A low TTC value indicates a high risk of collision at a given time instant.

To distinguish between severe and non-severe conflicts, a TTC threshold must be established to evaluate the severity of vehicle-following incidents (Archer, 2005). Setting a common TTC level to gauge dispute seriousness has been under debate, especially with the advent of CAV. According on a review of prior studies, multiple thresholds between 0.9 and 5.0 s have been suggested for various HDV traffic, and between 0.5 and 1.5 s for CAV scenarios (Das and Maurya, 2020).

The most typical HDV's TTC value is 1.5 s (Gettman et al., 2008). This value is also the SSAM's default. This value is suggested in our work for conflicts involving HDV or vehicles with minimal automation (L1 and L2 vehicles) as follower vehicle. Sensitivity analysis was performed to establish a fair threshold for conflicts when the follower is a vehicle with a high level of automation (L3 or L4 vehicles).

To highlight the ideal value for various situations, five distinct values (0.5, 0.75, 1.0, 1.25, and 1.5 s) for the TTC threshold were explored for each scenario, applying the various TTC values to assess whether there were any significant differences between them using one-way analysis of variance (ANOVA).

5.4.2. Conflict consequences as severity indicators

It is important to remember that being near to a collision that causes a minor crash is not the same as being near one that could cause serious injuries. Therefore, another measure to be used to account for the severity will indicate the probable consequences of a crash (Laureshyn et al., 2010). The dynamic consequences of a conflict can be extracted using a variety of SSM (Gettman et al., 2008; Wang et al., 2021). However, very few studies have taken this dimension into account (Laureshyn et al., 2017a).

The current work measures the severity of conflicts based on the measures MaxS and DeltaS as indicators of the conflict consequences (Gettman & Head, 2003; Svensson, 2010). High MaxS and DeltaS values suggest high severity of the conflicts. MaxS is defined as the maximum speed of any vehicle throughout the conflict. Whereas the difference in vehicle speed (i.e. the velocity of vehicles involved in a conflict) measured at the minimum value registered for TTC is what is meant by Delta S. Both indicators simulate road dynamics and are outputs of the SSAM analysis.

Additionally, the conflict severity associated with the various vehicle types involved in conflicts (HDV and L1, L2, L3, and L4 vehicles) is measured in this research using MaxS and DeltaS, accounting distinct vehicle interactions which lead to different traffic flow dynamics and, as a result, leading to distinct conflict severities.

5.4.3. Levels of severity (proximity/consequence)

The goal of CAV development designers, legislators, and road planners is to create a transportation system that uses CAV without any fatalities or serious injuries (Reed, 2021). Therefore, avoiding severe crashes while also reducing the overall number of collisions is a primary objective of the introduction of CAV. As a result, a better indicator could reflect the proximity to a serious (fatal/injurious) crash rather than one that merely expresses the proximity to a crash. Evidently, only a few traffic conflict indicators and techniques shown in literature (e.g. Brown, 1994; Hydén, 1987; Souleyrette and Hochstein, 2012; van der Horst and Kraay, 1986) have taken the severity of the consequences into account.

These traffic conflict techniques (such as the Swedish, Dutch, and Canadian approaches) have been adjusted and verified for HDV in several situations. Though fundamentally different could be for CAV, they serve the same purpose: to substantially create a subjective score that can be added to the objective nearness-in-time (proximity) indicator(s) to account for likely consequences (Figure 18).

In our case, the proposed proximity indicator in SSAM is TTC value, and an energy-based indicator was investigated to express the conflict consequences.

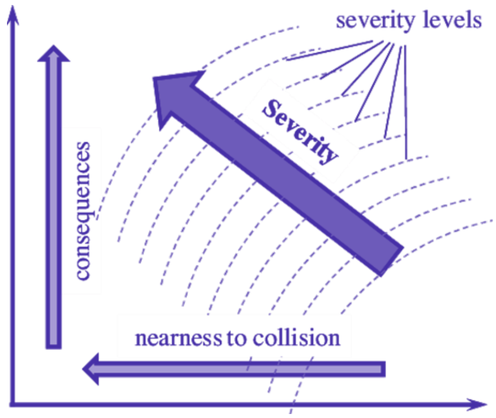


Figure 18: Theoretical concept of collision Proximity/consequences

Adapted from Laureshyn et al. (2017a)

Scientifically, significant fluctuations in velocity, both in magnitude and direction, indicate that a vehicle is being impacted by high forces that could result in serious harm. Thus, according to evidence offered by several experts, DeltaV is the best predictor of collision severity (Evan, 1994; Laureshyn et al 2017a; Shelby, 2011). DeltaV is the difference between the pre-collision and post-collision velocities.

In other words, it is assumed that a hypothetical collision is happened between two opposing vehicles and the consequences that are caused by the kinametic energy (vehicle mass and velocity) result in a change in the final velocity (i.e. pre-collision and post-collision trajectories of a vehicle throughout the contemplated conflict) (Figure 19).

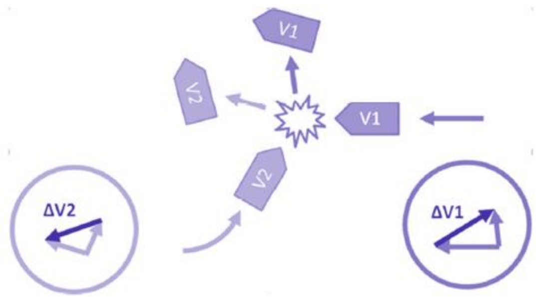


Figure 19: Illustration of DeltaV for two colliding vehicles
Adapted from Shelby (2011)

In the SSAM, MaxDeltaV represents the maximum velocity vector magnitude among colliding vehicles. Gettman et al. (2008) indicated that FirstDeltaV (Δv1) and SecondDeltaV (Δv2) are calculated based on the difference between the conflict velocity (pre-collosion) (from FirstVMinTTC (speed) and FirstHeading (heading)) and the post-collision velocity (from PostCrashV (speed) and PostCrashHeading (heading)). The higher value between FirstDeltaV (Δv1) and SecondDeltaV (Δv2) is called MaxDeltaV. The foregoing is defined as follows.

- FirstVMinTTC (SecondVMinTTC) is the speed of the first (second) vehicle at tMinTTC, which is the simulation time at which the minimum TTC value for a conflict is observed.

- FirstHeading (SecondHeading) is the heading of the first (second) vehicle during the conflict. This heading is approximated by the change in position from the start to the end of the conflict.

- PostCrashV is an estimate of the post-collision velocity of both vehicles. This estimate assumes that the vehicles crash at the estimated conflict angle and velocities observed at tMinTTC. An inelastic collision between the center of mass of both vehicles is assumed such that both vehicles subsequently move in the same direction and at the same velocity.

- PostCrashHeading is the estimated heading (at tMinTTC) of both vehicles following a hypothetical collision.

Basically, Souleyrette and Hochstein (2012)'s HDV criterion is used to provide two scores for a proposed CAV traffic conflict technique: a TTC score (x-axis) and a MaxDeltaV score (y-axis). The combined score, which is expressed as the severity level by region, is created by adding the two scores (Figure 20). The method is initially put into practice in a scenario of pure HDV functioning (i.e. all the vehicles in the simulation are HDV).

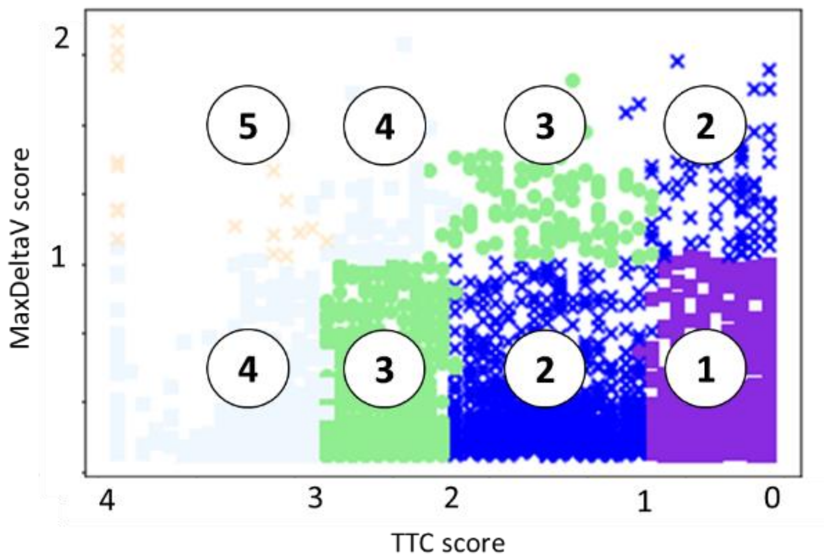


Figure 20: Conceptual illustration of conducting the overall severity score

Adapted from Miqdady et al. (2023b)

The process is then applied to every single pure scenario (i.e. that scenario which is conducted using one vehicle type only; HDV, L1, L2, L3 or L4 vehicles). For each pure scenario, 15 microsimulation runs are carried out, and the TTC distributions are represented to identify the inflection points. For the TTC distribution analysis, all conflicts that have a TTC value equal to or less than 5.0 s are considered.

According to Souleyrette and Hochstein (2012), the inflection points of the TTC cumulative distribution of the pure HDV and pure autonomous vehicle scenarios can be used to get these severe conflicts. These points are used as thresholds to delineate the few severe conflicts from all those that are not severe. Then, the non-severe conflicts are divided into three approximately equal groups. Each group (one severe conflict group and three non-severe conflict groups) assigns a TTC score, which is subsequently used to obtain the overall score. Table 8 summarizes the proposed TTC scores and thresholds to determine the overall scores of the pure HDV and automated vehicle operation scenarios.

Table 8: The assigned TTC score by vehicle type

TTC score	HDV		L1		L2		L3		L4	
	Thresholds	Sample size (%)	Thresholds	Sample size (%)	Thresholds	Sample size (%)	Thresholds	Sample size (%)	Thresholds	Sample size (%)
0	4.0 < TTC ≤ 5.0	30.0	4.2 < TTC ≤ 5.0	28.9	4.2 < TTC ≤ 5.0	30.4	4.3 < TTC ≤ 5.0	29.9	4.3 < TTC ≤ 5.0	32.8
1	2.5 < TTC ≤ 4.0	26.9	2.5 < TTC ≤ 4.2	31.9	2.5 < TTC ≤ 4.2	31.1	2.6 < TTC ≤ 4.3	33.6	2.6 < TTC ≤ 4.3	31.1
2	1.5 < TTC ≤ 2.5	27.6	1.0 < TTC ≤ 2.5	32.4	1.0 < TTC ≤ 2.5	32.3	0.75 < TTC ≤ 2.6	31.5	0.75 < TTC ≤ 2.6	31.5
3	TTC ≤ 1.50	15.3	TTC ≤ 1.0	6.6	TTC ≤ 1.0	6.1	TTC ≤ 0.75	4.8	TTC ≤ 0.75	4.4

Adapted from Miqdady et al. (2023b)

In Table 8 there are differences between the pure vehicle type operation scenarios (scenarios operated only by HDV, L1, L2, L3, or L4 vehicles) in terms of the thresholds (the inflection point) that identify serious conflicts (with a TTC score of 3). Vehicles with high automation levels (L3 and L4 vehicles) reach the inflection points at smaller values than other vehicles, demonstrating their autonomy. For the pure situations of L3 and L4 vehicles, L1 and L2 vehicles, and HDV, the inflection points (TTC thresholds) are identified to be 0.75, 1.0, and 1.5 s, respectively. The variation in the inflection point has an impact on the other thresholds, as seen in the table.

To determine the chance of conflict-related injuries and fatalities, Souleyrette and Hochstein (2012) employed Evan's (1994) equation, which was based on MaxDeltaV, to generate the consequence score. Their findings demonstrated that crucial (inflection) MaxDeltaV values of 30 and 60 km/h significantly increased the likelihood of severe conflicts. These two crucial values can be thought of as being the same for all automation levels and interactions because the Evan's equation only depends on MaxDeltaV and the consequences of a crash with specific MaxDeltaV values have the same impact on HDV and CAV (with varying automation levels).

As a result, the severity level regarding MaxDeltaV is separated into three scores according to Souleyrette and Hochstein (2012): score 1, MaxDeltaV ranging from 0 to 30 km/h; score 2, MaxDeltaV ranging from 30 to 60 km/h; and score 3, MaxDeltaV exceeds 60 km/h. The following step is to combine the TTC and MaxDeltaV scores to get a final score.

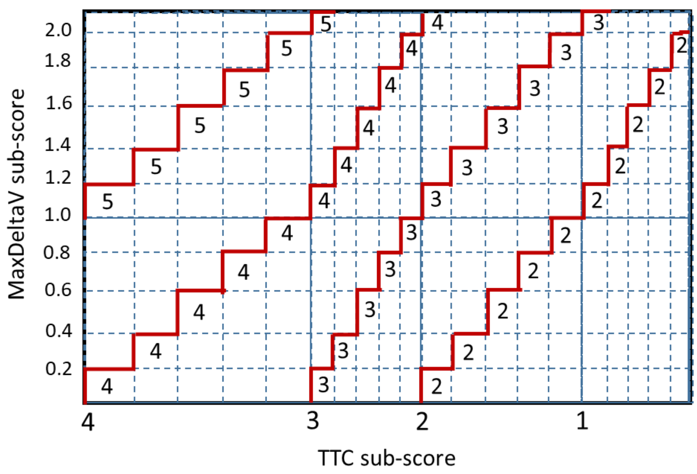


Figure 21: Establishing the iso-lines of severity levels
Adapted from Miqdady et al. (2023b)

By getting the overall score following the addition criterion (i.e. TTC score plus MaxDeltaV score) illustrated in Figure 20, similar graphs are created for the analysed automation levels, where each region score signifies an overall severity level. However, severity levels are better identified by lines or curves rather than by square areas, as suggested by previous studies (Souleyrette and Hochstein, 2012; Laureshyn et al., 2017a). For this reason, in each developed graph, the scores were re-divided to 5 sub-scores (in both TTC and MaxDeltaV range scores), with increments of 0.2 units (Figure 21). In the end, the step graded lines that resulted of the equal overall scores were reshaped in smooth lines (iso-lines).

5.5. Evaluating the safety impact of dedicated lane configurations

Dedicated Lanes (DLs) have been suggested as a possible deployment scenario for CAV on the road networks (Hamad & Alozi, 2022; Razmi Rad et al., 2020). However, the traffic safety impact of this scenario is not sufficiently studied. In our research, we present a study to understand more this issue, using several assigned mixed fleet scenarios, traffic conditions, and DLs policies.

Concretely, under the same simulation conditions (1 hr, 0.1 time step, 18 minutes warming time), the studied mixed fleet scenarios are re-employed on the same motorway segment and the safety impact of operating with and without a DL is discussed at both free-flow and congested traffic conditions. Traffic conflicts are identified by TTC thresholds used previously.

5.6. Applying a sensitivity analysis of the traffic modelling parameters

CAV are designed to alter numerous aspects of traffic behaviour. The improvements in technology bring out quicker reaction times and shorter headways. Different longitudinal road behaviour could be calibrated using both acceleration and deceleration. Additionally, different CAV degrees of sensitivity to the leader's movement or different platoon sizes may be present in the future. Parallel to this, lateral movements are expected to change also when CAV are introduced.

Therefore, applying a sensitivity analysis for the significant parameters contained within the aforementioned models is the best approach to comprehend how the CAV will influence traffic flow models and how much this change in traffic models will affect traffic safety. The precise methodological strategy that is used to apply the sensitivity analysis is illustrated in Figure 22.

The procedure (Figure 22) begins with the extraction of the key variables to be dealt with in the sensitivity analysis, which is frequently calibrated to reflect CAV or those that are considered to have a substantial impact on traffic safety. This process is described in depth in Chapter II (subsection 2.3.4). After the careful revision of the parameters reviewed, step-values are assigned for each parameter that is supposed to be analyzed. The standard deviation of the step value is also taken into consideration to not overlap the normal distribution of the chosen step values for one parameter because the step value is also known as the average value in the Gipps' models (i.e. the mean +/- 2 standard deviation of one step value will not overlap this range of other step values).

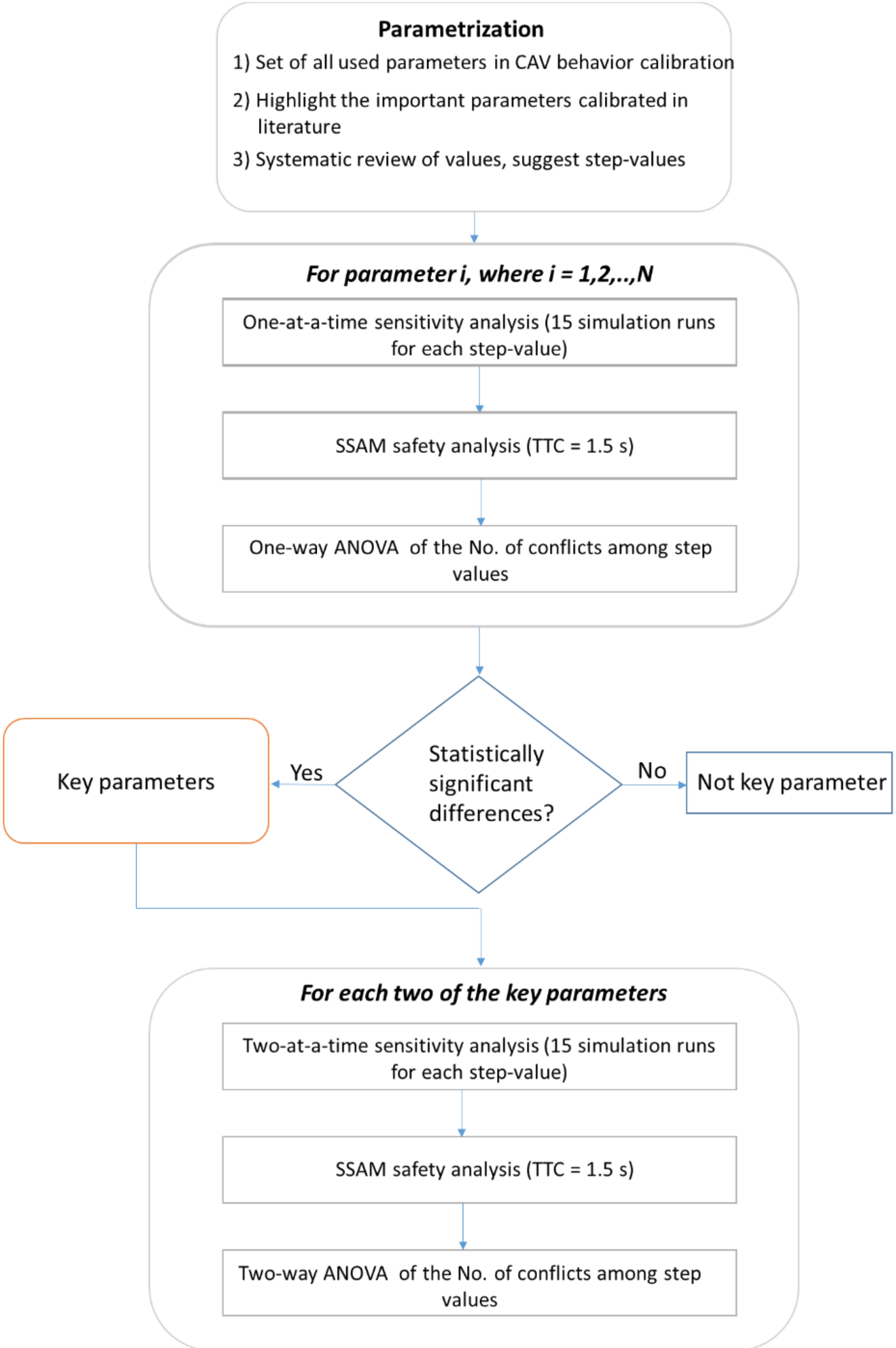


Figure 22: Framework of the applied sensitivity analysis

Next, in accordance with these step-values, a ceteris paribus sensitivity analysis is performed on the parameters for each step value of one parameter.

Half of the motorway segment (10 km) is used to handle the time-consuming and trajectory outputs of the enormous number of runs evaluated, but with keeping the same simulated time (1 hr of free-flow traffic condition) and equal time step (0.1 s) of the first analysis. Then, we are altering the value of one model parameter while leaving the others at their default values (which are proposed to reflect the human driven driving).

When TTC is less than the default threshold, the vehicle trajectories (the outputs) of these runs are then passed into the safety analysis tool (SSAM) to extract the number of conflicts. The threshold for a critical scenario is assigned in this analysis to be 1.5 s as in Batsch et al. (2021). In order to demonstrate the impact of changing the examined parameter on traffic safety, the variations between the results of the step values are then analyzed using ANOVA.

According to statistics, changing a parameter without demonstrating a significant impact on traffic safety suggests that the parameter's role in the effect of CAV behaviour modelling is less important. Contrarily, in CAV modelling, the variables that will have a substantial impact on traffic safety will be given great consideration and moving on to the next stage.

