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ASSESSMENT OF CONNECTED AND AUTONOMOUS VEHICLES IMPACTS ON URBAN ROAD SAFETY THROUGH MICROSIMULATION

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M. S. thesis presented to the Programa de Pós-Graduação em Engenharia de Transportes do Centro de Tecnologia from Universidade Federal do Ceará, as partial requirement to obtain the Master in Transportation Engineering degree. Field of study: Planning and Operation of Transportation Systems.

Tutor: Prof. Flávio José Craveiro Cunto, PhD

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“Somewhere, something incredible is waiting to be known.”

(Carl Sagan)

RESUMO

A introdução de Veículos Autônomos e Conectados (CAVs) em ambientes urbanos promete melhorar significativamente a segurança viária e a gestão do tráfego, especialmente quando a penetração no mercado for completa. No entanto, a fase de transição, onde CAVs e veículos convencionais irão compartilhar a mesma infraestrutura, ainda é pouco compreendida devido à presença limitada e localizada desses veículos. Este estudo tem como objetivo avaliar o impacto dos CAVs na segurança viária em um corredor urbano, analisando seu comportamento longitudinal em diferentes níveis de penetração de mercado e demandas de tráfego. Utilizando o microsimulador VISSIM, a pesquisa aplicou o algoritmo de Controle Adaptativo Cooperativo de Cruzeiro (CACC), que foi projetado para o controle longitudinal dos CAVs, e inclui comunicação Veículo-a-Infraestrutura. Como a microsimulação não modela diretamente os acidentes de trânsito, a pesquisa utilizou a teoria do *continuum* de segurança para avaliar conflitos—potenciais acidentes resultantes de interações arriscadas entre veículos. A análise focou em conflitos traseiros, avaliando tanto a frequência quanto a gravidade. Os resultados indicaram que, durante o período inicial de transição, a presença de CAVs poderia aumentar a ocorrência de conflitos—até seis vezes em baixa demanda de tráfego e duas vezes em alta demanda—principalmente envolvendo veículos convencionais (CNVs) como seguidores. No entanto, os cenários com automação total dos CAVs mostraram uma redução de 54% nos conflitos em comparação com o cenário atual, indicando que os CAVs têm potencial para melhorar a segurança viária. Além disso, o estudo utilizou um modelo logit multinomial para avaliar o impacto dos CAVs na gravidade dos conflitos, descobrindo que a probabilidade de conflitos de alta gravidade diminui com o aumento da penetração dos CAVs. Isso sugere que, embora a frequência de conflitos possa aumentar nas fases iniciais de implantação, a gravidade desses conflitos não aumenta de forma correspondente, ressaltando os benefícios potenciais dos CAVs na redução de acidentes graves.

Palavras-chave: Veículos autônomos e conectados. Microssimulação. Conflitos simulados. Severidade de conflitos. Modelo logit multinomial.

ABSTRACT

The integration of Connected and Automated Vehicles (CAVs) into urban environments promises significant improvements in road safety and traffic management, particularly at full market penetration. However, the transitional phase of CAV adoption remains poorly understood due to the limited and localized presence of these vehicles. This study aims to evaluate the impact of CAVs on road safety in an urban corridor by examining their longitudinal behavior across varying levels of market penetration and traffic demands. Utilizing the VISSIM microsimulator, this research implemented the Cooperative Adaptive Cruise Control algorithm, designed for longitudinal control of CAVs and incorporating vehicle-to-infrastructure communication. Given that microsimulation does not directly model crashes, the study applied safety continuum theory to assess conflicts—potential crashes arising from risky vehicle interactions. The analysis focused on rear-end conflicts, examining both frequency and severity. Results showed that during the initial transitional period, CAVs could increase conflict occurrences—up to six times in low vehicular demand and twice in high demand—primarily involving conventional vehicles as followers. However, scenarios with full CAV automation demonstrated a 54% reduction in conflicts compared to the base scenario, indicating CAVs potential to improve road safety. Additionally, the study employed a multinomial logit model to assess the impact of CAVs on conflict severity, finding that the probability of high-severity conflicts decreased with greater CAV penetration. This suggests that while conflict frequency may rise during initial deployment stages, the severity of these conflicts does not escalate correspondingly, emphasizing the potential benefits of CAVs in reducing severe accidents.