They are exposed to a two-at-a-time microsimulation that runs with a statistically adequate number of runs for each step-value, changing two parameters simultaneously while leaving the others at their default levels. Once more, using SSAM and the identical TTC threshold (1.5 s), the outputs of altering each of the two parameters are safety-wise assessed. The total number of conflicts is then subjected to a two-way analysis of variance (ANOVA) to determine the impact of the tested value combinations.

VI RESULTS & DISCUSSION

CHAPTER VI: RESULTS AND DISCUSSION

This chapter displays the results as an intent to achieve the thesis objectives by answering the research questions and testing the proposed hypotheses at the beginning of the investigation. The chapter also browses various discussions about the findings in comparison with previous studies in the context to provide the main contributions of this thesis and its additive key findings.

To achieve the assigned objectives, a preliminary analysis (Miqdady et al., 2021) was conducted to find a statistically sufficient number of replications to be run in all investigations' scenarios. Based on the Shahdah et al. (2015) and Eq. 1, 15 runs achieves the statistical robustness. Further, a statistically significant test was conducted to 30 and 50 runs for each scenario, and the outcomes did not significantly change from the 15 runs sample, showing that the sample size of 15 runs is representative.

6.1. Evaluating traffic safety among the levels and penetration of CAV

This section tries to provide the answer to the first research question:

> **RQ1** – Will the calibration of all levels of CAV in various mixed fleets scenarios representing CAV introduction can reflect different traffic safety impact than previous studies calibrating just one or two levels of automation?

It particularly checks the following hypotheses:

Hypothesis 1: calibrating all the CAV levels will generate wider knowledge about the safety impact of CAV introduction.

Hypothesis 2: the increase in the penetration rate of CAV in general will enhance traffic safety.

Hypothesis 3: HDV and vehicles with low level of automation will be more involved in conflicts than vehicles with high level of automation at mixed traffic fleet.

Hypothesis 4: the penetration of low levels of automation will provide no significant improvement in traffic safety, while high automation levels will do.

By acheving the related objectives:

- To calibrate the behaviour of CAV levels in a simulation model.
- To quantify the traffic safety impact of CAV penetration among some possible real-world introduction scenarios.
- To estimate the involvement of CAV levels in traffic conflicts and their likely responsibilities.

Concretely, this section offers the microsimulation results for the calibrated CAV levels (see parameters values in Section 5.2) in the context of quantifying the impact of CAV on traffic safety. As an indirect traffic safety measure, these results firstly present traffic flow dynamics. Later, SSAM-dependent prospective traffic conflicts are offered along with an analysis of these conflicts as a direct traffic safety measure, using the conflict identification criteria described in Section 5.3, where TTC along vehicle trajectory is below TTC threshold (with diferent TTC threshold for high automation vehicles).

6.1.1. Fleet mix scenarios

For traffic microsimulation, nine potential fleet combinations are taken into consideration within this investigation. These hypothetical situations are shown in Table 9**Error! Reference source not found.** to provide a closer picture of the introduction of CAV levels in the real world. The other *Li* vehicles are the levels of CAV, where *i* ranges from 1 to 4, and HDV is the human-driven vehicle.

Table 9: Fleet mix scenarios considered

Scenario	HDV	L1	L2	L3	L4
A	100%	0%	0%	0%	0%
B	75%	10%	10%	5%	0%
C	50%	10%	25%	10%	5%
D	40%	15%	20%	15%	10%
E	20%	20%	25%	20%	15%
F	5%	10%	30%	30%	25%
G	0%	0%	10%	40%	50%
H	0%	0%	0%	25%	75%
I	0%	0%	0%	0%	100%

In fact, scenario A accurately depicts the initial state in which all vehicles are HDV. Scenario B is the first time a CAV is introduced, and only 25% of almost L1 and L2 vehicles are sharing the road. Then, two hypothetical scenarios that reflect the growth of CAV at differing automation degrees are described (C and D). Later, in scenario E, a completely mixed fleet is used to depict a probable equal penetration of all vehicle categories. Scenarios F, G, and H depict fleet combinations with high levels of automation. Finaly, scenario I describes a scenario in which all the vehicles are L4.

6.1.2. Traffic flow dynamics

One of the main traffic safety indicators is to draw clear insight into traffic flow dynamics (ATKINS, 2016; Stanek et al., 2018; Talebpour & Mahmassani, 2016). This work adopts Ye & Yamamoto (2019)'s method in analyzing traffic trajectories by their exposure to risky situations, including high acceleration/deceleration or velocity differences between the leader and the follower among different fleet mixes. The acceleration distributions of the various scenarios (from A to I) are shown in Figure 23.

Even though the distribution patterns exposed for these scenarios are very similar, it is possible to identify two different patterns: one for scenarios A to E, and another one for scenarios F to I.

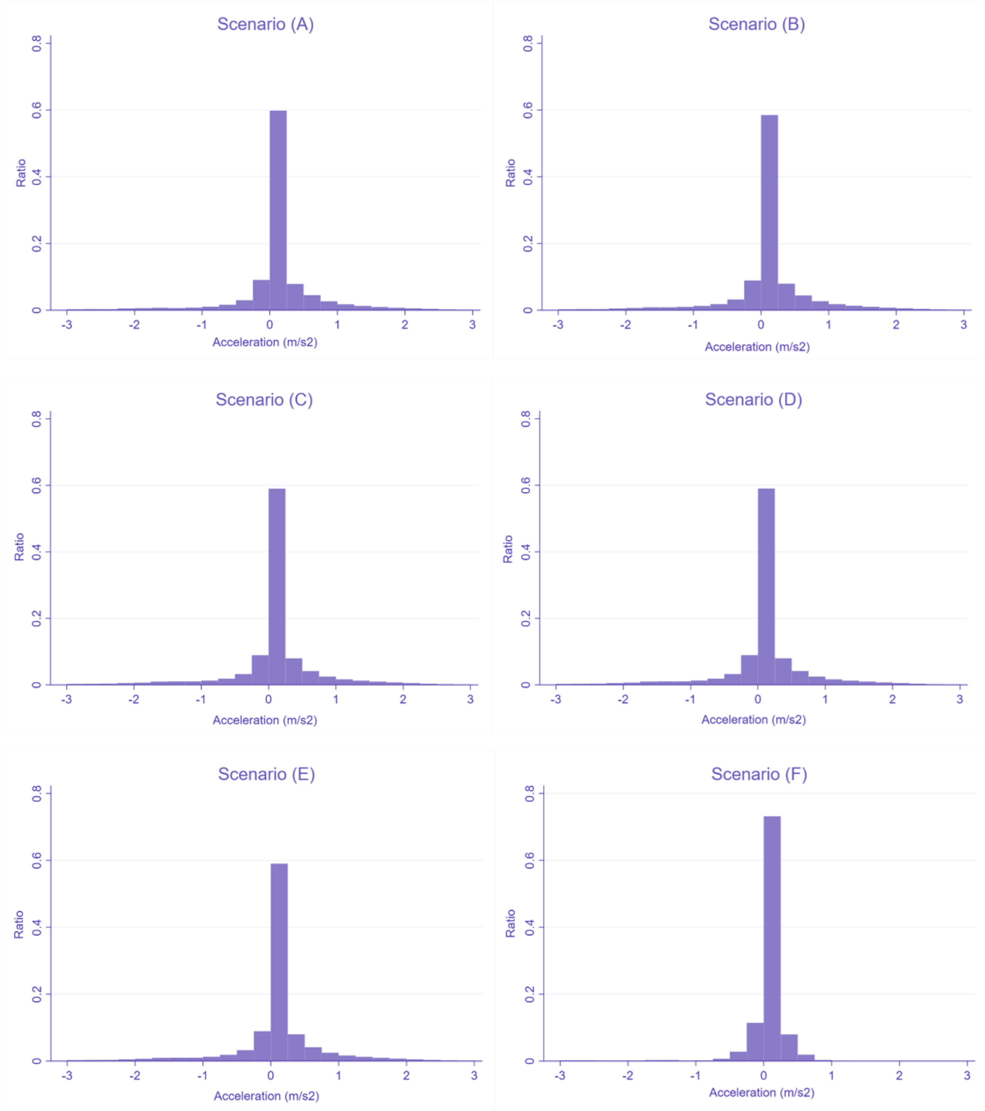
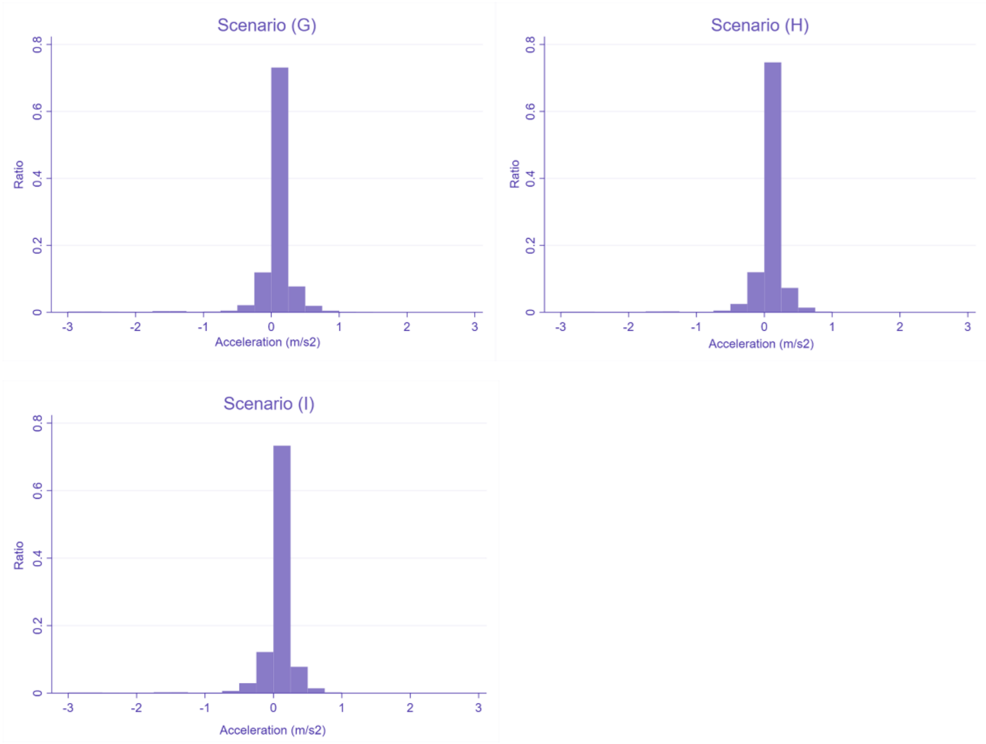


Figure 23: Acceleration distribution under the proposed scenarios (A to I)
Adapted from Miqdady et al. (2023a)



Note: acceleration values outside the range -3 m/s² to 3 m/s² are negligable and were not represented in these plots

Figure 23: Acceleration distribution under the proposed scenarios (continued)

Focusing on the second pattern, when the penetration rate of L3 and L4 vehicles is over 50% (from scenario F onward), the ratio of the acceleration values around 0.00 m/s² increased, diminishing the ratio of acceleration values higher than 1.00 m/s² or lower than -1.00 m/s². This indicates smoother and harmonized driving patterns. This result is expected given the behavior parameters used for L3 and L4 vehicles design. For example, as imprudent lane changing is banned for them, less extreme acceleration values might be shown. Moreover, as L3 and L4 vehicles are modeled for cooperation in creating gaps, acceleration rates closer to 0 m/s² are also expected.

Ye and Yamamoto (2019) also found that the increase of CAV penetration rate leads to gradual increase of the ratio of 0.00 m/s² acceleration rate. In addition, they pointed out that the aforementioned behavior is expressed by more traffic safety on the road. The findings of Sinha et al. (2020) marked similar results by finding that high variation of acceleration records are decreasing with more CAV in traffic flow.

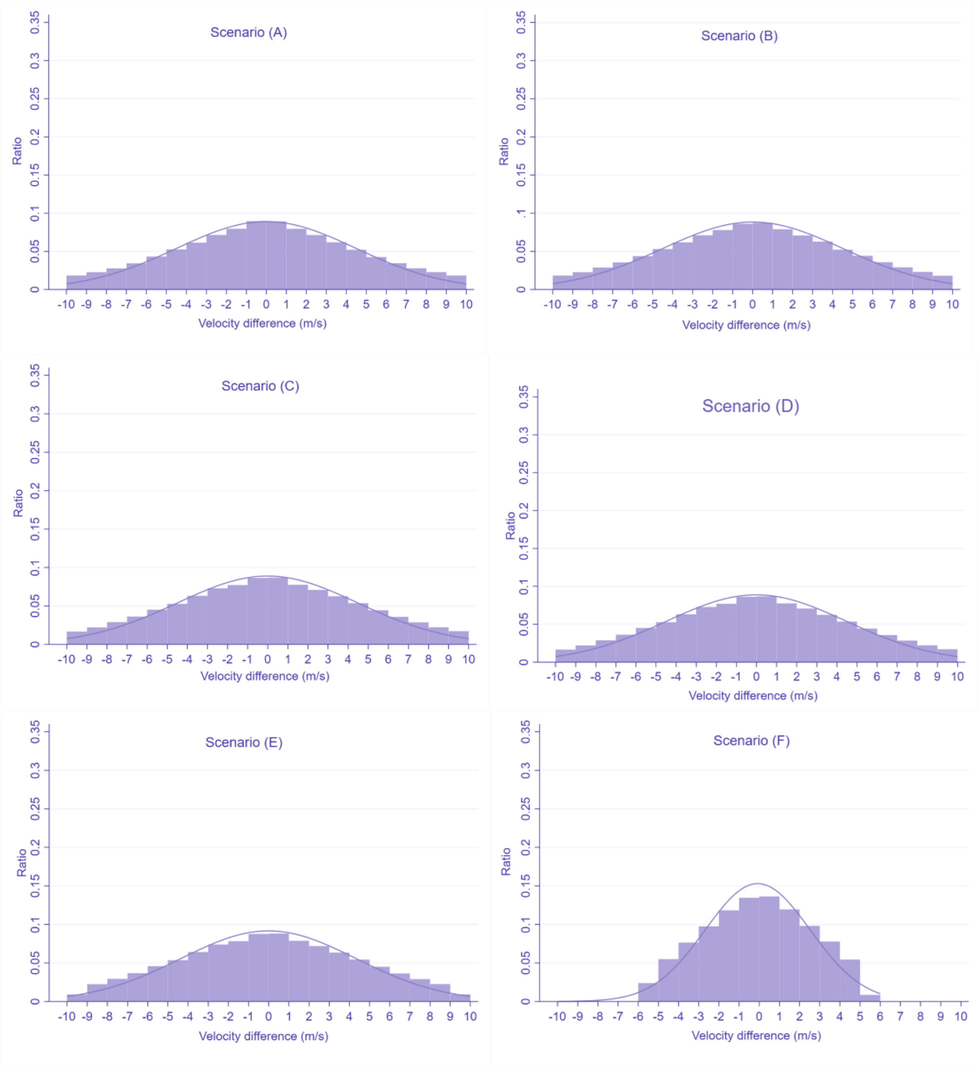


Figure 24: Velocity-difference distribution under the proposed scenarios (A to I)

Adapted from Miqdady et al. (2023a)

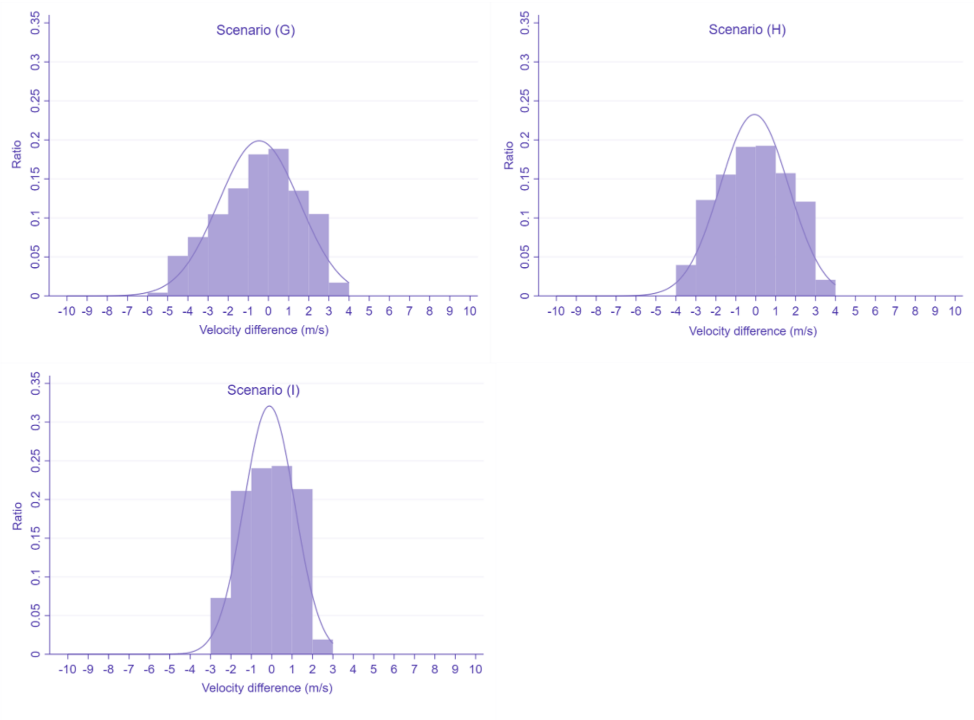


Figure 24: Velocity-difference distribution under the proposed scenarios (continued)

Regarding the difference in velocity between the leader and the follower vehicles, Figure 24*: Velocity-difference distribution under the proposed scenarios (continued)* shows that, for all scenarios, it follows a bell-shaped distribution. However, a closer look to each scenario reveals the gradual change in this shape. The first five scenarios (A-E), where the greatest number of vehicles are HDV, L1 and L2 vehicles, presented a bell shape with a low peak and a wide velocity range. The bell peak starts to increase at high sharing percentages of L3 and L4 vehicles (above 50%), which are scenarios from F to I. At these scenarios, the difference in velocity between vehicles is reduced and tends to cluster around low values. This phenomenon shows that traffic flow homogenizes with high L3 and L4 vehicles penetration rates.

According to earlier research (Talebpour & Mahmassani, 2016; Ye & Yamamoto, 2019), velocity difference had a propensity to cluster around 0.00 m/s at high L4 and L2 penetration rates (respectively). In particular, Ye & Yamamoto (2019) emphasized that the anticipated reduction in the frequency of these risky situations, namely, situations with a high velocity difference, would improve traffic safety.

Finally, it should be highlighted, that these more harmonized driving patterns (related to acceleration and velocity-difference distributions) found at scenarios with high proportions of L3 and L4 vehicles, are partly a consequence of a safer and more cooperative behavior of L3 and L4 vehicles.

6.1.3. Traffic conflicts among different scenarios

This work presents several aspects of traffic conflict analysis that lead us to a better understanding of the safety impact of penetration rates of different levels of CAV vehicles at the traffic flow. Firstly, using TTC (1.50 s and 0.75 s) and PET (5.00s) thresholds (as discussed in subsection 5.3), Table 10 shows the average results of the number of conflicts resulting from our study for each scenario, differentiated by the total number of conflicts and conflict type. In addition, this table shows the percentage of reduction in the number of total conflicts considering scenario A (where all the vehicles are HDV) as a reference. Moreover, analysis of variance (ANOVA) identifies whether the differences in the number of conflicts between scenarios are statistically significant.

Table 10: Number of conflicts by scenario and type of conflict

Scenario	Total conflicts		Rear-end conflicts		Lane-change conflicts	
	Avg. (St. dev.)	% Reduction	Avg. (St. dev.)	%	Avg. (St. dev.)	%
A	3251a*(647.26)		3072 (620.72)	94.5	179 (30.35)	5.5
B	2637 b (503.62)	18.9	2473 (482.84)	93.8	164 (25.98)	6.2
C	1675 c (247.79)	48.5	1542 (22.32)	92.1	133 (23.29)	7.9
D	1137 d (135.15)	65.0	1039 (125.93)	91.4	98 (15.42)	8.6
E	899d, e(103.93)	72.3	818 (96.17)	90.9	81 (12.16)	9.0
F	648 e, f (75.21)	80.1	591 (70.17)	91.2	57 (8.86)	8.8
G	398 f, g (38.43)	87.7	369 (35.94)	92.7	29 (5.33)	7.3
H	199 g (22.92)	93.9	179 (20.89)	89.9	20 (4.73)	10.1
I	192 g (19.54)	94.1	175 (16.04)	91.1	17(4.82)	8.9

**For each value contains a, b…letter, it denotes values of statistically significant differences ($p < 0.05$). Two or more values with the same letter denote a homogeneous subgroup.*

Adapted from Miqdady et al. (2023a)

In general, as the CAV penetration rates increase, from B to I scenarios, the number of conflicts decreases. This reduction is higher for higher penetration rates of CAV and for higher automation levels, reaching reductions from 18.9% up to 94.1% from scenario B to scenario I respectively. Moreover, the ANOVA statistical analysis shows statistically significant differences with a 95% confidence level for the average number of conflicts between most of the scenarios.

In Table 10, from Scenario B to Scenario D, where CAV volume has been progressively increased across the scenarios (from 0% in Scenario A to 25%, 50%, and 60%, respectively), the reduction in the number of conflicts is statistically significant, close to

20 percentage points between them (18.9%, 48.5%, and 65.0%, respectively).

In contrast, when the percentage of vehicles with a high level of automation (L3 and L4 vehicles) is over 35% (i.e. scenario E) and the presence of HDV is low or non-existent, the differences in the number of conflicts are not statistically significant between all these scenarios (scenarios E, F, G, H, and I), but homogenous groups of scenarios are identified with statistical inter-group differences.

This indicates that scenario E (with 20% HDV, 20% L1, 25% L2, 20% L3, 15% L4) represents again (as in traffic flow dynamics) the beginning of the saturation level of CAV penetration gained safety benefits.

The results from scenario D and E (identified in Table 10) shape subgroup *d*, where the composition of vehicles is highly mixed, differ from those of the last three scenarios G, H, and I that conform to subgroup *g*, where the penetration rates of vehicles with a high level of automation (L3 and L4 vehicles) are either 90% or 100%. This suggests that the most significant reductions in the number of conflicts are going to be reached in the first stages of CAV penetration during the transition period, while during later stages, even though the number of potential conflicts continues to decrease, these reductions will not be significant.

In the literature, although there was no statistically significant comparison for the safety saturation CAV penetration level, it can be noted that it was presented at different rates. Papadoulis et al. (2019) and Morando et al. (2018), for example, stated that 75% of L4 vehicles should operate the road to obtain the saturation level. While the findings of Virdi et al. (2019) confirmed the results of the current study, with saturation penetration at 30% of L4 vehicles, particularly at roundabouts and priority intersections (unsignalized intersections). This change in results is related to the different calibrations of L4 behavior.

In particular, in scenario B, where the operating levels of the CAV (almost L1 and L2) represent 25% of the traffic flow, a reduction of less than 20% is obtained for the resulting conflicts with respect to the total human driving scenario (A). This supports earlier research (Papadoulis et al., 2019; Rahman et al., 2019; Guériau & Dusparic, 2020). However, many of the mentioned studies studied the first introduction of CAV as L4; thus, our results add to the literature that the first introduction of CAV will even provide significant safety improvement even if they have low levels of automation (L1 and L2).

For instance, Virdi et al. (2019) suggested a significant reduction even with a 10% CAV penetration rate. They justified that such a significant reduction was due to a full-scale CAV cooperation that was adopted in their simulation, while other studies adopted low autonomous features, including adaptive cruise control and lane guidance, to simulate the highly promising features of CAV. In addition, they used a TTC threshold of 0.5 s to identify conflicts that involve a CAV, which is a very low value that can identify a low number of conflicts.

In the two suggested scenarios for various automation levels operating almost as the medium of the traffic fleet (scenarios C and D, 50% and 60%, respectively), the results show a significant reduction of 50%-65% with respect to scenario A. This reduction was below the values reported by Papadoulis et al. (2019) and Virdi et al. (2019) (93.8% reduction). The corresponding difference in reduction could be justified as both previous studies considered only L4 vehicles, whereas the 50% CAV in the current study is related to L1, L2, L3, and L4 vehicles. This indicates that using mixed levels of automation (closer to reality) does not significantly improve traffic safety, as has been acknowledged in previous studies.

On the contrary, our value is larger than that of Morando et al. (2018) (23.5% reduction) and Rahman et al. (2019) (around 12% reduction) values, who analyzed either without connectivity or low levels of automation (L1 and L2 vehicles) alone. Furthermore, several considerations in the model calibration may lead to differences in the results of these research studies, such as the parameters included in the calibration, the magnitude and direction in modifying the default model parameters (increasing/decreasing), and whether the calibration follows the conception of cautious or assertive CAV behavior.

In scenario I, where the traffic flow is composed only of L4 vehicles, the reductions at this level of CAV penetration rate agree with with Papadoulis et al. (2019) and Virdi et al. (2019) (over 90% of reduction analyzing L4 vehicles), which upholds a complete removal of conflicts. Indeed, it is the projected benefit of high technological advancement, which all acknowledged studies have highlighted. Nevertheless, these reductions are higher than those identified in previous studies (Morando et al., 2018; Rahman et al., 2019; Xie et al., 2019; Guériau & Dusparic, 2020). This variation in the results is expected due to the distinct calibration of CAV and the different levels of CAV mixed in traffic within each study.

Table 10 also shows the effect of the CAV penetration rates on the type of conflict. The resulting conflicts at this motorway are mostly rear-end conflicts in all scenarios (89.9%-94.5%), in accordance with previous studies, such as, El-hansali et al. (2021). Rear-end conflicts show a slight reduction with respect to scenarios A and B, which are mostly operated by HDV.

Therefore, once the number of HDV is reduced (with a penetration rate equal to or lower than 50%), the percentage of rear-end conflicts diminishes from 1 to 4 percentage points. On the other hand, the opposite effect was observed in the case of lane-change conflicts. When the CAV levels share the road, the percentage of lane-change conflicts may increase, which agrees with El-hansali et al. (2021), In general, the corresponding change in the results within scenarios is related to the distinct behavior of HDV and CAV levels in the car-following and lane-change processes (*i.e.* imprudent lane change, cooperation in creating gaps, and aggressiveness level) (ATKINS, 2016; Stanek et al., 2018).

6.1.4. CAV involvement in traffic conflicts

Furthermore, this study analyzes traffic conflicts to examine how often CAV levels or HDV are involved in the conflicts resulting in each scenario by defining an involving ratio (Eq. 20). Figure 25 shows conflicts involving ratios for HDV and CAV levels.

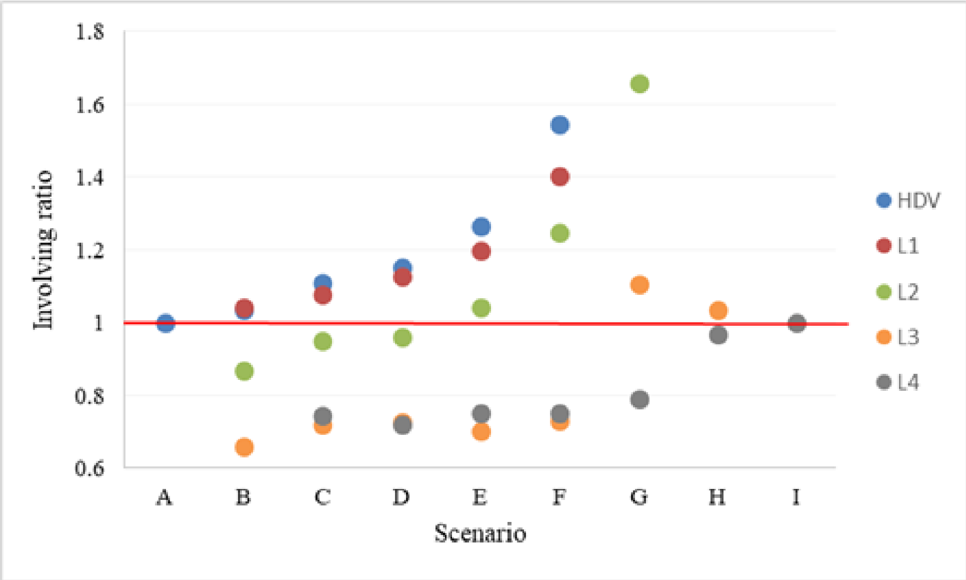


Figure 25: Conflict involving ratios for CAV levels

Adapted from Miqdady et al. (2023a)

For example, in scenario B, the involving ratios of HDV and L1 vehicles (1.03, 1.04) indicate that these types of vehicles are involved in conflicts 3% and 4% more than the expected values regarding their sharing percentages in the fleet. Alternatively, L2 and L3 vehicles' involving ratios (0.87, 0.66) demonstrate that these types of vehicles are involved in conflicts 13% and 34% less than the expected values regarding their sharing percentages in the fleet.

Figure 25 shows that the conflict involving ratios related to HDV, L1, or L2 vehicles are steadily increasing in the totally mixed scenarios (i.e. scenarios C, D, E, and F, that include all types of vehicles) and by increasing CAV penetration rates in general. On the whole, L2 vehicles showed lower involving ratios than HDV and L1 vehicles. However, its involving ratio was below one if the majority of the shared vehicles are HDV and L1 (at scenarios B, C, or D), and started to be over one in scenarios including L3 and L4 vehicles (E and F). Whereas, its involving ratio is suddenly increased in scenario G where they are sharing the road only with L3 and L4 vehicles.

In contrary, the involving ratio of L3 vehicles was in the most of cases below one except in G and H scenarios. This could be explained because L3 vehicles in scenarios G and H are sharing the road only with L4 vehicles (which have a more cautious behavior), therefore, it could reveal that L3 vehicles would expose more traffic conflicts than L4 vehicles. This finding agrees with the involving ratio of L4 vehicles that always settles below the value one. Xie et al. (2019) obtained convergent results as they found that traffic mixed of HDV with L1 or L2 vehicles exposed a higher number of conflicts, while safety benefits come out by high penetration rates of L3 and L4 vehicles.

The distribution of two-vehicle interactions at conflicts was also analyzed (see Eq. 21). Considering that all possible interactions would be difficult to handle, and because of the high similarities identified in conflict involving ratio between L1 and L2 vehicles as well as between L3 and L4 vehicles, the four levels of CAV were merged into two groups: L1 and L2 vehicles as low CAV levels (LCAV), and L3 and L4 vehicles as high CAV levels (HCAV) (see Table 11).

The conflict distribution per vehicle interaction is shown in Table 11 exhibits the conflict distribution by vehicle interaction as a conflict proportion to the total number of conflicts in the scenario, normalized by the sharing percentages of the vehicle types, obtaining an involving ratio of that interaction (the values in bold). The table includes the results along the scenarios B to G (A and I scenarios were excluded because all the vehicles were HDV and L4 vehicles respectively).

In general, Table 11 shows that when HDV is the follower vehicle (-HDV), the involvement ratio is always larger than one. Moreover, the involvement ratio increases with increasing the penetration rates of CAV (scenarios E, F, G), indicating the higher probabilities of HDV's responsibility in such scenarios. Specifically, it ranges from 1.26 to 2.2 (as shown in the first gray shaded row), indicating that HDV are involved in conflicts as followers between 8% and 122% more than its sharing percentage on fleets.

Similar findings from earlier investigations have been noted. Morando et al. (2018) found that if the penetration rate of L4 vehicles is 50%, the ratio of HDV-HDV and L4-HDV conflicts by the total conflicts equals to 0.88. In parallel, Sinha et al. (2020) demonstrated that crash rate of HDV-HDV is much higher than L4-HDV while L4 vehicles penetration rate is up to 50%.

A similar pattern is shown in scenarios E, F, and G related to conflicts involving LCAV as a follower (HDV-LCAV, LCAV-LCAV, and HCAV-LCAV). It fact, the highest involving ratio is reached on scenario G for the interaction HCAV-LCAV (2.56). Therefore, when LCAV and HCAV are the unique types of vehicles on the fleet, the LCAV are responsible for most of the conflicts. Additionally, in scenario G, the high penetration rate of HCAV (90%) leads to highly involving them in conflicts (a 74 % of conflicts HCAV is the follower vehicle). This result agrees somehow Morando et al. (2018). When L4 vehicles presented a 75% penetration rate L4-L4 and L4-HDV represented 95% of total conflicts.

Table 11: Conflict distribution & involving ratio by type of interaction (Miqdady et al. 2023)

INTERACTION	Scenario					
	B	C	D	E	F	G
HDV-HDV*	0.60** (0.56) ***1.07***	0.29 (0.25) ***1.19***	0.20 (0.16) ***1.28***	0.06 (0.04) ***1.52***	0.01 (0.00) ***1.85***	0
LCAV-HDV	0.16 (0.15) ***1.09***	0.21 (0.18) ***1.17***	0.18 (0.14) ***1.29***	0.13 (0.09) ***1.49***	0.04 (0.02) ***2.16***	0
HCAV-HDV	0.05 (0.04) ***1.30***	0.12 (0.07) ***1.58***	0.17 (0.10) ***1.67***	0.13 (0.07) ***1.83***	0.06 (0.03) ***2.36***	0
Sum –HDV***	0.81 (0.75) ***1.08***	0.62 (0.50) ***1.24***	0.55 (0.40) ***1.38***	0.32 (0.20) ***1.62***	0.11 (0.05) ***2.22***	0
HDV-LCAV	0.13 (0.15) ***0.87***	0.16 (0.18) ***0.91***	0.14 (0.14) ***1.00***	0.10 (0.09) ***1.13***	0.03 (0.02) ***1.39***	0
LCAV-LCAV	0.04 (0.04) ***0.93***	0.12 (0.12) ***1.01***	0.13 (0.12) ***1.05***	0.24 (0.20) ***1.20***	0.25 (0.16) ***1.55***	0.02 (0.01) ***2.25***
HCAV-LCAV	0.01 (0.01) ***1.29***	0.07 (0.05) ***1.32***	0.12 (0.09) ***1.38***	0.24 (0.16) ***1.52***	0.40 (0.22) ***1.80***	0.23 (0.09) ***2.56***
Sum –LCAV	0.18 (0.20) ***0.90***	0.35 (0.35) ***1.00***	0.39 (0.35) ***1.11***	0.58 (0.45) ***1.29***	0.68 (0.40) ***1.70***	0.25 (0.10) ***2.50***
HDV-HCAV	0.00 (0.04) ***0.09***	0.01 (0.08) ***0.16***	0.02 (0.10) ***0.21***	0.02 (0.07) ***0.23***	0.01 (0.03) ***0.34***	0
LCAV-HCAV	0.00 (0.01) ***0.08***	0.01 (0.05) ***0.15***	0.02 (0.09) ***0.21***	0.03 (0.16) ***0.22***	0.06 (0.22) ***0.30***	0.05 (0.09) ***0.61***
HCAV-HCAV	0.00 (0.00) ***0.00***	0.01 (0.02) ***0.23***	0.02 (0.06) ***0.26***	0.04 (0.12) ***0.34***	0.14 (0.30) ***0.46***	0.69 (0.81) ***0.85***
Sum –HCAV	0.00 (0.05) ***0.00***	0.03 (0.15) ***0.20***	0.06 (0.25) ***0.24***	0.09 (0.35) ***0.26***	0.21 (0.55) ***0.38***	0.74 (0.90) ***0.82***

**The second vehicle in the interaction column represents the follower vehicle. E.g. in LCAV-HDV, HDV is the follower.*
***The first value is the conflict distribution by type of interaction, the value in brackets is the probability of that interaction in the fleet, the bolded value is the involving ratio of the vehicle interaction (see Eq. 3)*
****The gray shaded rows represent the sum of all interactions where the follower vehicle is indicated after Sum-.*
Adapted from Miqdady et al. (2023a)

However, whenever a HCAV in a conflict (interaction) is the follower, the results indicate a considerably low involvement ratio. It ranges from 0.20 to 0.82 (as shown in the last gray shaded rows), indicating that HCAV are involved in conflicts as followers from 80% to

18% less than its sharing percentage on fleets. The highest involving ratio for HCAV as a follower (0.85) is reached for the interaction HCAV-HCAV in scenario G.

After looking at vehicles involved in traffic conflicts, the follower (i.e. the second vehicle in a conflict) was considered as the vehicle mostly carrying the load in decision making and presenting proper behavior. Table 12 presents the follower conflict-involving ratio for each vehicle type in each scenario (see Eq. 21).

The conflicts where HDV is the follower vehicle is higher than the expected ones in all scenarios, and it increases as the penetration rate of CAV levels increases (i.e. its ratio is always over one and its value increases across the scenarios, ranging from 1.08 to 2.22). This result shows that HDV, that is fully reliant on human's behavior, contributes more in increasing traffic conflicts. L1 vehicles, with limited assistant systems, also present a similar effect on safety and they could be a major inductor to generate conflicts in all scenarios.

Table 12: The follower conflict involving ratio for several vehicle types

	Vehicle type				
Scenario	**HDV**	**L1**	**L2**	**L3**	**L4**
A	1 (100%)*	-	-	-	-
B	1.08 (75%)	1.05 (10%)	0.75 (10%)	0.09 (5%)	-
C	1.24 (50%)	1.20 (10%)	0.92 (25%)	0.16 (10%)	0.16 (5%)
D	1.38 (40%)	1.32 (15%)	0.95 (20%)	0.21 (15%)	0.23 (10%)
E	1.62 (20%)	1.48 (20%)	1.14 (25%)	0.25 (20%)	0.27 (15%)
F	2.22 (5%)	1.95 (10%)	1.59 (30%)	0.34 (30%)	0.43 (25%)
G	-	-	2.56 (10%)	1.17 (40%)	0.54 (50%)
H	-	-	-	1.11 (25%)	0.96 (75%)
I	-	-	-	-	1 (100%)

** between ( ) value is the penetration rate of vehicle in that scenario*

Adapted from Miqdady et al. (2023a)

On the other hand, L2 vehicles with more driving control in both the longitudinal and lateral directions have a lower propensity to participate as followers at potential conflicts than HDV and L1 vehicles in scenarios B, C, and D, where L2 vehicles are considered more advanced CAV. However, they reach larger values (1.14, 1.59, and 2.56) when they share traffic flow with more advanced CAV (L3 and L4 vehicles) in scenarios E, F, and G, respectively.

L3 vehicles show the same pattern as L2, but with much lower conflict ratios, indicating the safety benefit of increasing driving assistance technologies. Lastly, L4 vehicles present ratios below 1 in all scenarios, and they could be considered as the safest vehicles, as they hardly contribute as followers towards causing either rear-end or lane change conflicts.

These results present evidence about the concept in literature that CAV may increase the safety benefit and enhance driving performance as the level of connection and automation of the vehicles increases. Nevertheless, previous research that examined vehicle engagement in conflicts did not analyze the participation of the follower vehicle as a tentative inductor of traffic conflicts; moreover, they only analyzed L2, L4, or both types of vehicles as a unique type of CAV when they presented results and did not perform a systematic and complete exploration of the outcomes (Morando et al., 2018; Virdi et al., 2019; Xie et al., 2019; Sinha et al., 2020; Guériau & Dusparic, 2020; Sharma et al., 2021).

6.2. Estimating conflict severity related to CAV levels

Zheng et al. (2014) reviewed the literature and found that a multidimensional definition of severity besides the application of a sensitivity analysis to choose the SSM's threshold were required to build an adequate traffic conflict technique for evaluating traffic conflict severity. Thus, in order to develop a trustworthy method for evaluating the traffic conflict among CAV, this work took into account these two research comprehensive approaches in estimating traffic conflict severity. This part of research employed the results of SSAM brought out in Section 6.1, so that the studied scenarios are the same as those exhibited in Table 9 (Subsection 6.1.1).

Concretely, the present approach uses three dimensions: 1) the proximity to a collision, 2) potential conflict consequences, and 3) combination of proximity and consequences; the conflicts are classified by severity level. Initially, sensitivity analysis was performed to determine the threshold of proximity to a collision involving CAV. Because the TTC threshold is the margin value for severe conflicts, a sensitivity analysis of this threshold is performed to identify the key values producing severe conflicts when CAV of various levels are introduced on roads. Thereafter, the consequences of conflict severity are presented using some SSM (i.e. maximum speed (MaxS) and vehicle speed difference (DeltaS)). A comparison of these values is conducted considering several scenarios and types of vehicle interaction. Finally, a TTC/DeltaV diagram is developed for each automation level to derive several severity levels.

Accordingly, this section provides the answer to the second research question:

> **RQ2** – Could the employment of different safety measures reflect more understanding of the safety dimensions regarding CAV introduction?

And it contributes to the related hypothesis:

Hypothesis 2: the increase in the penetration rate of CAV in general will enhance traffic safety.

Hypothesis 4: the penetration of low levels of automation will provide no significant improvement in traffic safety, while high automation levels will do.

Hypothesis 5: increasing the level of automation and its penetration in the traffic stream will generate less serious conflicts.

By acheving the related objective:

> - To estimate the traffic conflict severity among the different scenarios based on some severity dimensions (proximity, consequences, and proximity/consequences) and a traffic conflict technique concerning CAV levels.

6.2.1. Proximity threshold sensitivity analysis

When applying the several TTC values (0.50, 0.75, 1.00, 1.25 and 1.50 s) to assess whether there are any significant differences between them using one-way analysis of variance, Table 13 lists the total number of conflicts resulted in each scenario. The table lists the changes resulting from using any value if compared to the basic value (1.50 s).

According to Table 13, in general:

- TTC does not present a significant influence on the number of conflicts at scenarios with low penetration rates of HCAV (scenarios D or below).
- TTC presents a very significant influence on the number of conflicts at scenarios with high penetration rates of HCAV (scenarios G or over).
- At intermediate scenarios (E or F), representing moderate penetration rates of HCAV, the number of traffic conflicts starts to present significant differences if the TTC value is below 1.0 s.

These results emphasize the importance of using different TTC values to obtain a reliable assessment of traffic safety related to high penetration of HCAV. Moreover, the results verify the theoretical vision of CAV introduction: when CAV penetration rate is high, traffic flow improves by achieving more harmonized speeds and by reducing reaction times that probably have a direct effect on the TTC threshold.