Keywords: Connected and autonomous vehicles. Microsimulation. Simulated conflicts. Conflict severity. Multinomial logit model.

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1 INTRODUCTION

The last decade has witnessed a rapid advance in Connected and Autonomous Vehicles (CAVs) development and implementation in urban environments, marked by significant technological strides and their increasing integration into urban transportation systems (AHMED *et al.*, 2022). CAVs facilitate communication between all traffic participants and progressively reduce human involvement in driving. This technology is anticipated to bring several benefits to urban roads, including enhanced traffic flow and improved safety.

The Society of Automotive Engineers (SOCIETY OF AUTOMOTIVE ENGINEERS INTERNATIONAL, 2018) categorizes autonomous vehicles (AV) into six levels, ranging from level 0 to level 5. The differentiation among these levels is based on the degree of human involvement in the driving process, with human participation decreasing as the integration of Advanced driving assistance systems (ADAS) increases. The connected systems can be implemented at any automation level. Levels 0 to 2 can already be seen on urban roads with low penetration, but levels 3 to 5 will take a long time to be tested enough until their commercial availability. By 2040 it's expected that 3 in 4 vehicles circulating will be autonomous (BLOOMBERG PHILANTHROPIES, 2017), especially autonomous and connected, and until a fully autonomous scenario becomes reality there will be a long transition period where conventional vehicles (CVN) and CAVs will share urban space.

CAVs are being tested and used in an urban context marked by numerous losses of life in road crashes: approximately 1,35 million people die each year as a result of crashes, especially children and young adults aged 5-29 years, which classifies it as a global epidemic (World Health Organization, 2018). It's known that a large number of these losses involved a drunk driver or a distracted driver: 94% of recent crashes involve human error as a contributing factor (SINGH, 2015). Therefore, it's expected that reducing human decision-making as a driver, after the CAV implementation on a large scale, will reduce dangerous situations in traffic (RAHMAN *et al.*, 2019a).

The impact of the coexistence of CAVs and CNV on road safety remains uncertain, as CAVs require extensive testing—amounting to hundreds of millions of kilometers in real-world situations to demonstrate their reliability in reducing fatalities and injuries (KALRA; PADDOCK, 2016). Some automotive industries are in the testing phase of implementing CAVs with high automation levels in urban traffic, especially in the USA, where already have some crash reports involving these vehicles (FAVARÒ *et al.*, 2017; NHTSA, 2022b; NHTSA, 2022a). However, CAV's crash data is still limited to specific regions and situations, once it is still in the testing period. In this sense, the evaluation of CAV's safety impacts has been a major challenge due to the insufficiency of real-world CAV exposure data (PAPADOULIS *et al.*, 2019). Without enough information, it's difficult to use conventional road safety analysis methods to study CAVs' and humans' coexistence, which implements statistical analysis relating crashes temporal data and road geometry and its operational characteristics (CUNTO; LOUREIRO, 2011). Because of the mentioned limitation, recent researchers are utilizing microsimulation as a strategy to do an ex-ante evaluation of CAVs on road safety, considered a safer, more efficient, and cheaper way to carry out these predictions compared to the test with real situations (RAHMAN; ABDEL-ATY, 2018).

Nevertheless, studies focused on investigating CAV impacts using microsimulation don't have sufficient real trajectory data of CAVs to calibrate their behavior and to develop a standardized study. Raju and Farah (2021) pointed out that the great majority of related works implement different models to represent CAV functions on a microsimulation, once there is a vast amount of literature sources to define what could be an autonomous vehicle. Since these studies have variability in the assumed methodology, their findings comparability and applicability are compromised (GORA *et al.*, 2020).

Additionally, the microsimulation approach to investigate road safety is supported by road safety continuum theory: traffic conflicts are used as a proxy measure to crashes (HYDÉN, 1987) using the Surrogate Safety Assessment Model (SSAM). This methodology observes dangerous interactions between vehicles, named conflicts, that can be analyzed by proxy road safety measurements. These are based on space-time proximity between vehicles that reflect high-risk collision situations.