These results support the values suggested in previous studies. Morando et al. (2018) used two TTC values (0.75 and 1.0 s) to identify conflicts involving CAV; both values were assumed to be appropriate. Other studies used 0.75 s as the TTC value (Guériau & Dusparic, 2020) for fixed conflicts in CAV participation. Some studies have reduced the TTC threshold to 0.5 s (Papazikou et al., 2020; Virdi et al., 2019). Papazikou et al. (2020), claimed that CAV operating with assertive driving styles could lead to different circumstances resulting in a low TTC threshold. However, Virdi et al. (2019) claimed that if the distance traveled by CAV is reduced to one-third, then the threshold defining the conflict is also proporionally reduced. Certain studies have also applied the same TTC value to HDV or CAV interactions (El-Hansali et al., 2021; Papadoulis et al., 2019) without considering the higher capabilities of CAV compared with HDV. Therefore, these investigations do not provide sufficiently soundness results for measuring the traffic safety impact of CAV introduction.

Table 13: Sensitivity analysis of different values of TTC threshold (for -L3 and -L4)

Scenario	TTC threshold		No. of conflicts	% Change
	-HDV, -L1, or -L2	-L3 or -L4		
A (0)*	1.5	-	3251	-
		0.50	2636	-0.69
		0.75	2637	- 0.68
B (5)	1.5	1.00	2637	- 0.60
		1.25	2640	- 0.56
		1.50	2655	-
		0.50	1671	-6.08
		0.75	1675	- 5.86
C (15)	1.5	1.00	1697	- 4.62
		1.25	1724	- 3.11
		1.50	1779	-
		0.50	1131	-11.10
		0.75	1137	- 10.61
D (25)	1.5	1.00	1156	- 8.40
		1.25	1200	- 5.64
		1.50	1272	-
		0.50	890 a**	- 16.85
		0.75	900 a	- 15.91
E (35)	1.5	1.00	935 a	- 12.69
		1.25	980 a,b	- 8.50
		1.50	1071 b	-
		0.50	628 a	- 31.22
		0.75	648 a	- 28.29
F (55)	1.5	1.00	709 a,b	- 22.36
		1.25	770 b	- 15.66
		1.50	913 c	-
		0.50	255 a	- 66.13
G (90)		0.75	298 a	- 60.46
	1.5	1.00	415 b	- 44.88
		1.25	528 c	- 29.99
		1.50	754 d	-
		0.50	149 a	- 79.03
		0.75	198 b	- 72.02
H (100)	-	1.00	341 c	- 51.91
		1.25	467 d	- 34.06
		1.50	709 e	-
		0.50	133 a	- 82.79
		0.75	192 b	- 75.12
I (100)	-	1.00	365 c	- 52.67
		1.25	517 d	- 32.99
		1.50	771 e	-

**The value in ( ) denotes to the percentages of L3 plus L4 in the scenario*

***For each value containing a, b…letter in a scenario (in the No. of conflicts column), it denotes values of statistically significant differences ($p < 0.05$). Two or more values with the same letter denote a homogeneous subgroup.*

Adapted from Miqdady et al. (2023b)

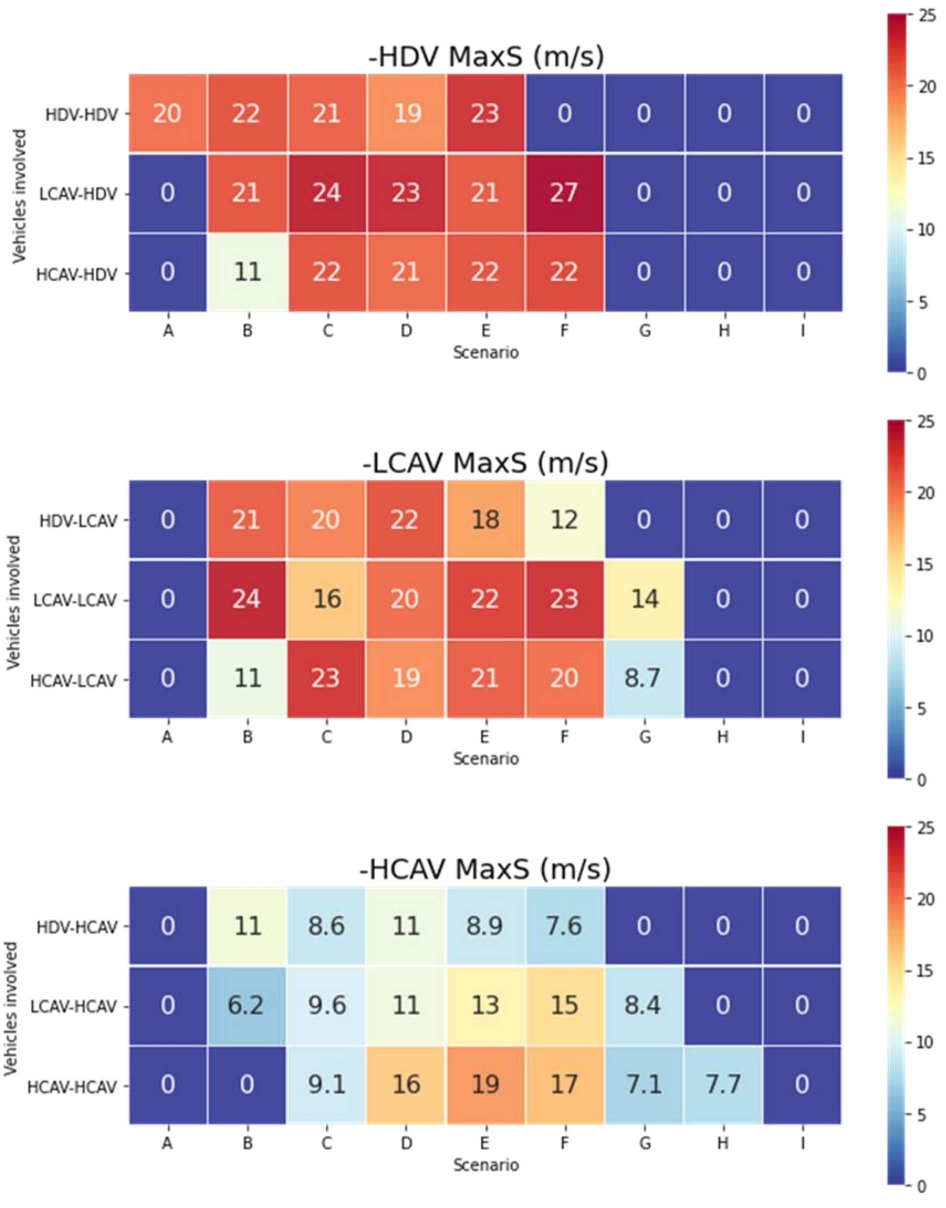
6.2.2. Conflict consequences as severity indicators

MaxS and DeltaS were used in this study to assess conflict severity in relation to different types of vehicles involved in conflicts (HDV and L1, L2, L3, and L4 vehicles) in the scenarios investigated. Different vehicle interactions can cause different traffic flow dynamics, potentially resulting in conflicts between vehicles with different maximum vehicle speeds and variations in vehicle speeds; as a result, the severity levels differ.

Figure 26 shows the variations in MaxS and DeltaS of different vehicles involved in a conflict within different traffic fleet scenarios. For simplicity and clarity in presenting the results, L1 and L2 vehicles and L3 and L4 vehicles are grouped as low and high CAV, respectively they are called LCAV and HCAV. They are referred to as LCAV and HCAV in Figure 26. The shown values are extracted as the average value of 15 runs in each scenario. The blue–yellow–red scale indicated the increase in severity towards the red color. In addition, each figure is divided into three groups based on the vehicles involved in the conflict: –HDV, –LCAV, and –HCAV, indicate that the follower vehicle is a HDV, LCAV, and HCAV, respectively.

As shown in Figure 26a, the higher MaxS during conflicts is typically observed in scenarios in which the penetration rate of HCAV is from low to moderate (less than 55%, or scenario F) . By contrast, high penetration rates of HCAV (scenarios G, H, and I) result in lower MaxS during conflicts.

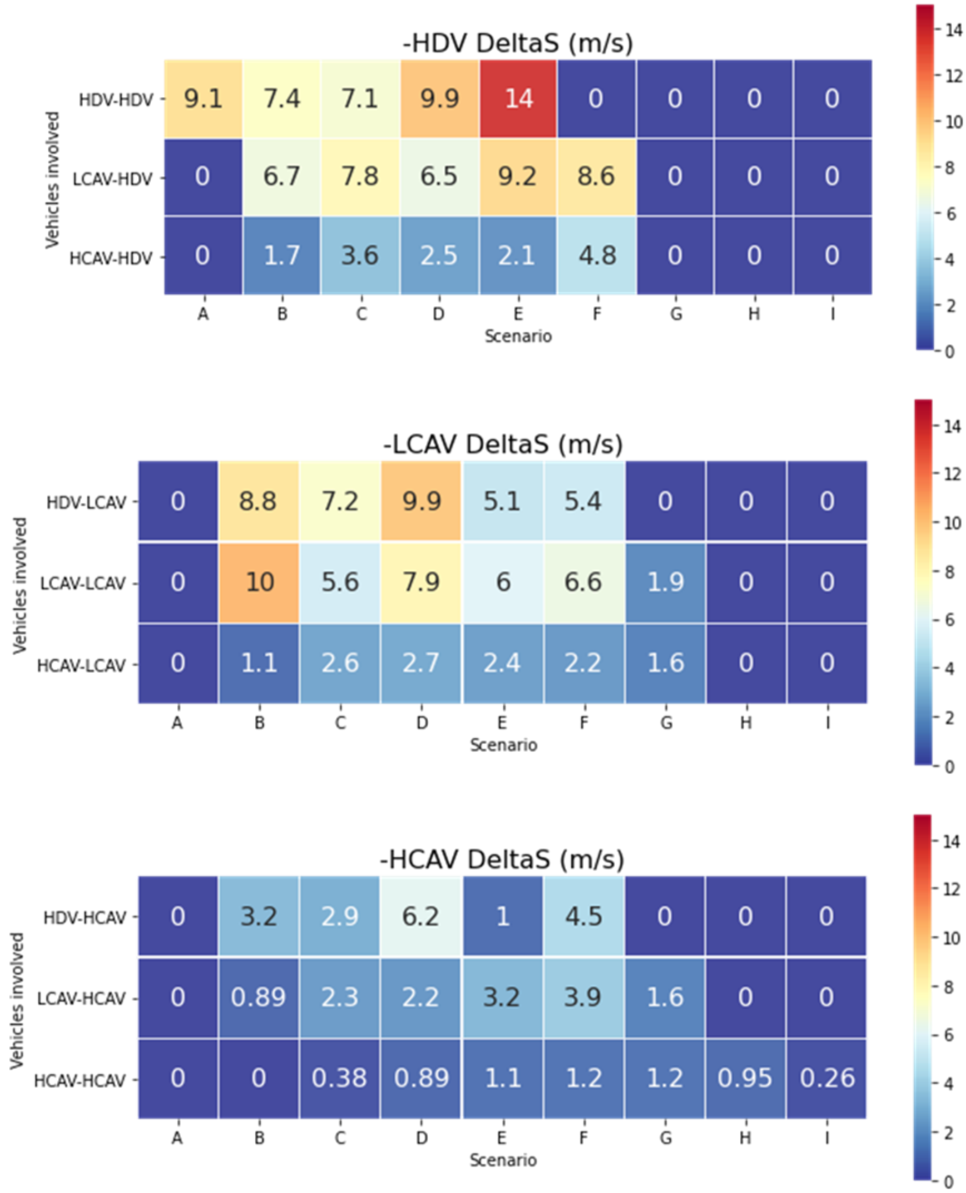
A similar conclusion is reached regarding the observed difference in vehicle speeds (DeltaS) in the conflict (Figure 26b). Sinha et al. (2020) reported a pattern similar to that of the aforementioned results. They obtained low crash rates and flat distributions of DeltaS values as the penetration rates of CAV with a high automation level (L4 vehicles) increased. In addition to SSAM, Rahman et al. (2019) observed, using other surrogate safety indicators (e.g. TET, TIT, number of critical jerks, and time exposed rear-end crash risk index), that an increase in the penetration rate of vehicles with low automation levels (i.e. L1 and L2 vehicles) decreased the conflict severity. They found that the highest reduction in severity was achieved when the penetration rate was 100% CAV. By contrast, the reduction was insignificant when the penetration rate was less than 40%.



(a)

Figure 26: MaxS (a) and DeltaS (b) among several vehicle interactions and scenarios

Adapted from Miqdady et al. (2023b)



(b)

Note: LCAV groups L1 and L2 vehicles; HCAV groups L3 and L4 vehicles.

-HDV refers to the conflicts where HDV is a follower vehicle, the same for –LCAV and –HCAV

Figure 26: MaxS (a) and DeltaS (b) among several vehicle interactions and scenarios (continued)

The interactions of vehicles within a conflict are also evaluated to determine the effect of CAV introduction on micro-level traffic conflict severity. Consistent with the results of Sinha et al. (2020), the conflicts shown in Figure 26 involving CAV generally have low severity. Severity further decreases if the involved CAV have high levels of automation (i.e. L3 and L4 vehicles). This effect is restrictively indicated by MaxS, whereas DeltaS better represents the conflict severity consequences because it is an energy-based indicator (Wang et al., 2021).

Specifically, DeltaS's results show that:

- HDV–HDV interaction presents the highest severity among all vehicle interactions.
- In addition, as the supposed behavior of LCAV does not considerably differ from the HDV behavior, the LCAV–LCAV interaction exhibits relatively high severity.
- When a HDV is the follower vehicle (such as LCAV–HDV and HCAV–HDV), severity is higher than if the follower vehicle is a LCAV or HCAV.
- The largest reduction in severity is achieved when a HCAV is the follower vehicle.

This highlights the benefit of increasing the level of automation, as implicitly discussed by Rahman et al (2019). By contrast, Sinha et al. (2020) analyzed the collisions in the HDV–HDV and CAV–HDV interactions based on the effect of the penetration rate of L4 vehicles (not mixed fleets of vehicles with several automation levels were consider, neither HDV–CAV or CAV–CAV interactions were analyzed) and they did not find a significant difference between the severity of both types of interactions.

6.2.3. Level of severity among scenarios

One of the primary goals of this part of research is to estimate the change in traffic conflict severity between the current HDV scenario and the 100% L4 vehicle scenario. The developed severity levels charts (Figure 27) are used in this part to determine the number of conflicts classified with each level of severity among the simulated scenarios.

The reshaping of the sub-scores iso-lines calculated in Figure 21 (Subsection 5.4.3) are represented as smooth contour lines for HDV and all L1–L4 vehicles as shown in Figure 27. In the figure, the variation of the magenta color from light to dark represents the increment in severity level.

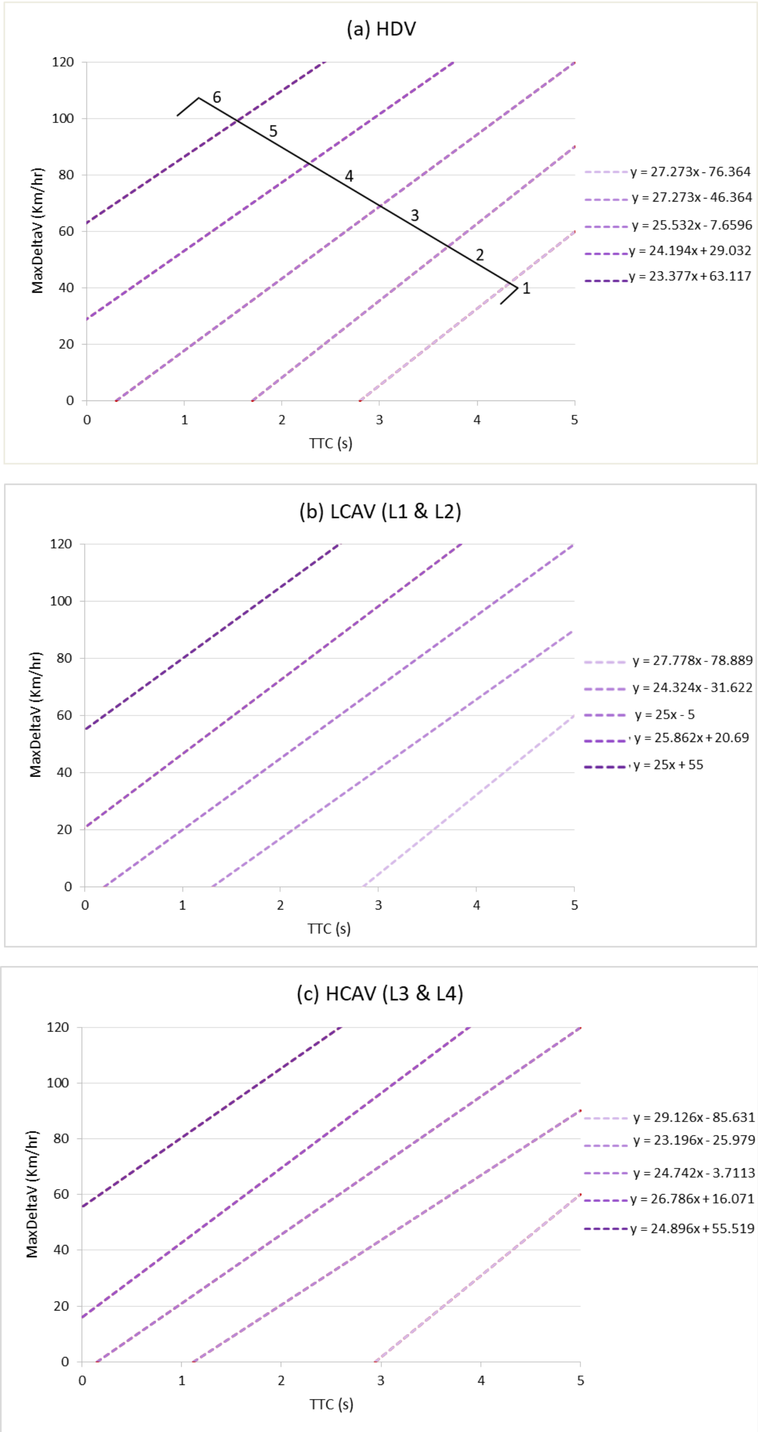
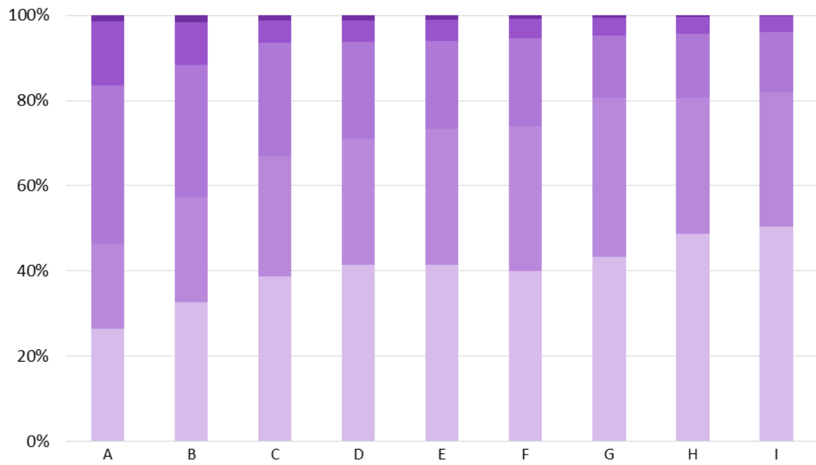


Figure 27: The developed severity levels for HDV and different automation levels: (a) for HDV, (b) for L1 & L2 vehicles, and (c) for L3 & L4 vehicles

Adapted from Miqdady et al. (2023b)

The total conflicts for each scenario were divided into subgroups based on the type of follower vehicle (i.e. from HDV to L4). The chart that should be used for severity level classification was then chosen based on the subgroup of the follower vehicle. If the follower vehicle in conflict is a HDV, Figure 27a is used, if the follower vehicle is a L1 or L2 vehicle, Figure 27b is used, and if the follower vehicle is an L3 or L4 vehicle, Figure 27c is used. Figure 28 depicts the results of applying the severity level charts for conflict severity classification as a percentage of total conflicts among the simulated scenarios.

As shown in Figure 28, a significant reduction in the percentage of conflicts (from the total number of conflicts) with high severity levels (severity level4 or higher) in the transition scenarios between the roads operated only with HDVs (scenario A) and those solely operated with L4 vehicles (scenario I) is observed. The reduction in the percentage of conflicts with severity level4 from scenarios A to I was −74.76% (from 14.98% to 3.78% of the total number of conflicts). For severity level5 or higher, the reduction in the percentage of conflicts was −86.11% (from 1.44% to 0.2%). The scenarios with high vehicle variation (D, E, and F) have also exhibited notable reductions compared with scenario A. These were between −66.62% (from 14.98% to 5%) and −69.82% (from 14.98% to 4.52%) for severity level4 and between −21.52% (from 1.44% to 1.13%) and −40.97% (from 1.44% to 0.85%) for severity level5 or higher.



	A	B	C	D	E	F	G	H	I
Severity level5 or higher	1.44	1.66	1.23	1.13	1.07	0.85	0.52	0.38	0.2
Severity level4	14.98	9.96	5.18	5	4.98	4.52	4.19	3.9	3.78
Severity level3	37.11	31.04	26.76	22.87	20.52	20.64	14.62	14.98	14.1
Severity level2	19.97	24.74	28.15	29.49	31.98	33.96	37.39	32.05	31.58
Severity level1	26.48	32.58	38.65	41.48	41.43	40	43.26	48.67	50.31
Total conflicts	**8836**	**7638**	**5544**	**4336**	**3508**	**3252**	**2920**	**3010**	**2970**

Figure 28: Severity levels frequency (%) among scenarios
Adapted from Miqdady et al. (2023b)

Considering the first introduction of CAV in scenario B where CAV share the road with a percentage of 25% (5% of the CAV have high automation levels (L3 and L4), the most severe conflicts (severity level4 plus level5 or higher) were reduced by 29.23% (from (14.98% + 1.44%) to (9.96% + 1.66%)). In scenario C, where half of the operated vehicles are CAV (15% are L3 and L4 vehicles), the reduction in severity level4 plus level5 or higher was remarkable (−60.96%). This noteworthy reduction in the high severity conflicts from scenarios B and C indicates that scenario C is a significant scenario in CAV introduction with respect to the traffic safety vision of policymakers.

Furthermore, Figure 28 captures the reduction in moderate severity conflicts along the transition toward the fully automation vehicles. For example, the number of conflicts with severity level3 was gradually decreased by increasing the penetration rates of CAV. The reduction in scenario I was −62.0% (from 37.11% to 14.1% of the total conflicts). Two scenarios also had significant reductions in moderate severity conflicts. The highly mixed scenarios, D and E, which include more than 50% CAV, exhibit notable reductions compared with previous scenarios. Scenario G, which includes 90% L3 and L4 vehicles, has shown a distinct reduction of −60.60% (from 37.11% to 14.62%).

Finally, Figure 28 indicates that the less severe (potential) conflicts are the representative conflicts of scenarios in which the fleet consists of L3 and/or L4 vehicles (scenarios G, H, and I). The percentage of conflicts (with severity level1 plus level2) in these scenarios exceeds 80% of the total number of conflicts.

In general, these results agree with those of previous studies that considered the severity term in CAV traffic safety studies. For instance , Rahman et al. (2019) claimed that the duration for a vehicle to be under severe conditions decreased with increasing CAV penetration rates. In addition, the number of evasive actions that mitigate severe crashes decreases as the CAV penetration rate increases. Further, Sinha et al. (2020) used the crash rate term to express the severity that has also decreased by increasing the penetration rates of CAV scenarios.

The findings highlight also the outstanding impact of CAV operation on road traffic safety. The use of CAV reduces the total number of conflicts while also preventing severe conflicts. Evidently, the resulting conflicts are mostly with low severity.

6.3. Traffic safety impact of dedicated lane configurations

This section provides the answer to the third research question:

RQ3 – How will the employment of dedicated lanes (DLs) for CAV introduction affect traffic safety?

It particularly checks the following hypothesis:

Hypothesis 2: the increase in the penetration rate of CAV in general will enhance traffic safety.

Hypothesis 6: roads configured with DLs will satisfy good traffic safety results at high CAV's penetration rates.

By achieving the related objectives:

- To estimate the traffic safety impact of using a DL for CAV introduction, allowing to set an optimal strategy of deploying a DL.

To reach the proposed objective some circumstances related to the deployment of DL on the modelled segment should be clarified:

- Sections with only two-lanes in the simulated motorway are always considered without a DL, based on the studies which emphasized that installing a DL on two-lane highways did not perform well along the introduction period of CAV (Chen et al., 2017; Hamad & Alozi, 2022; Mohajerpoor and Ramezani, 2019; Razmi Rad et al., 2020). Whereas, those sections with three- or four-lanes are configured with a DL for CAV on the left handside of the road. As a result, the total length of sections that are modelled with a DL is 9,038 m in the northbound direction and 9,419 m in southbound direction (i.e. about half of the motorway modeled).
- Following He et al. (2022), only L3 and L4 vehicles (passenger cars and trucks) are assumed to operate in the DL. So, only HCAV will used the DL.
- In Zhang et al. (2020), they considered that one third of the vehicles will pass on the DL if a roadway is of three lanes. Consequenctly, this analysis follows the same logic that the scenarios where the percentage of HCAV is below 30%, following, the configuration considered is one DL with mandatory policy for HCAV. Whereas, in scenarios where the percentage of HCAV is more than 30%, it is considered a configuration with one DL with optional policy, which is recommended as well by the results of He et al. (2022).

- Two traffic conditions are considered for this analysis: free-flow (off-peak) and congested (peak) conditions. Consequently, a new traffic demand (peak-hour demand) is used to analyze the congested condition, keeping the same microsimulation characteristics considered before (with free-flow condition) but increasing the warming time to 25 minutes.

Subsequently, this section presents the traffic safety results of applying two configurations of DL in both peak and off-peak traffic flow conditions. As it is explained previously, the applied configurations are: zero DL and one DL for CAV (with mandatory policy if the percentage of HCAV is below or equal to 30% at traffic flow, and optional policy if it is above 30%).

Table 14 displays the scenarios considered for testing the impact of DL configurations, where the potential percentage of vehicles on the DL (i.e. L3 plus L4 vehicles) is displayed in the shaded columns. Basically, the considered scenarios are with the same vehicle composition that were used in the previous parts of the thesis (in Section 6.1 and 6.2), except for scenario E and G, that they were modified to achieve uniformity in the introduction of HCAV along the scenarios: 5%, 15%, 25%, 30%, 55% and 75%.

Also, as the configuration with only one DL is applied exclusively on sections with three- or four-lanes in the studied motorway, the results are presented to discuss that influence on the traffic safety for the entire motorway segment as well as for only those sections with DL.

Table 14: Employed mix fleet in testing dedicated lane configurations

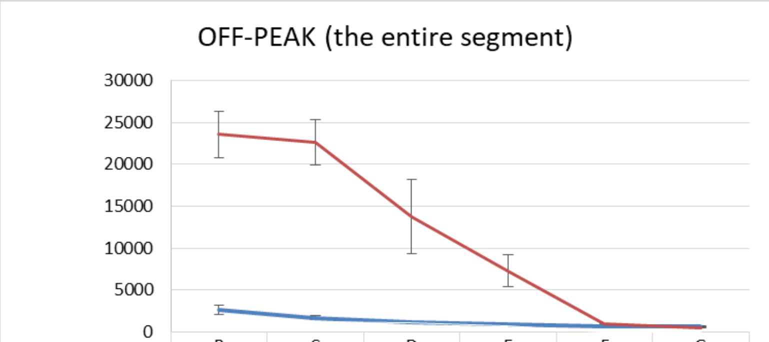
Scenario	HDV	L1	L2	L3	L4	Policy
B	75%	10%	10%	5%	0%	Mandatory
C	50%	10%	25%	10%	5%	Mandatory
D	40%	15%	20%	15%	10%	Mandatory
E*	20%	20%	30%	15%	15%	Mandatory
F	5%	10%	30%	30%	25%	Optional
G*	0%	0%	25%	40%	35%	Optional

**Scenario with different vehicle composition than what used in Section 6.1*

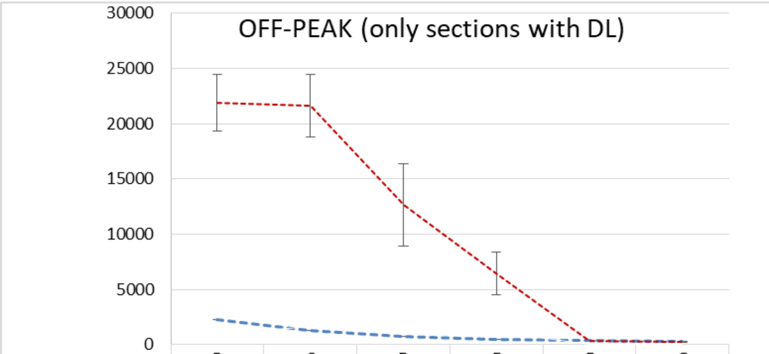
6.3.1. The optimum strategy regarding DL configurations

The next figures (Figure 29 and Figure 30) exhibit the conflicts obtained in both road configurations (zero DL and one DL for HCAV), allowing to evaluate the traffic safety impact of these both operational configurations that could be implemented during the transition period between manual driving and autonomous driving.

Figure 29 reflects the traffic safety impact of zero and one DL configurations in off-peak traffic flow condition, to assess when it could be useful from traffic safety perspective to choose one DL configuration during the transition period between manual and autonomous driving. Figure 29 shows the resulted conflicts at both configurations and the computed percentage of change between these two values at each scenario. For example, the percentage of change caused by employing a DL in scenario B at off-peak condition for the entire segment is +793.44% (i.e. the number of conflicts increased from 2,637 to 23,560 when one DL is considered). In this case (scenario B) we have a mandatory use of the DL for HCAV.



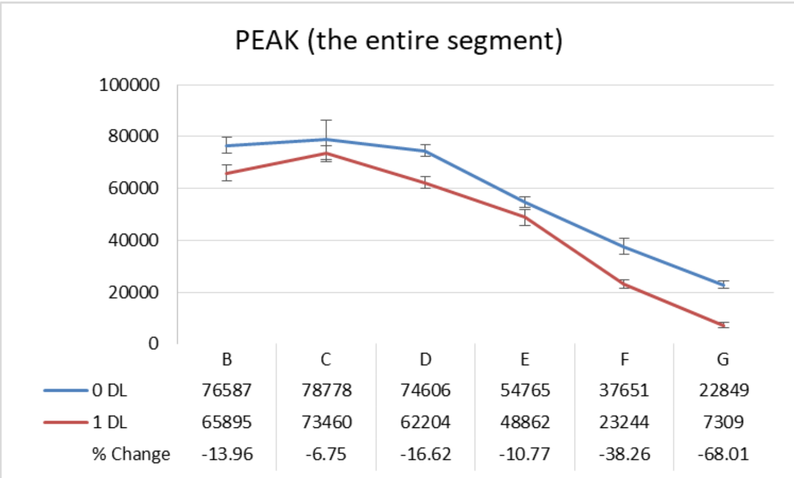
	B	C	D	E	F	G
0 DL	2637	1675	1137	900	648	641
1 DL	23560	22634	13733	7300	920	501
% Change	793.44	1251.28	1107.83	711.11	41.97	-21.84



	B	C	D	E	F	G
0 DL	2239	1230	709	500	406	302
1 DL	21895	21628	12650	6480	296	203
% Change	877.89	1658.37	1684.2	1196	-27.09	-32.78

Figure 29: Resulted conflicts of DL configurations in off-peak condition

According to the mentioned figure (Figure 29), zero DL configuration generally performs better than one DL (i.e. generates fewer conflicts) with CAV introduction at low traffic volumes, which is not different in the whole section case than analyzing only sections configured with a DL. However, there is a point where it generates an opposite impact on traffic safety, and configuring a DL could enhance traffic safety on roads with free flow condition.In this case, the optimum strategy is to configurate a DL with optional policy only when the penetration rate of HCAV is above 55% (scenario G). In terms of traffic efficiency, earlier studies came up with a number of optimum points, regarding CAVs penetration rate, for implementing a DL, including 30% (Hamad and Alozi, 2022), 40% (Zhong et al., 2020), 50% (Mohajerpoor and Ramezani, 2019), and 80% (optional policy) (He et al., 2022). They also concurred that if traffic flow is light, zero DL is a superior configuration especially for low CAV penetration rates in general (i.e. LCAV and HCAV).



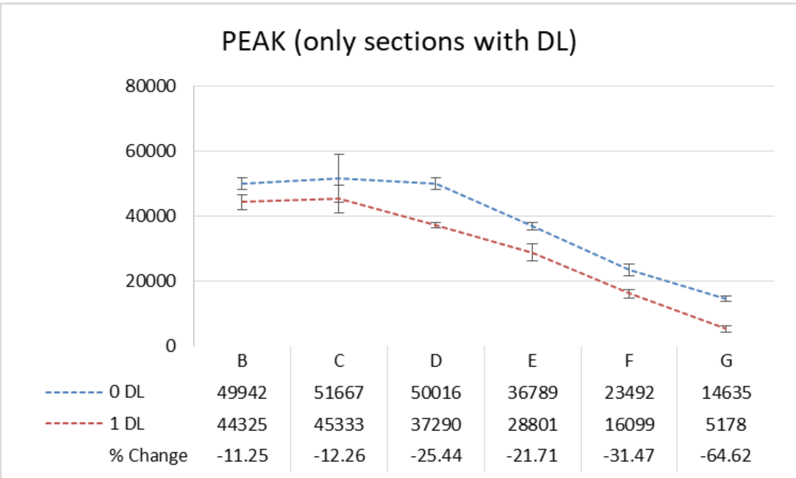


Figure 30: Resulted conflicts of DL configurations in peak condition

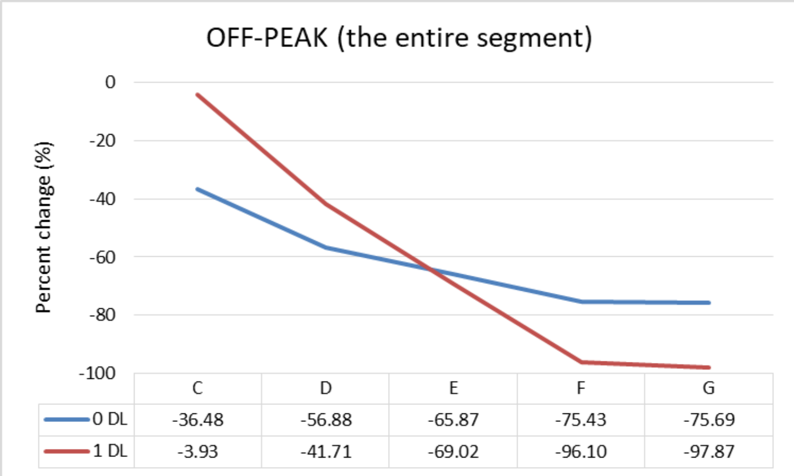
Additionally, at the 55% point (scenario F), the presence of DL with optional policy registered 41.97% more conflicts at the overall segment than the zero DL. However, when only looking at the three- and four-lane sections that are configured with DL in our case, they registered 27.09% fewer conflicts than the base case (i.e. zero DL), demonstrating the impact of this level of penetration on traffic safety on these sections even though it was unable to improve the traffic safety of the entire segment.

In contrast to the off-peak conditions, during peak conditions we obtain a different outcome (Figure 30*)*, suggesting that using one DL could increase traffic safety in all scenarios and under all conditions (i.e. low penetration rates of CAV with mandatory policy and high penetration rates of CAV with optional policy). The results are consistent for both the entire segment level and for the sections containing the DL, with conflicts reduction ranging from 6.75 to 68.01% for the entire segment and from 11.25 to 64.62% for the segments with the DL.

6.3.2. Traffic safety feasibility of DL among scenarios

This subsection investigates in depth whether one DL is beneficial from the standpoint of traffic safety. To put it more precisely, it enables comparison of the percentage change in the stream conflicts between each scenario and scenario B, which serves as the baseline scenario, demonstrating whether one DL configuration results in greater reduction than zero DL configuration during the CAV introduction period. Once more, the results are divided by traffic flow conditions (off-peak vs. peak) as well as by segment as a whole or only the DL-equipped sections. Figure 31 demonstrates this comparison (zero DL vs. one DL) that is related to the off-peak traffic condition. Considering B as the base scenario, the reduction pattern, in general, is similar in both the entire segment and only the sections with DL, with lower reduction of one DL case compared to zero DL at low penetration rates of HCAV (scenarios C and D) and higher reduction in scenarios with higher percentages of HCAV (scenarios F and G).

Scenario E shows different outcomes depending on the section analyzed: one DL provides a slightly better safety at the entire segment level, while this is not the case when only sections that have been configured with DL are taken into account. Nevertheless, the reduction at this scenario still shows a huge reduction if compared with scenario D under off-peak conditions (i.e. the reduction is -42.22% in scenario D, while it is -70.4% in scenario E).



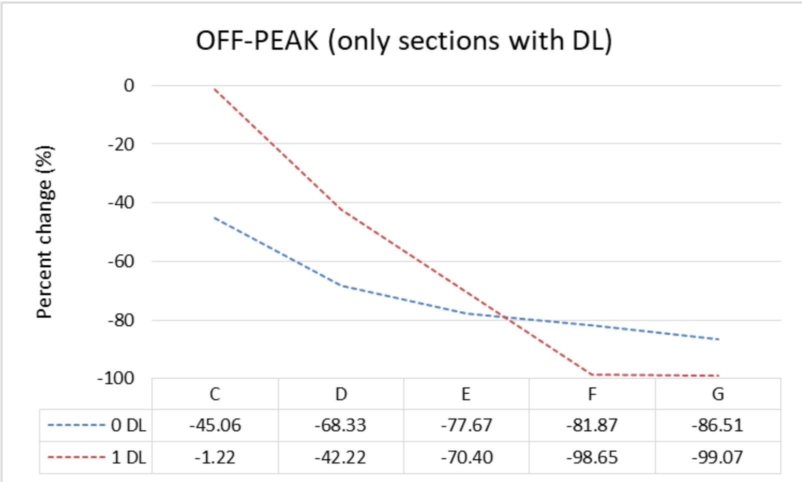
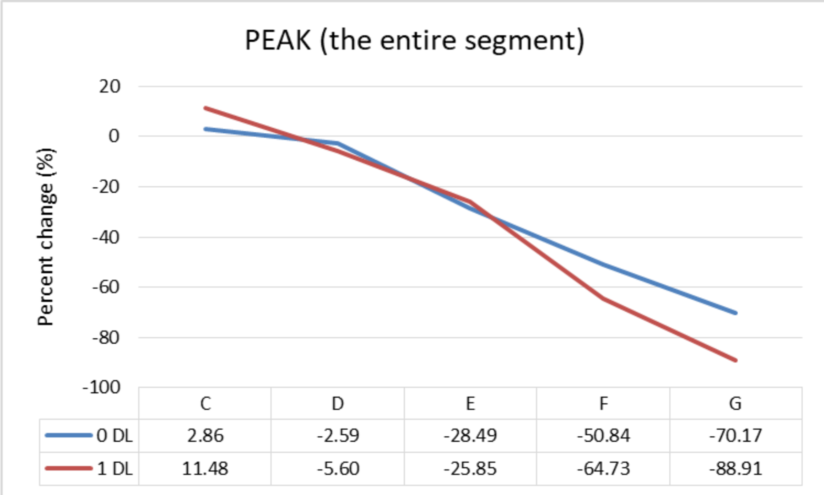


Figure 31: DL configurations conflicts reduction regarding CAV introduction (off-peak condition)



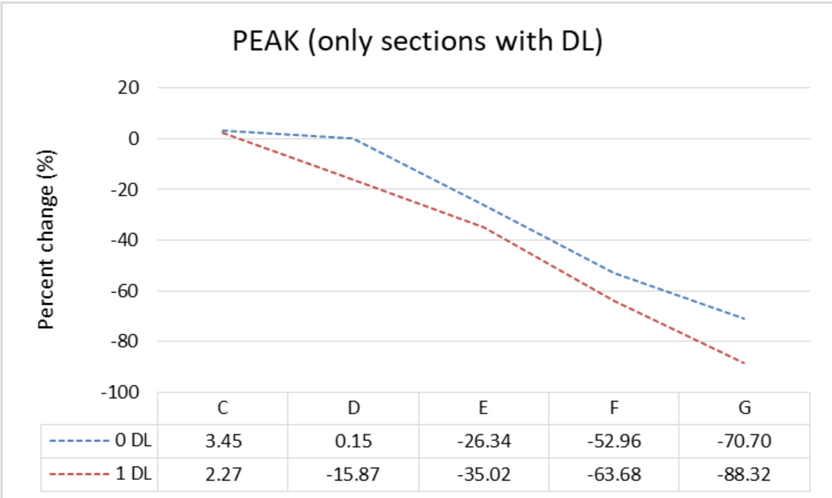


Figure 32: DL configurations conflicts reduction regarding CAV introduction (peak condition)

On the other hand, the reduction of conflicts during peak conditions regarding zero DL and one DL configuration is presented in Figure 32. A distinct pattern is reflected as opposed to off-peak conditions. The safety impact of DL on the entire segment level is not shown up until the segment is operated with high penetration rates of HCAV (55% and 75%, respectively, in scenarios F and G).

The existence of only 15% of HCAV on the road (scenario C) reduces the overall safety of the highway for one DL configuration (the number of conflicts increase if compared to scenario B). Later, with 25% and 30% HCAV on the road (scenarios D and E), operating mandatory on the DL, the safety of the motorway segment in both zero DL and one DL configurations nearly matches. On the other hand, when considering only the sections configured with DL (three- and four-lane sections) a larger reduction due to one DL configuration is visibly apparent. Particularly, the drop begins when the penetration rate of HCAV is 25% (scenario D).