1.1 Problem statement and research questions

It's expected that connected and autonomous vehicles with high automation levels will be integrating urban fleets in significant percentages in the following decades, and their impacts on traffic need to be evaluated. To assess CAVs impacts in future scenarios with different traffic situations, the microsimulation approach, the most appropriate methodology to investigate CAVs impacts currently, needs to be able to simulate these vehicles' specificities. To simulate a CAV network, the ideal would be to use real CAVs trajectories in urban scenarios as calibration target measurement, but these data are complex and expensive to collect. Considering the high prices and efforts of such calibration, there are many attempts in the literature to represent CAVs on a microsimulation using algorithms built with theoretical models. This situation originated the first question that motivated this M.S. dissertation: **Which are the main strategies to represent CAVs in a microsimulation and how do they incorporate safety aspects to the driving process?**

The models built to represent Connected and Autonomous Vehicles (CAVs) in microsimulation are often tailored to specific environments, such as a single signalized intersection or a freeway segment. Consequently, when applying these algorithms to different scenarios, such as a segment of an urban arterial corridor, adaptation becomes necessary. This leads to the formulation of the second research question driving this M.S. dissertation:**How can existing CAV algorithms be appropriately adapted and integrated into a microsimulation model to accurately represent CAV behavior within an urban arterial corridor segment?**

Until cities achieve full vehicle automation, there will be a prolonged transition period during which conventional vehicles and CAVs will coexist on the same road infrastructure. This interaction between CAVs and conventional vehicles is still poorly comprehended, especially regarding road safety. Previous related researches indicate the relevance of executing safety evaluation of the transition period in different scenarios varying CAVs market penetration, road geometry, and traffic configurations to identify the tendency of conflicts generated on each case (PAPADOULIS *et al.*, 2019; MORANDO *et al.*, 2018). In this context, the last research question is: **What is the impact of CAVs market penetration on urban road safety, considering different vehicle demands?**

1.2 Research Objectives

To approach each question mentioned, this dissertation is oriented by a general objective and by three specific objectives. This research aims to assess the impact of connected and autonomous vehicles on urban road safety using microsimulated conflicts. The specific objectives are as follows:

a) To identify the most significant models utilized in microsimulation to represent CAVs' behavior with a focus on their impact on road safety performance;
b) To adapt a CAV algorithm to be implemented in a microsimulation model for a segment of an urban arterial corridor;
c) To analyze the effects on road safety using microsimulation of different transitio-

nal scenarios, varying traffic composition between CAVs and CVNs, considering different vehicle demands.

1.3 Dissertation outline

This thesis is structured in five chapters. Chapter 1 provides a contextualization of the problems that motivated this research, outlines the central research problem, and presents the research questions. From these, the main and specific objectives of the study were defined.

Chapter 2 offers a review of CAV definitions and explores various simulation techniques used to assess their impact on road safety. It also discusses the potential benefits and challenges associated with integrating CAVs into urban traffic systems.

Chapter 3 outlines the methods and procedures employed in this study. It details the data collection process, the simulation models used, and the analytical techniques applied to evaluate the impact of CAVs on traffic safety.

Chapter 4, "Results and Discussions,"presents the findings of the study, including a detailed analysis of the simulation results. It discusses the implications of these findings for urban traffic safety and the potential role of CAVs in reducing traffic conflicts and improving overall safety.

Chapter 5, "Conclusions and Future Work,"summarizes the key findings of the study and provides recommendations for future research. It discusses the limitations of the current study and suggests areas for further investigation to enhance the understanding of CAVs' impact on traffic safety and their integration into urban road networks.

2 AUTONOMOUS AND CONNECTED VEHICLES: AN OVERVIEW OF DEFINITIONS, SIMULATION TECHNIQUES AND ROAD SAFETY IMPACTS

To discuss the impacts of CAVs on urban traffic safety it is important first to establish definitions of these vehicles' particularities. Therefore, this chapter's first section defines CAVs and their leading concepts. Then, to attend to the first specific objective of this study, once this dissertation method uses simulated data to assess conflict generation, the following section presents how CAV behavior can be represented in simulations, and the strengths and weaknesses of the main models are compared. Finally, after understanding the main definitions of CAVs and how they are represented in simulation, CAV's safety impacts are evaluated under different approaches, from real crash data analysis to simulated conflicts.