The results in Zhang et al. (2020), who studied the safety impact of DLs with penetration rates of CAV up to 30%, revealed thatwhen using a single mandatory DL configuration, the maximum reduction in potential crash risk reached up to about 53% in off-peak conditions and about 48% in peak conditions. At this amount of CAV penetration (scenario E), however, our data does not demonstrate as better safety gains, where off-peak condition does not result in any safety gain (711% to 1196% more conflicts) and peak condition demonstrates between 10.77% and 21.71% less conflicts (Figure 31, Figure 32). The reasonable discrepancy between both studies is due to different inputs, including different CAV calibration in traffic flow and lane-change models, the inclusion of all levels of automation in this study while only discussing one level in their study, and, finally, different measures of safety (crash-risk/conflicts) in each study. Practically, they utilized surrogate safety measures that estimate the time that the vehicle is exposed to risk based on the time-to-collision (TTC) integration (e.g. time exposed time-to-collision (TET), and time-integrated time-to-collision (TIT)), whereas the current study employed the TTC for conflict identification.

On the other side, He et al. (2022), who calibrated all levels of automation and penetration rates and implemented various DL policies, comprise the bulk of our analysis, although they examined traffic efficiency no traffic safety. They demonstrated that the most effective strategy to increase traffic efficiency on the roads is to operate a DL with high automation levels at high penetration rates. Additionally, traffic efficiency studies that considered both peak and off-peak traffic volumes confirm that the one DL configuration has a greater impact during peak conditions (congestion) than it does during lower traffic volumes, which generally resulted in the zero DL configuration's superior performance (Chen et al., 2017; Hamad and Alozi, 2022; Zhong et al., 2020).

6.4. Traffic safety sensitivity analysis regarding CAV calibration parameters

This section provides the answer to the fourth research question:

RQ4 – How will the change of the values of traffic behaviour parameters affect traffic safety? What are the key traffic parameters that affect traffic safety?

It particularly checks the hypothesis:

Hypothesis 7: reaction time and car following parameters are key parameters in enhancing traffic safety on roads.

By acheving the related objectives:

- To explore the sensitivity of traffic safety to changes in the parameters that define the CAV behaviour (CAV calibration parameters), and to identify which are the key parameters affecting traffic safety.

6.4.1. The simulation runs

Based on the critical review conducted in subsection 2.3.4, various step values were assigned to each of the paramteres proposed to be tested. Table 15 shows the introduced step values for the examined parameters in the sensitivity analysis and the total number of runs applied for each parameter.

Primarily, 15 runs were applied for each step-value for each parameter analysed in the ceteris paribus analysis, and then 15 runs were applied for each pair of step values of the parameters analysed in the two-at-a-time sensitivity analysis. In total, 2,985 runs were conducted in this study: 615 runs for the ceteris paribus analysis and 2,370 runs for the two-at-a-time analysis after the significant parameters from a safety perspective were identified.

Table 15: The proposed values to be tested with each parameter

Parameter	values	Total number of runs (for ceteris paribus)
Reaction time (s)	0.1/0.2/0.3/0.4/0.5/0.6/0.7/0.8	120
Clearance (m)	0.5/1.0/1.5/2.0	60
Max. acceleration (m/s^2)	1.0/2.0/3.0/4.0	60
Normal deceleration ($-m/s^2$)	2.0/3.0/4.0	45
Sensitivity factor	0.5/0.7/0.9/1/1.1/1.3	90
Platoon size (No.)	4.0/6.0/8.0/10.0	60
Lateral clearance (m)	0.2/0.3/0.4/0.5	60
Look ahead distance factor	0.8-1.2/0.9-1.2/1.0-1.25/1.1-1.3	60
Overtake speed threshold (%)	80/85/90/95	60

6.4.2. The key parameters

This analysis takes an important step toward understanding how the proposed changes in CAV behaviour can affect road traffic safety. As outlined in a previous section (subsection 2.3.4), some parameters have been proposed to be analysed for calibrating the CAV behaviour. The parameters included the reaction time, clearance, maximum acceleration, normal deceleration in the flow, sensitivity to leader deceleration, platoon size, lateral clearance, looking-ahead distance, and overtaking speed threshold. The results of changing their values one-at-a-time were obtained as the number of simulation-based traffic conflicts.

The results are illustrated in Table 16. The shaded values represent the default values in Gipps' models (i.e. it is related to human driving behaviour). Table 16 also shows the number of conflicts as the average value of the 15 runs and the standard deviation for each parameter value examined. The results of the ANOVA among the examined values of each parameter appear with letters in the last column (Homogeneous subgroups) to identify statistically significant differences among the number of conflicts. The same letter indicates the same homogeneous subgroup between the different values of that parameter. Therefore, the parameters that showed only one letter are not considered for the next step (two-at-a-time analysis).

Technology advancement provided by CAV is proposed to decrease the reaction time and change the clearance which promises to significantly enhance traffic safety.Xie et al. (2019) confirmed these predictions when they tested several values of reaction time related to automation levels; shorter reaction times resulted in a lower number of conflicts in both freeways and urban streets and within different traffic volumes.

In addition, this analysis (Table 16) shows that traffic safety conflicts are highly sensitive to driver reaction times. Stanek et al. (2018) also emphasised the significant change that faster reaction time of CAV could produce in both shorter headways and lane change's shorter gap acceptance. Precise findings of the current study indicate the following: each 0.1 s change in reaction time presented statistically significant differences ($p<0.05$) in the number of conflicts arisen, except for 0.2 to 0.5 s that shape two homogeneous groups. Reaction time equal to 0.2 and 0.3 s represents group b, and reaction time equal to 0.3, 0.4, and 0.5 s represents group c. Therefore, the main significant steps are as follows: if compared to the base value, the first 0.1 and 0.2 s decrease (0.7 and 0.6 s reaction time) have shown about 25 and 38% improvement respectively in traffic safety. Reaction time equal to 0.3, 0.4 and 0.5 s has registered a value higher than 50% of traffic conflict reduction, and a drop of about two third of the default resulted conflicts is reached with 0.2 and 0.3 s reaction time. Lastly, reaction time equal to 0.1 s improved traffic safety by about 77%.

However, Table 16 demonstrates that in standstill situation, traffic safety does not exhibit a strong sensitivity to the distance between vehicles (clearance). Nevertheless, the assertive driving style (0.5 m clearance) duplicates the traffic conflicts of the suggested human driving clearance (1.0 m). Though there are no statistically significant differences between the other values which represent the cautious driving (1.5 and 2.0 m), they show a reduction in traffic conflicts if compared with the default value (1.0 m). Precisely, they represent 70.2% and 64.7% of the default value's result. Xie et al. (2019) examined traffic safety among levels of automation (with decreasing clearance by increasing automation level) and found higher traffic conflicts for small clearances. They also highlighted that this effect increases with higher traffic volumes (moderate and congested traffic conditions).

Table 16: One way ANOVA analysis results for the examined parameters

Parameter	Examined values	No. of conflicts Mean (std.)	Homogeneous Subgroups*
Reaction time (s)	0.1	50(10.32)	a
	0.2	74(10.84)	b
	0.3	87(10.70)	b,c
	0.4	99(12.86)	c
	0.5	105(18.07)	c
	0.6	137(20.17)	d
	0.7	165(19.23)	e
	0.8	218(24.86)	f
Clearance (m)	0.5	497(95.22)	a
	1.0	218(24.86)	b
	1.5	153(13.32)	c
	2.0	141(10.52)	c
Max. acceleration (m/s^2)	1.0	1613(313.50)	a
	2.0	237(32.95)	b
	3.0	218(24.86)	b
	4.0	199(28.34)	b
Normal deceleration (m/s^2)	- 2.0	330(96.01)	a
	- 3.0	250(56.93)	b
	- 4.0	218(24.86)	b
Sensitivity factor	0.5	1299(57.48)	a
	0.7	649(44.17)	b
	0.9	211(16.07)	c
	1.0	218(24.86)	c
	1.1	546(328.01)	b
	1.3	1517(205.33)	d
Platoon size (No.)	4.0	215(25.57)	a
	6.0	202(22.31)	a
	8.0	206(24.90)	a
	10.0	218(24.86)	a
Lateral clearance (m)	0.2	208(21.59)	a
	0.3	218(24.86)	a
	0.4	202(21.90)	a
	0.5	199(23.79)	a
Look ahead distance factor	0.8-1.2	218(24.86)	a
	0.9-1.2	222(25.69)	a
	1.0-1.25	216(23.86)	a
	1.1-1.3	210(17.62)	a
Overtake speed threshold (%)	80	202(26.38)	a
	85	200(16.67)	a
	90	218(24.86)	a
	95	214(16.79)	a

**Different letters (a, b, etc.) denote statistically significant differences ($p < 0.05$) between the values of one parameter. Two or more values with the same letter denote a homogeneous subgroup.*

Note: The shaded values are the default values in Aimsun models

The behaviour related to longitudinal movement is expected to change with the introduction of CAV. A wide range of assumptions are made in calibrating the car-following model parameters to represent the CAV behaviour, as explained in Section 2.3.4. In summary, Table 16 shows that low values of maximum acceleration and normal deceleration may dramatically reduce traffic safety on the road. However, this could change if all vehicles exhibit the same cautious behaviour (Virdi et al., 2019).

Table 16 also shows that the normal values around the default values did not show statistically significant differences. However, as these parameters define the dynamics in the driving models, CAV behaviour calibration in the literature is mainly dependent on these parameters (e.g. ATKINS, 2016; Sinha et al., 2020; Talebpour & Mahmassani, 2016).

Moreover, regarding previous studies which calibrated CAV behaviour by assigning values of different parameters simultaneously (including acceleration and deceleration parameters), the results were as follows: studies which used low values (e.g. 1.0 and 1.5 m/s^2) for CAV acceleration (e.g. Guériau & Dusparic, 2020; Zhang et al., 2020) presented a considerable effect on traffic safety enhancement, however, they calibrated the acceleration with other performance parameters that could enhance traffic safety on the road (i.e., with low reaction time or lower speed deviation). Whereas, the use of values around the default value (e.g. ATKINS, 2016; Sinha et al., 2020; Xie et al., 2019) did not significantly change the effect on traffic safety, which is confirmed by our sensitivity analysis.. This indicates that acceleration and deceleration could present significantly different effects if they are calibrated individually or with other parameters.

Another parameter could point out the car-following issue, which is the sensitivity factor to leader deceleration. Both the underestimation (<1.0) and overestimation (>1.0) of the leader deceleration on the road negatively affect traffic safety. Many errors in programming, performance, or even the application of highly cautious or assertive driving behaviour can lead to a CAV which behaves as a highly sensitive or very low sensitivity to its leader vehicle deceleration. Table 16 also presents an interesting finding. Traffic safety is highly sensitive to these two situations, and is more sensitive in the overestimation case (when the sensitivity factor is above 1).

For example, traffic safety will not be statistically significantly affected if the leader deceleration is underestimated by 10% (sensitivity factor = 0.9), but it is not the case when an overestimation of 10% (sensitivity factor = 1.1), which will multiplicate traffic conflicts by 2.5 times (from 100% to 250%) which is in the same significant group as the underestimation of 30% of leader deceleration (sensitivity factor = 0.7).

This indicates that the aggressiveness of the vehicle deceleration to its leader, which normally decelerates (overestimation), increases the potential of crashes significantly when compared to the case when the vehicle maintains its normal deceleration while the leader could present breaking behaviour. Finally, to calibrate the CAV to present a precise and highly efficient estimation of the leader dynamics, 1.0 or 0.9 sensitivity factor is recommended.

In addition, the platoon size that will be performed in the CAV by a co-operative adaptive cruise control system was tested in this study. Four, six, eight, and ten vehicles in a platoon did not show a statistically significant difference in traffic safety. Nevertheless, decreasing the number of vehicles in the platoon slightly enhanced the traffic safety and decreased the number of traffic conflicts. This result was previously reported by both Aramrattana et al. (2021) and Faber et al. (2020) who explained that a higher number of vehicles in a platoon reflects more braking actions which may result in a higher number of conflicts.

As CAV could also affect traffic behaviour in lateral movements, we selected three parameters that reflect lateral movements and lane-changing manoeuvres to be analysed. First, several values of lateral clearance between vehicles were tested, and the results showed that increasing the lateral clearance could enhance traffic safety. However, there were no significant differences. It should be highlighted that this analysis in urban and/or congested cases could have a significant effect on traffic safety.

Moreover, the upstream distance to the point where the vehicle is aware of its target lanes (look-ahead distance) for the lane-change process was studied by changing the range of the minimum and maximum look-ahead factors. Owing to the projected facilitation of CAV lane changing, all the ranges tested were for values above the default one. The results did not show any statistically significant differences among the ranges tested.

The last parameter selected is the overtake-speed threshold. In the overtaking case of the vehicle moving forward, whenever a vehicle is constrained to drive slower than the overtake-speed threshold as a percentage of its desired speed, it will try to overtake. The tested thresholds for overtaking did not show statistically significant differences in the number of traffic conflicts. However, it can be indicated that the lower thresholds (80% and 85%) provided by Mesionis et al. (2020) and Papazikou et al. (2020), have shown a slight enhancement in traffic safety if combined with very low values of reaction time and aggressiveness measures.

6.4.3. Key parameters combinations

As mentioned previously, the key parameters are those that have shown a statistically significant impact on traffic safety when their values have changed and are frequently employed in CAV behaviour calibration. Consequently, based on the results in the previous subsection, platoon size, lateral clearance, look-ahead distance factor, and overtaking speed threshold are not considered for the two-at-a-time sensitivity analysis, as they are non-key parameters. In contrary, a two-at-a-time sensitivity analysis accompanied by a two-way ANOVA is performed by combining the key parameters.

Figures 33 to 42 and Tables 17 to 26 display the findings of this analysis on the number of conflicts (based on 15 runs at each two-way step value).

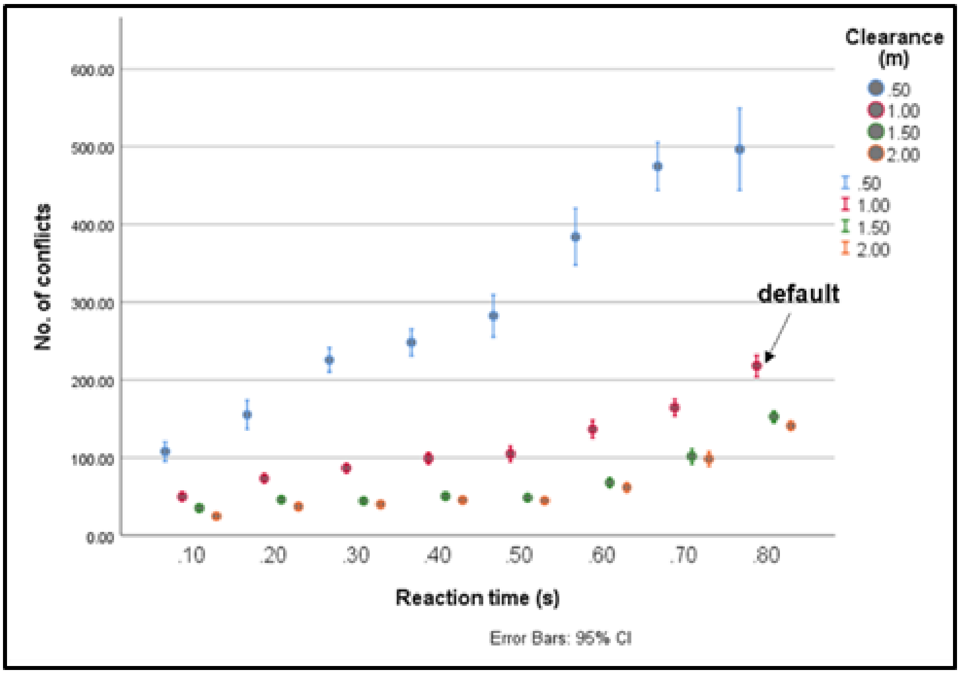


Figure 33: Reaction time (s) vs clearance (m) two-at-a-time analysis

Figure 33

Figure 33 shows that traffic safety is improved by simultaneously decreasing the reaction time and increasing clearance. A short clearance (0.5 m) demonstrates the highest number of conflicts regardless of the reaction time. However, the effect is smoothed with very short reaction times (below 0.3 s), which show a number of conflicts lower than the result of the default value (i.e. when the reaction time is 0.8 s and clearance is 1.0 m). These results go in line with Stanek et al. (2018) discussion that CAV will provide both shorter reaction time and clearance together, which indicates that lower reaction times will overcome the risk derived by lower clearance values.

Figure 34 shows how both the reaction time and the maximum acceleration are extremely significant parameters for traffic safety. Every small step in these parameters generates a significant group (see Table 18). In addition, combinations which include low maximum acceleration (1 m/s²) reflect the highest adverse impact on traffic safety, regardless of the reaction time. Nevertheless, the shortest reaction times (0.1 s, 0.2 s) showed better safety in these cases. For the rest of the combinations with other than 1 m/s² maximum acceleration, a gradual improvement in traffic safety is registered by decreasing the reaction time and increasing the maximum acceleration. Only two studies have considered these two parameters at the same time (Miqdady et al., 2023a; Zhang et al., 2020). In Zhang et al. (2020), a low value of acceleration (1 m/s²) was combined with 0.5 s of reaction time, and their results varied between deteriorating and enhancing traffic safety on the road. However, their results were related to special road configuration and policy operation (exclusive lanes). Whereas, in Miqdady et al. (2023a), two different combinations for reaction time and maximum acceleration to calibrate CAVs at the same traffic model were used (0.5 s & 1 m/s² and 0.1 s & 1 m/s²). They found similar results to this study (the combination 0.1 s & 1 m/s² provided lower number of conflicts).

A similar pattern was identified in the reaction time/normal deceleration case (Figure 35). The scale clearly indicates that traffic safety improves by simultaneously decreasing the reaction time and increasing the normal deceleration at the same time. The results agree those findings in Miqdady et al. (2023a), where their calibrated combination 0.1 s & -3 m/s² resulted in less conflicts than the 0.5 s & -3 m/s² combination, indicating the crucial impact of reaction time parameter.

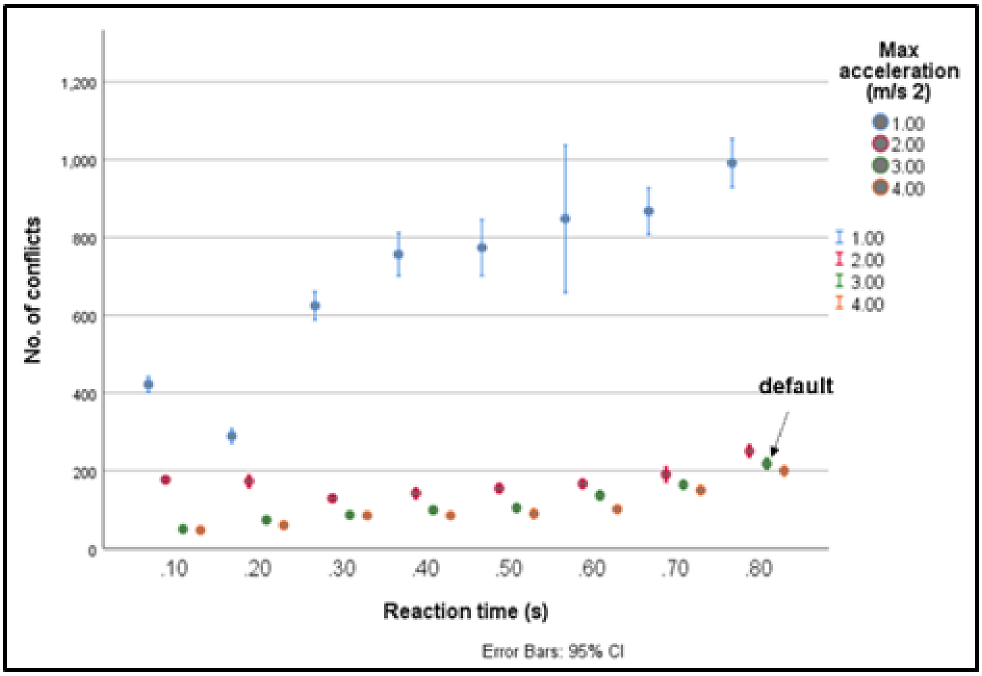


Figure 34: Reaction time (s) vs maximum acceleration (m/s²) two-at-a-time analysis

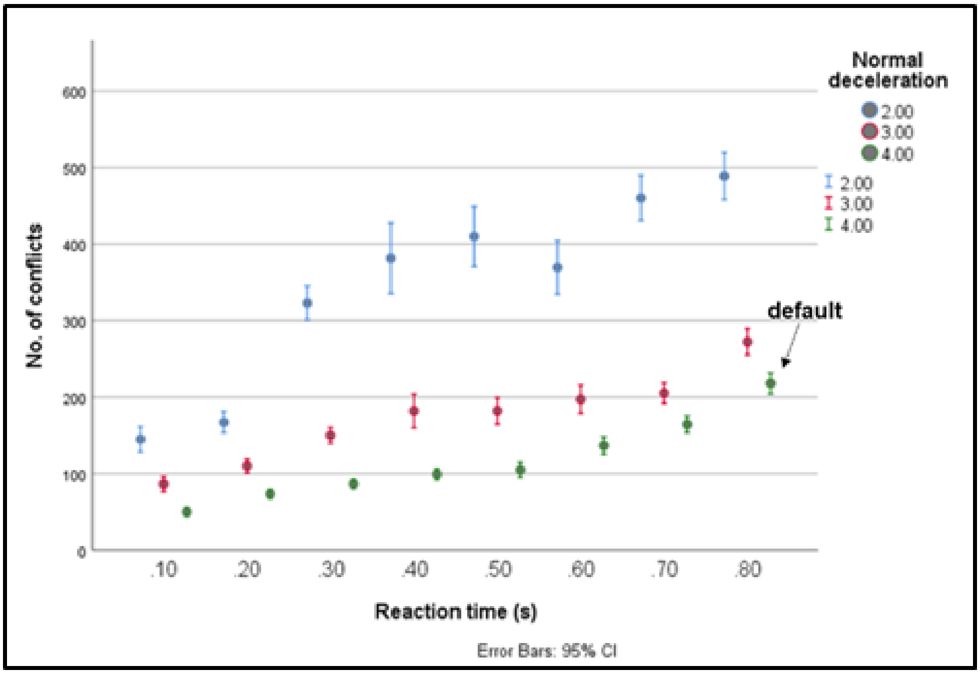


Figure 35: Reaction time (s) vs normal deceleration (m/s²) two-at-a-time analysis

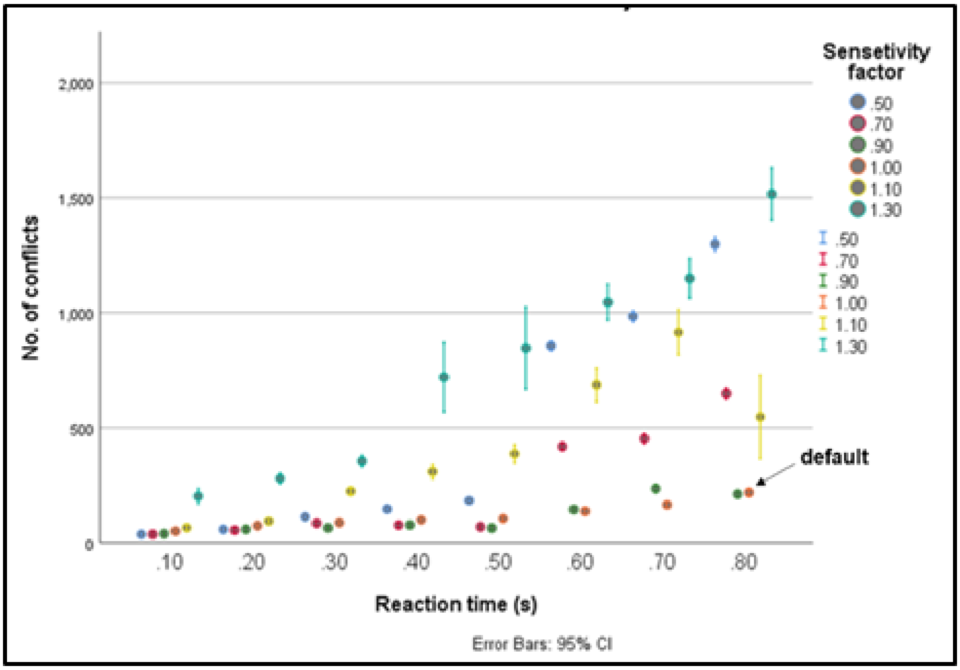


Figure 36: Reaction time (s) vs sensitivity factor two-at-a-time analysis

Considering both reaction time and sensitivity factor together (Figure 36), the results underline that, in general, traffic safety is more sensitive to reaction time as the number of conflicts decreases, mainly while decreasing the reaction time. Very short reaction times (0.1–0.3 s) resulted in the highest improvement in traffic safety, regardless of the fit of estimation of the leader deceleration. In contrast, the effect of under/over estimation of the leader deceleration (i.e. the error in estimation) on traffic safety is adversely increased with an increase in the reaction time to take action and averting traffic incidents.

These results agree with the Levitate project's results (Mesionis et al., 2020; Weijermars et al., 2021), which after calibrating Gipps' models for CAV behaviour with two different combinations of reaction time and sensitivity factor (0.1 s & 0.5 and 0.1 s & 0.7), they identified that the combination 0.1 s & 0.7 generated a lower number of conflicts. Likewise, Miqdady et al. (2023a) found that 0.5 s & 1.1 combination generates a higher number of conflicts than 0.1 s & 1.2.

Studying the effect of clearance and maximum acceleration together reflects the following: combining both high clearance/maximum acceleration values indicates a high traffic safety improvement (Figure 37, Table 21), Most of these two-way values follow homogeneous groups and represent a similar number of conflicts. The most significant groups with negative effects on traffic safety were 0.5 m & 1 m/s^2 and 1.0 m & 1.0 m/s^2. A similar effect was demonstrated by the clearance/normal deceleration combination (Figure 38,

Table 22). Increasing both values results in an enhancement in traffic safety. The combinations used in CAV calibration in Miqdady et al. (2023a) confirms the results of the current study, in that there are slight differences while clearance is larger than 1.0 m.

On the other hand, Figure 39 and Table 23 shows that combining low values of maximum acceleration (1 m/s^2 or even 2 m/s^2) with different values of normal deceleration generates a significant negative effect on traffic safety. However, none of the other combinations, even with low deceleration (-2 m/s^2), showed statistically significant differences in the number of conflicts. Thus, traffic safety is more sensitive to maximum acceleration. However, in one hand, both factors are regarded as sensitive factors in CAV calibration and in driving behaviour in general (ATKIN, 2016; Stanek et al., 2018). And, on the other hand, as previously shown in this section, the changes regarding the two factors are affected by reaction time combined value as well.

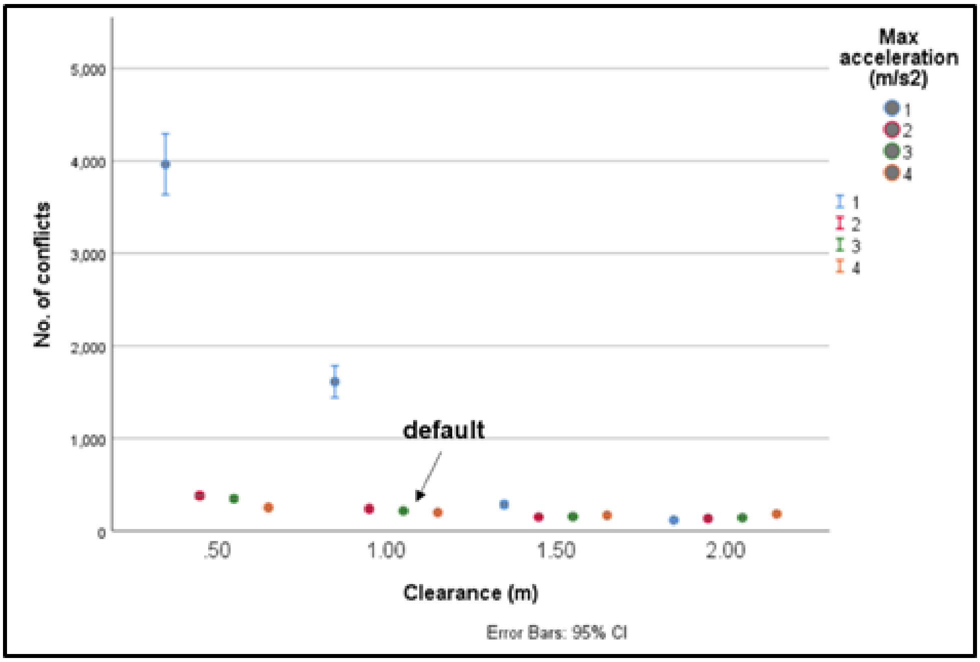


Figure 37: Clearance (m) vs maximum acceleration (m/s²) two-at-a-time analysis

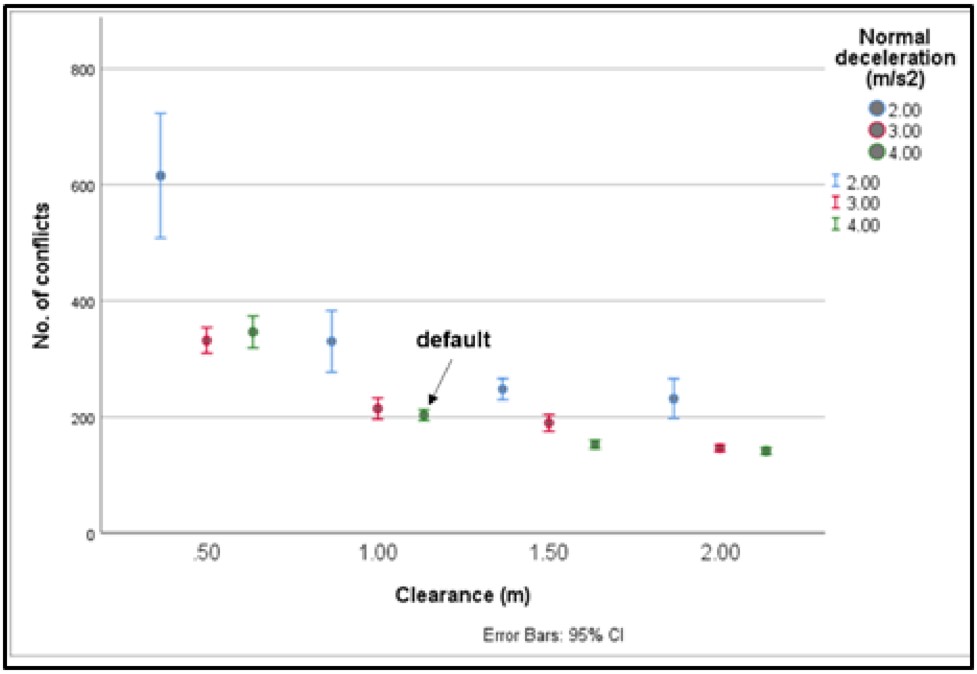


Figure 38: Clearance (m) vs normal deceleration (m/s²) two-at-a-time analysis

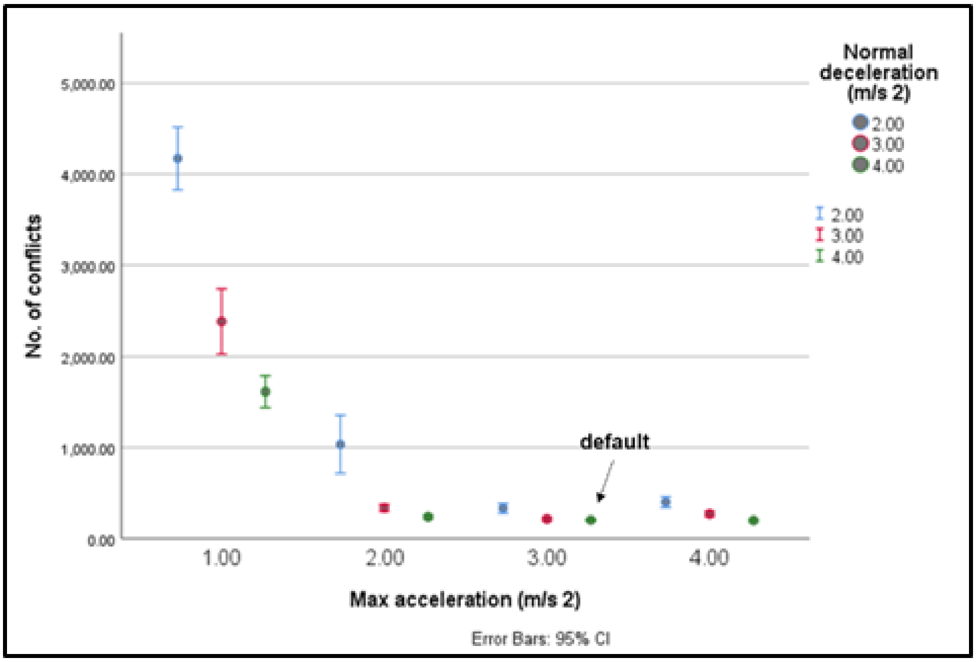


Figure 39: Maximum acceleration (m/s²) vs normal deceleration (m/s²) two-at-a-time analysis

Regarding the sensitivity factor parameter combinations, sensitivity factor/clearance (Figure 40, Table 24) shows an interesting result: the under/overestimation of the leader deceleration, even with high percentages (30%), could be overcome by introducing sufficiently long clearance values (1.5, 2.0 m). However, shorter clearances (0.5, 1.0 m) would adversely affect traffic safety if combined with under/overestimation cases. The outcomes obtained by Miqdady et al. (2021) showed that under large clearance value for CAV (1.5 m), if the sensitivity factor is near to the default value (i.e. lower under/overestimation); a value equal to 1.1, resulted in better traffic safety than with larger values (1.2).

In the sensitivity factor/maximum acceleration analysis (Figure 41, Table 25), the greatest traffic safety improvement is registered when the sensitivity factor is equal to 0.9 or 1.0, and the maximum acceleration shift between 2–4 m/s² (i.e. the combinations 0.9 & 2.0 m/s², 0.9 & 3.0 m/s², 0.9 & 4.0 m/s², 1.0 & 2.0 m/s², 1.0 & 3.0 m/s², and 1.0 & 4.0 m/s²) without statistically significant differences among the means. A sensitivity factor of 0.7 also presents good safety values. This indicates that a low underestimation of leader deceleration (0.7 and 0.9) can be addressed by increasing the maximum acceleration. On the other hand, high undere/overestimation (sensitivity factor = 0.5 or 1.3) combinations show the worst results regardless of the maximum acceleration applied. Keeping the default value of maximum acceleration, Levitate project (Papazikou et al., 2020) tested the values of 0.5 and 0.7 of sensitivity factor and it was found in their traffic safety evaluation (Weijermars et al., 2021) that 0.7 & 3.0 m/s² combination resulted in lower number of conflicts than 0.5 & 3.0 m/s^2 combination, which is sounding the current results.

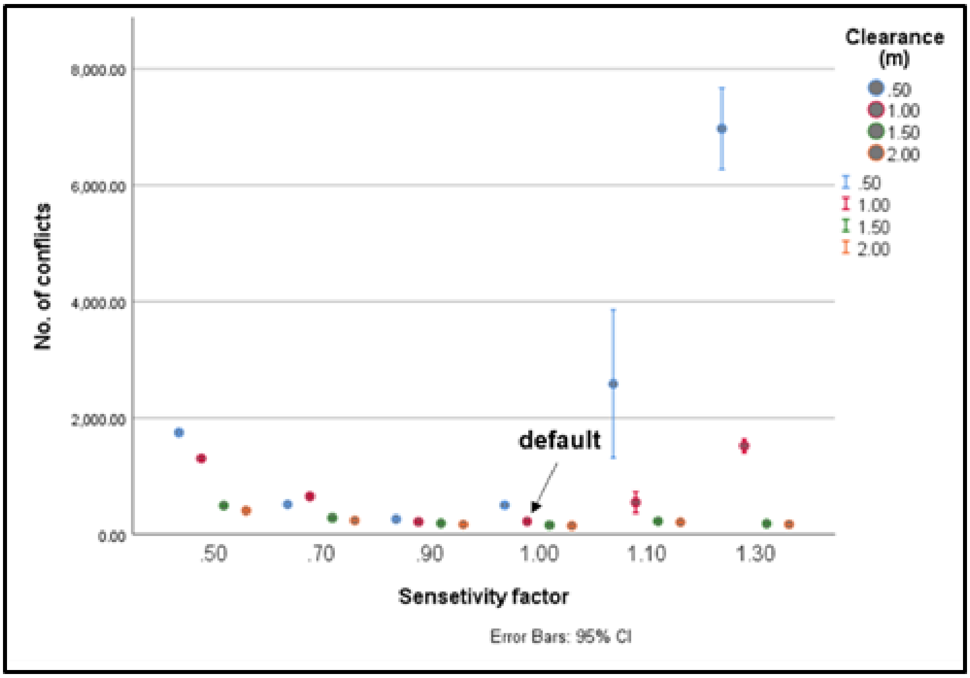


Figure 40: Sensitivity factor vs clearance (m) two-at-a-time analysis

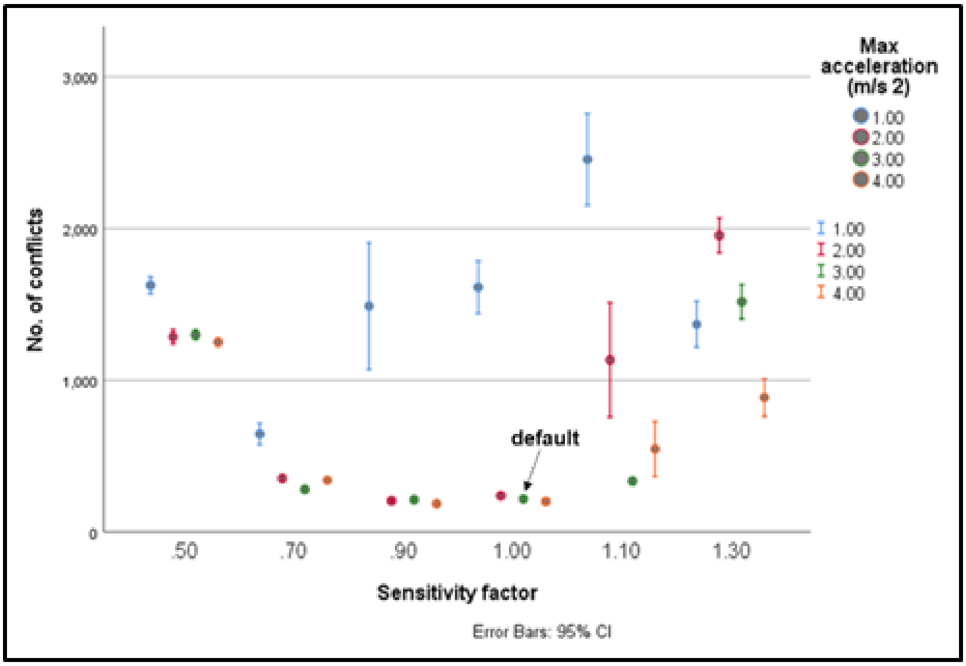


Figure 41: Sensitivity factor vs maximum acceleration (m/s^2) two-at-a-time analysis

Finally, from Figure 42 and Table 26 , the high sensitivity to leader deceleration (0.9 or 1) presents the minimum brought out traffic conflicts without statistically significant differences among their means, regardless of the normal deceleration on the road (2, 3, or 4 m/s²). The logical relationship between these two parameters is shown in Figure 42. If the deceleration in traffic flow is already high (-4 m/s²) and greatly underestimated (0.5 and 0.7), the risk will be higher, and traffic safety will worsen significantly. On the other hand, a small overestimation of the leader deceleration could be overcome by higher deceleration values (1.1 & -4 m/s² combination). However, if the overestimation of leader deceleration is high (1.3), the negative effect on traffic safety will be significant, although the deceleration value is high (1.3 & -4 m/s² combination).

Likewise, under the same normal deceleration value (for example -3.0 and -4.0 m/s²), the 30% underestimation shows significantly better traffic safety than that of 50% of underestimation, which agrees with earlier studies (Papazikou et al., 2020; Weijermars et al., 2021).

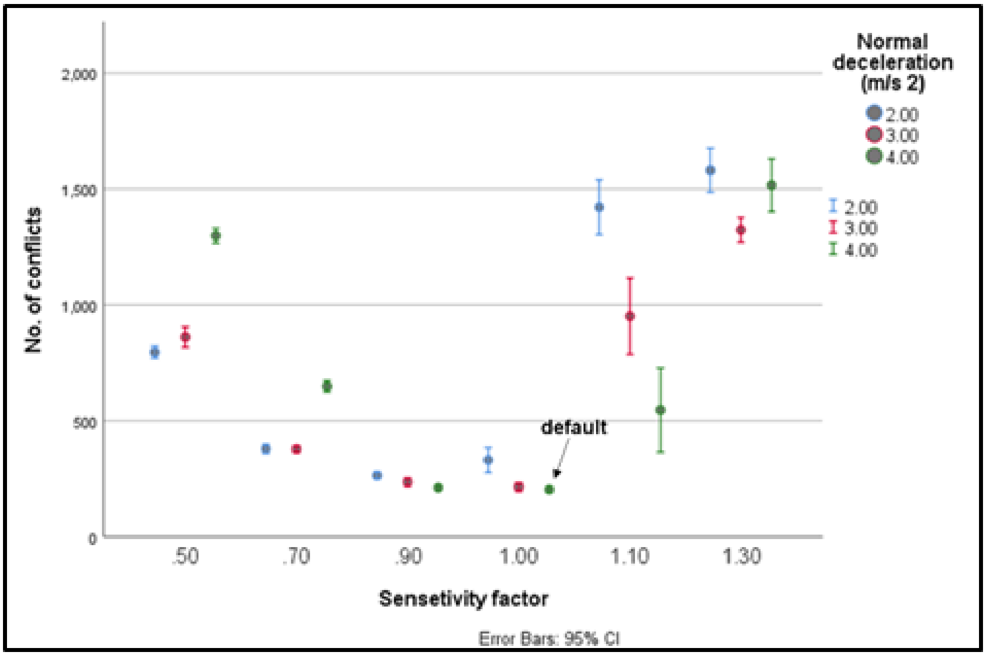


Figure 42: Sensitivity factor vs normal deceleration (m/s²) two-at-a-time analysis

Table 17: Two-way ANOVA results of reaction time vs clearance

		Clearance (m)											
		0.5			1.0			1.5			2.0		
		Mean	St.d	Group	Mean	St.d	Group	Mean	St.d	Group	Mean	St.d	Group
Reaction time (s)	0.1	108	22.3	e,g,h	50	10.3	a,b,c	35	7.3	a,b	25	7.1	a
	0.2	155	33.4	i	73	10.8	b,c,d,e,f	46	6.7	a,b	37	7.2	a,b
	0.3	226	27.9	j	87	10.7	c,d,e,f	44	5.5	a,b	40	4.9	a,b
	0.4	248	30.7	j,k	99	12.8	d,e,f,g	50	6.2	a,b,c	46	5.6	a,b
	0.5	282	48.6	k	105	18.1	d,e,g,h	49	8.3	a,b,c	45	7.6	a,b
	0.6	384	66.2	l	137	20.1	g,h,i	68	11.6	b,c,d,f	62	10.5	a,b,c,f
	0.7	475	55.6	m	164	19.2	i	101	17.5	d,e,g,h	99	16.9	d,e,f,g
	0.8	497	95.2	m	218	24.8	j	153	13.3	i	141	10.5	h,i,

Table 18: Two-way ANOVA results of reaction time vs maximum acceleration

		Max acceleration (m/s²)											
		1			2			3			4		
		Mean	St.d	Group	Mean	St.d	Group	Mean	St.d	Group	Mean	St.d	Group
Reaction time (s)	0.1	422	36.0	j	177	11.1	d,e,f,g,h	50	10.3	a,b	47	6.3	a
	0.2	289	33.5	i	173	28.5	d,e,f,g,h	73	10.8	a,b,c,d	60	8.9	b,c,d
	0.3	624	64.6	j	129	15.1	a,b,c,d,e,f,g	86	10.7	a,b,c,d,e	85	12.9	a,b,c,d,e
	0.4	757	100.3	K	142	25.2	a,b,c,d,e,f,g	99	12.8	a,b,c,d,e,f	85	10.1	a,b,c,d,e
	0.5	774	130.8	k,l	155	22.2	b,c,d,e,f,g,h	105	18.1	a,b,c,d,e,f	90	22.3	a,b,c,d,e
	0.6	848	342.2	k,l	167	20.5	d,e,f,g,h	137	20.2	a,b,c,d,e,f,g	101	17.3	a,b,c,d,e,f
	0.7	868	107.6	l	190	34.7	e,f,g,h,i	164	19.2	c,d,e,f,g,h	150	21.7	a,b,c,d,e,f,g,h
	0.8	992	113.1	l	250	28.6	h,i	218	24.8	g,h,i	200	22.8	f,g,h,i,

Table 19: Two-way ANOVA results of reaction time vs normal deceleration

		Normal deceleration (m/s²)								
		2			3			4		
		Mean	St.d	Group	Mean	St.d	Group	Mean	St.d	Group
Reaction time (s)	0.1	145	30.0	c,d,e	86	17.9	a,b	50	10.3	a
	0.2	167	24.7	e,f,g	110	16.2	a,b,c	73	10.8	a,b
	0.3	323	40.0	J	150	18.6	d,e,f	86	10.7	a,b
	0.4	382	83.4	k	182	39.7	e,f,g,h	99	12.8	a,b,c
	0.5	410	70.7	k	182	31.3	e,f,g,h	105	18.1	b,c,d
	0.6	370	63.3	j,k	197	33.7	f,g,h	137	20.2	c,d,e
	0.7	460	53.9	l	205	24.0	g,h	164	19.2	e,f,g
	0.8	489	55.7	l	272	31.0	i	218	24.8	h

Table 20: Two-way ANOVA results of reaction time vs sensitivity factor

		Sensitivity factor																	
		0.5			0.7			0.9			1.0			1.1			1.3		
		Mean	St.d	Group	Mean	St.d	Group	Mean	St.d	Group	Mean	St.d	Group	Mean	St.d	Group	Mean	St.d	Group
Reaction time (s)	0.1	36	9.7	a	36	12.2	a	38	11.2	a	50	10.3	a,b	64	18.2	a,b,c	202	59.1	c,d,e,f,g,h,i
	0.2	57	15.5	a,b	54	18.4	a,b	57	16.8	a,b	73	10.8	a,b,c,d	93	13.7	a,b,c,d,e,f,g	279	41.3	h,I,j,k
	0.3	112	7.6	a,b,c,d,e,f,g	84	16.1	a,b,c,d,e,f	64	9.8	a,b,c	86	10.7	a,b,c,d,e,f	223	23.7	f,g,h,i,j	355	44.6	j,k,l
	0.4	146	9.9	a,b,c,d,e,f,g,h	76	19.7	a,b,c,d	76	11.8	a,b,c,d,e	99	12.8	a,b,c,d,e,f,g	309	57.0	i,j,k	719	274	p,q
	0.5	183	5.9	b,c,d,e,f,g, h,i	68	10.6	a,b,c	63	16.4	a,b,c	105	18.1	a,b,c,d,e,f,g	386	71.2	k,l	846	322.3	m,q
	0.6	856	37.8	m,q	418	28.4	k,l,n	144	10.9	a,b,c,d,e,f,g,h	137	20.2	a,b,c,d,e,f,g	686	133.3	o,p	1045	141.5	r,s
	0.7	984	43.5	m,r	453	39.8	l,n	235	29.0	g,h,i,j	574	19.2	a,b,c,d,e,f,g,h	915	177.7	m,r	1149	155.5	s
	0.8	1299	57.5	t	649	44.2	o,p	211	16.0	d,e,f,g, h,i	218	24.8	e,f,g, h,I,j	546	328.0	n,o	1516	205.3	t

Table 21: Two-way ANOVA results of clearance vs maximum acceleration

		Max acceleration (m/s²)											
		1			2			3			4		
		Mean	St.d	Group	Mean	St.d	Group	Mean	St.d	Group	Mean	St.d	Group
Clearance (m)	0.5	3964	595.7	d	379	59.9	c	346	49.1	b,c	251	31.9	a,b,c
	1	1612	313.5	d	237	32.9	a,b,c	218	24.8	a,b,c	199	28.3	a,b,c
	1.5	284	59.7	a,b,c	148	16.5	a,b	153	13.3	a,b	168	16.2	a,b,c
	2	114	20.2	a	131	38.2	a,b	141	10.5	a,b	183	22.3	a,b,c

Table 22: Two-way ANOVA results of clearance vs normal deceleration

		Normal deceleration (m/s²)								
		2			3			4		
		Mean	St.d	Group	Mean	St.d	Group	Mean	St.d	Group
Clearance (m)	0.5	616	193.9	f	332	40.4	d,e	346	49.1	e
	1	330	96.1	d,e	214	32.5	a,b,c	218	24.8	a,b,c
	1.5	248	48.7	c,d	190	25.8	a,b,c	153	13.3	a,b
	2	232	61.6	b,c	146	10.4	a	141	10.5	a

Table 23: Two-way ANOVA results of maximum acceleration vs normal deceleration

		Normal deceleration (m/s²)								
		2			3			4		
		Mean	St.d	Group	Mean	St.d	Group	Mean	St.d	Group
Max acceleration (m/s²)	1	4175	620.5	b	2384	644.9	b	1612	313.5	b
	2	1033	577.2	b	334	67.8	a	237	32.9	a
	3	330	96.0	a	214	32.5	a	218	24.8	a
	4	399	106.1	a	269	44.6	a	199	28.3	a

Table 24: Two-way ANOVA results of sensitivity factor vs clearance

		Clearance (m)											
		0.5			1.0			1.5			2.0		
		Mean	St.d	Group	Mean	St.d	Group	Mean	St.d	Group	Mean	St.d	Group
Sensitivity factor	0.5	1745	56.9	c	1299	57.4	b,c	491	15.8	a	404	37.3	a
	0.7	511	34.9	a	694	44.2	a,b	279	14.5	a	302	85.9	a
	0.9	257	23.1	a	211	16.1	a	185	19.3	a	193	38.2	a
	1.0	497	95.2	a	218	24.8	a	153	13.3	a	151	17.7	a
	1.1	2582	2296	d	546	328.1	a	222	21.6	a	177	39.1	a
	1.3	6972	1264	e	1516	205.3	c	179	7.9	a	181	22.6	a

Table 25: Two-way ANOVA results of sensitivity factor vs maximum acceleration

		Max acceleration (m/s²)											
		1			2			3			4		
		Mean	St.d	Group	Mean	St.d	Group	Mean	St.d	Group	Mean	St.d	Group
Sensitivity factor	0.5	1626	99.7	g,h	1286	86.8	e,f,g	1299	57.5	e,f,g	1250	51.5	d,e,f
	0.7	644	128.3	b,c	351	43.6	a,b	649	44.2	d,c	339	22.0	a,b
	0.9	1488	755.7	e,f,g	203	16.1	a	211	16.1	a	184	18.3	a
	1.0	1612	313.5	f,g,h	237	32.9	a	218	24.8	a	199	28.3	a
	1.1	2456	547.4	i	1133	681.9	d,e	546	328.0	a,b,c	546	328.0	a,b,c
	1.3	1368	273.4	e,f,g	1954	206.3	h	1516	205.3	f,g	885	224.1	c,d

Table 26: Two-way ANOVA results of sensitivity factor vs normal deceleration

		Normal deceleration (m/s²)								
		2			3			4		
		Mean	St.d	Group	Mean	St.d	Group	Mean	St.d	Group
Sensitivity factor	0.5	796	47.2	d,e	861	79.7	e	1299	57.5	f
	0.7	379	35.5	a,b	378	26.5	a,b	649	44.2	c,d
	0.9	264	26.9	a	235	32.7	a	211	16.1	a
	1.0	330	96.0	a	214	32.5	a	218	24.8	a
	1.1	1422	213.7	f,g	952	298.3	e	546	328.0	b,c
	1.3	1581	170.7	g	1324	95.1	f	1516	205.3	g

VII CONCLUSIONS, LIMITATIONS AND FUTURE RESEARCH

CHAPTER VII: CONCLUSIONS, LIMITATIONS AND FUTURE RESEARCH

This chapter presents the main conclusions of this doctoral thesis, explains the limitations and propose some possible related future lines of research.

7.1. Conclusions

The aim of this work was to evaluate the traffic safety of the transition period between manual driving and autonomous driving. By employing a two-stage methodology: based on the outputs of simulated future probable scenarios (the first stage), the SSAM tool was used (the second stage) to assess traffic safety within frequency and severity perspectives.

The simulation-based-SSAM method has shown its usefulness in testing nine different fleet mixes after an intention of calibrating the variety of levels of automation that could be faced in the transition period on freeways. Practically, the work achieves several objectives: (1) quantifying traffic conflict by fleet mix as well as by vehicle type; (2) estimating conflict severity through different severity definitions; (3) assessing the need of dedicated lanes (as a probable scenario in the transition period) in term of enhancement of traffic safety; and (4) applying a traffic safety sensitivity analysis to the main driving behaviour parameters used in this methodology.

In general, according to the set of research hypotheses established in Section 3.3, and tested along this thesis, the results met all the hypotheses:

(1) Calibration of all CAV levels rather than only one or two levels resulted in a further understanding about how the progressive implementation of CAV would affect traffic safety.
(2) The general increase in CAV penetration rate improved traffic safety.
(3) The number of traffic conflicts will decrease with an increase in the level of automation.
(4) Low levels of automation will not significantly improve traffic safety, whereas high levels of automation will do it.
(5) Less severe conflicts are attributed to an increase in the level of automation of CAV and its introduction into the traffic stream.

(6) With high volumes of HCAV the freeway with one dedicated lane delivered satisfying traffic safety results. However, the opposite occurs with low volumes of HCAV (i.e. during off-peak periods or with low proportions of HCAV).
(7) Key factors in boosting traffic safety on roads are reaction time and car following parameters.

Specifically, the main achieved conclusions of the mentioned analysis presented in this doctoral thesis are the following:

General conclusions

- This work shows the effectiveness and usefulness of the simulation-based-SSAM methodology to model the CAV behaviour and evaluate its impact on traffic safety.
- CAV are expected to perform with different behaviour if compared to human-driven vehicles. Accordingly, they have been calibrated to perform different reactions and dynamics in longitudinal and lateral movements. Moreover, traffic flow dynamics obtained by studying mixed fleets of CAV introduction, represented by vehicle acceleration/deceleration and velocity difference distribution, show the impact of CAV penetration, especially in the case of HCAV (L3 and L4 vehicles), in harmonising the traffic flow and reducing the jerk movements.
- Increasing CAV penetration rates on our roads will enhance traffic safety. It will reduce traffic conflicts and downgrade the severity of these conflicts. The main vehicles responsible for this enhancement will be those with high automation levels (i.e. HCAV).

Conflict frequency

- The number of traffic conflicts will decrease as the penetration of CAV into the traffic flow increase. However, this investigation has found that significant conflict reduction could be achieved in the early stages of CAV introduction (up to 60% of CAV penetration). Scenarios with further penetration rates will improve safety, but not to the same extent as in scenarios with lower penetration rates.
- The vehicle-type involvement ratio will decrease with increasing levels of automation and connectivity. However, this is mainly related to the vehicle-types shared in the traffic fleet. For instance, L2 vehicles are less involved in conflicts when HDV or L1 vehicles are prevalent; whereas their involvement in conflicts is greater in scenarios where they share the road with HCAV only. Likewise, considering the follower vehicle to be the main responsible for decision-making in a conflict, the main finding is that the involvement ratio of follower vehicles decreases as connectivity and automation levels increase.

Moreover, HCAV exhibit less than the expected responsibility (based on their representativeness in the traffic flow) in almost all scenarios.

Conflict severity

- Traffic conflicts severity estimation was analysed using three different approaches: (i) discussing the proximity threshold; (ii)evaluating the conflict consequences; and (iii)developing a traffic conflict technique to identify the levels of severity for the levels of automation. In general, all the approaches agree showing that high levels of automation downgrade traffic conflicts severity significantly.
    i. The proximity threshold (based on TTC) in scenarios where HCAV is the follower vehicle yields interesting results. If the presence of HCAV is low in the traffic flow (below 35%), the number of conflicts for all the TTC considered in the analysis (i.e. 0.5, 0.75, 1.0, 1.25, and 1.5 s) is not statistically significant. By contrast, when HCAV present moderate sharing percentages (35%–55%) the TTC starts to show a significant difference at 1.0 s. In scenarios where the operation percentage of HCAV is high (over 55%) TTC presents significant differences in the number of conflicts for all values. Therefore, the importance of applying different TTC threshold values for such scenarios must be recognized.
    ii. MaxS and DeltaS (considered severity indicators) show that if HCAV penetration is 55% or over most of the conflicts show a low severity (low speeds and low speed differences among vehicles involved in conflicts). In addition, the highest severity is identified when HDV are the follower vehicles, followed by situations where the follower vehicle is a LCAV (L1 and L2 vehicles).
    iii. Proximity/consequence charts (based on TTC and MaxDeltaV) have been also used to investigate the severity in each scenario. The results indicate that increasing the percentages of CAV significantly decreases the number of conflicts with high severity. When HCAV represents approximately 100% of the traffic flow severe conflicts are anticipated to disappear, and those with low severity are reduced.

Influence of dedicated lanes

- From a traffic safety perspective, the dedicated lanes should not be considered under low traffic volumens (i.e. off-peak conditions) with exception of very high penetration rates of HCAV (over 55%).
- In contrast, the dedicated lanes provide better safety outcomes under high traffic volumens (i.e. peack conditions) for almost all penetrations scenarios.

Influence of CAV's parameters on traffic safety

- The ceteris paribus sensitivity analysis of the parameters has highlighted the significant impact of varying the clearance, reaction time, sensitivity factor, maximum acceleration, and normal deceleration on traffic safety.
- The reaction time parameter shows a negative linear correlation with traffic safety.
- Clearance, maximum acceleration, and normal deceleration at extremely low values exhibit an extremely negative impact on traffic safety.
- The sensitivity factor for CAV is recommended to be close to 1.0.
- Traffic safety of motorways under off-peak traffic conditions is not highly dependent on the lateral movement parameters.
- The platoons with four and six vehicles provide better traffic safety than those with eight or ten vehicles.
- Maximum acceleration of 1 m/s^2 combined with any other parameter results in the highest number of conflicts.
- Among the maximum acceleration/normal deceleration combinations, those with high acceleration and deceleration yield the best safety results. However, the maximum acceleration is more sensitive within these combinations.
- Traffic safety improves by decreasing the reaction time and simultaneously increasing the maximum acceleration or normal deceleration.
- Low underestimation (−10 to −30%) of the leader deceleration can be addressed by increasing the maximum acceleration and clearance. However, in the case of high under/overestimation (−50% and +30%) of the leader deceleration, increasing the maximum acceleration is not sufficient to mitigate the negative effect on traffic safety, whereas a larger clearance achieves this outcome.
- In reaction time/sensitivity factor combinations, traffic safety is more sensitive to reaction time. Moreover, regardless of the fit of the assessment of the leading deceleration, very short reaction times (0.1–0.3 s) show the largest improvement in traffic safety.

Finally, the following are the main strength of this work in comparison with previous studies:

- A wide range of parameters are calibrated to robustly cover CAV behaviour.
- All CAV levels are modelled, analyzed, and discussed.
- Nine different scenarios of fleets, different CAV levels, penetration rates, and vehicle types (passenger cars and heavy vehicles) are taken into consideration to present a thorough and near-real scheme of CAV introduction.
- Traffic safety is studied from various perspectives, including through traffic flow dynamics, conflicts frequency, involving in conflicts by vehicle type, conflict severity using three different approaches and conflict severity by vehicle type.

- The influence of a dedicated lane on traffic safety is studied considering several CAV penetration rates and two traffic conditions (peak and off-peak).
- The key parameters which affect traffic safety, that are used in microsimulation models for representing CAV behaviour, have been identified through a comprehensive sensitivity analysis.

7.2. Limitations and future research

Although this thesis provides valuable contributions regarding the investigation of traffic safety during the transition period between manual and autonomous driving, it is normal to have limitations in terms of conditions and cases. As a result, the following potential investigations could be added to the current literature to help in understanding the safety impact of CAV introduction:

1. Additional research is required to validate the calibration of CAV traffic flow models. The parameters used for CAV calibration have a direct impact on the safety analysis. Therefore, if different values are assigned to these parameters, the results may differ. Consequently, the following lines of investigation could be explored:
    - All the analysis and assumptions in this work only apply and examin the cautious driving style of CAV. Another similar procedure could be applied to investigate the aggressive driving style that may appear when most of vehicles on the roads are CAV.
    - The sensitivity analysis conducted in this study is limited to two-at-a-time analysis. It is suggested to further optimize traffic safety by performing sensitivity analyses of all calibrated parameters to determine the combined effect of these parameters. Moreover, sensitivity analysis with different parameter distributions should be used to gain a better understanding of the effects of calibrating these parameters.
    - Whenever real data and information on CAV behaviour among varios levels of automation and connectivity in flow and lane-change dynamics are available, the simulation models should be calibrated accordingly to re-analyze traffic safety.
    - Furthermore, while applying the CCAV FHWA algorithm, some parameters' constrains in the algorithm could represent the transition from human to autonomous driving system. However, there was no clear performance of this transition in terms of vehicle parameter calibration as seen in other parameters of car-following and lane-changing models. As a result, future work could focus on the driving transition in L2 and L3 vehicles in microsimulation models and its effect on CAV behaviour and traffic safety.

2. This thesis is limited to a specific traffic flow condition and road type section. Therefore, the traffic safety impact of CAV introduction should be investigated under various traffic volumes, road types and sections, and circumstances (e.g. road surface conditions, weather condition, events, policies).

3. In terms of safety evaluation, this thesis provides a thorough investigation of traffic conflict analysis and studies severity across several dimensions. However, it is unclear whether the SSM (Surrogate Safety Measure) validated in conventional traffic conditions is applicable when modelling safety in mixed autonomy or fully automated traffic.

    - To solve this issue, various TTC (Time to Collision) threshold values are tested and applied in our work. However, once real data is available, the validity of the SSM must be thoroughly reviewed and validated. Therefore, new CAV data sources will be critical for the development of a universal SSM set that can accommodate all levels of automation.

    - Moreover, untill real data on CAV behaviour is available, more complex safety measures could be applied and developed by deriving and integrating time-based and energy-based SSM (e.g. TIT, TET, Extended DeltaV) to measure both longitudinal and lateral safety.

    - Subsequently, when CAVs are operating on our roads with mixed traffic fleets and providing real crash data to be quantified and analyzed, further studies should be conducted to validate the safety results obtained from simulation-based studies.

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