2.1 Connectivity and automation definitions

Autonomous, automated, and connected vehicles represent different advancements in vehicle technology within the automotive industry. Autonomous vehicles (AVs), commonly known as self-driving cars, can navigate and operate without human control by utilizing sensors, cameras, radar, and artificial intelligence to make driving decisions and detect obstacles. Automated vehicles, while sometimes used interchangeably with autonomous vehicles, refer more broadly to vehicles that can perform specific driving functions independently. This includes lower levels of automation, featuring Advanced Driver Assistance System (ADAS) such as lane-keeping assist or automatic emergency braking. In contrast, connected vehicles focus on communication capabilities, enabling vehicles to interact with each other, infrastructure elements like traffic lights and road signs, and external systems including cloud services and traffic management centers through wireless technologies. In essence, autonomous vehicles are capable of self-driving, automated vehicles can independently manage certain driving tasks, and connected vehicles communicate with their surroundings to improve overall road safety and efficiency (AHMED *et al.*, 2022). Although automated vehicles are also known as autonomous with lower automation levels, this research will use only the term autonomous to facilitate communication.

Connected vehicles can exchange data with any road user, and this fact is related to its' types of communication systems: Vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), infrastructure-to-vehicle (I2V), vehicle-to-pedestrian (V2P), and vehicle-to-anything (V2X). Regarding these vehicles' perspective, Jadaan et al. (2017) point out that there are two prevailing approaches: the first is known as the Google approach, where CVs are envisioned as fully autonomous vehicles, utilizing connectivity to drive themselves; the second is the U.S. Vehicle Manufacturers' approach, where CVs retain manual control but utilize continuous real-time connectivity among vehicles and infrastructure.

Vehicle-to-vehicle (V2V) communications involve a wireless network where automobiles exchange messages containing information about their current status, such as speed, location, direction of travel, braking actions, and stability loss, with a communication range of up to 300 meters (JADAANA *et al.*, 2017). In Vehicle-to-Infrastructure (V2I) communication, vehicles transmit data or connect to the Internet using stationary roadside infrastructure known as Road Side Units (RSUs), which are positioned at key locations like intersections, traffic lights, bus stops, and petrol stations. RSUs interact with the vehicle to send and receive information such as traffic updates and accident alerts, to and from passing vehicles.

CV safety applications are designed to increase situation awareness and mitigate road crashes through V2V and V2I communications. Vehicle data exchange enables implementations such as cooperative collision warnings and cooperative collision mitigation or avoidance, incorporating active braking. Besides, vehicle and infrastructure data exchange enables variable speed limits and advisories provided directly to drivers or their vehicles, active support for lane guidance, and provides traffic signal status information in real-time for in-vehicle display, and signal violation warnings to drivers (SHLADOVER, 2017).

Autonomous vehicles (AV) basic concept is that they are built with technology that allows them to drive by themselves, partially or totally, which means that they are responsible for making decisions during the driving process. The levels of automation proposed by SAE (2018) are based on three main variables: Dynamic Driving Tasks (DDTs), Object and Event Detection and Response (OEDR), and Operational Design Domain (ODD), and this taxonomy is presented in summary form in Figure 1.

Dynamic Driving Tasks (DDTs) encompass all the operational and tactical functions necessary for vehicle operation in on-road traffic, including actions like steering, braking, accelerating, monitoring the vehicle and its surroundings, and executing maneuvers such as lane changes and turns. Object and Event Detection and Response (OEDR) refers to the system's ability to detect and appropriately respond to objects and events in the driving environment, such as recognizing other vehicles, pedestrians, road signs, and obstacles, as well as making decisions to avoid collisions or adapt to changing road conditions. The Operational Design Domain (ODD) defines the specific conditions under which an autonomous driving system is designed to function, including factors such as geographic location, roadway type, traffic conditions, weather conditions, and time of day. Together, these variables establish the framework for categorizing the capabilities and limitations of different levels of vehicle automation, which are defined in the following topics:

- **Level 0 - No Automation:** Drivers will perform all the DDTs and OEDR: the driver is fully responsible for the driving process (braking, steering, and accelerating) all the time, and he must observe the environment and safely operate all vehicles controls.
- **Level 1 - Assisted driving automation:** Drivers will still perform some of the DDTs and be responsible for the OEDR: the vehicle assists the driver with primary control tools (such as steering or braking). The car has tools such as adaptive cruise control. ODD of level 1 is limited.
- **Level 2 - Partial automation:** The system will perform the lateral and longitudinal DDTs while the drivers will be still responsible for the OEDR: the vehicle has the automation of at least two primary control functions, and continues to rely on the driver to monitor the environment and intervene if an event occurs that exceeds the system's capacity. ODD of level 2 is limited.
- **Level 3 - Conditional automation:** The system will be responsible for the DDTs and the OEDR: the vehicle operates autonomously in certain traffic situations, such as highways, for example, but even in these circumstances the driver must be alert to operate the vehicle in case of a request made by the system. The "congestion pilot"mode traffic jam pilot is used in Level 3 cars, which completely assumes longitudinal and lateral direction when detecting a traffic jam on a highway. ODD of level 3 is limited.
- **Level 4 - High automation:** The system will be responsible for the DDTs and the OEDR: the need for a driver becomes almost expendable, and can only be requested in extreme weather situations or driving on unmapped roads. ODD of level 4 is limited.
- **Level 5 - Full Automation:** The system will be responsible for the DDTs and the OEDR: differs from the previous one by completely eliminating the need for a driver, with all controls and driving responsibilities being performed by the vehicle systems. Unconditional DDTs will be carried by the ADAS and unlimited ODD.

Most initial automation systems available were unconnected, however as higher levels of automation are developed, it will be increasingly important for the automation systems to be cooperative to produce transportation system benefits (SHLADOVER, 2017). Hence, in

Figure 1 – Levels of Automation.

	LEVEL 0	LEVEL 1	LEVEL 2	LEVEL 3	LEVEL 4	LEVEL 5
LEVEL	No Automation	Driver Assisted Automation	Partial Automation	Conditional Automation	High Automation	Full Automation
DRIVER	Human driver			Automated driving system		
TECHNOLOGY	None	Assisted Technology		Automated Technology		
OPERATION	Manually	Independent of one another	Simultaneously together	Under limited conditions		Under all conditions
FEATURES	Conventional cruise control	Adaptive cruise control OR Lane changing	Adaptive cruise control AND Lane changing	Traffic jam pilot	Driverless taxi	100% self driving

Source: Society of Automotive Engineers International (2018)

this research, the assessed vehicle will be a connected and autonomous vehicle (CAV).

Given the characteristics of CAVs, it is anticipated that their technology will bring significant benefits to urban road safety and traffic operation. However, to validate these expectations, especially since CAVs are not yet prevalent enough on urban roads, alternative methods to observational studies are needed. In this context, traffic microsimulation emerges as a key approach to assess the impacts of CAVs from various traffic perspectives.

2.2 CAVs' microscopic modeling

The previous section mentioned the microsimulation relevance to assessing different CAVs impacts on urban traffic, once there is CAV field data limitation, and this section focuses on describing how CAVs representations are built in microsimulations.

2.2.1 Conventional vehicles' microsimulation

Microsimulation is responsible for representing the behavior of individual vehicles, being used to predict the likely impacts related to changes in traffic patterns. Microscopic models consider each vehicle individually, and due to this data disaggregation, it becomes the most suitable for predicting impacts on traffic operation and safety, because as each vehicle is simulated individually, the effect of changes is more noticeable. Therefore, the main advantage of microsimulation is the facility to model different scenarios, the possibility of modeling several different modes of transport as well as the behavior of each driver.

Driving behavior models are the base of microsimulation, which can be summarized in a mathematical description of the decision-making attributed to the driving process. Models of driving behavior capture drivers' tactical maneuvering decisions in different traffic conditions. The literature on modeling driving behavior focuses on a few essential elements: car-following models, lane change models, and gap acceptance models. Car-following models are related to the vehicle's longitudinal movement, and Olstam and Tapani (2004) have classified these models into three categories, as shown in Table 1.

Table 1 – Car-following models based on utilized logic.

Model Class	**Model Logic and Assumption**
Gazis-Herman-Rothery (GHR) model	"The following vehicles' acceleration is proportional to the subjected vehicle (own vehicle), the speed difference between the follower and the leader, and the space headway."
Safety-distance model	"The follower always keeps a safe distance to the vehicle ahead."
Psychophysical car-following model	"These models use threshold values. Drivers react to vehicles when the set threshold for relative velocity (speed difference between a follower and a lead vehicle) or spacing is reached."

Source: Olstam and Tapani (2004)

Gazis-Herman Rothery's (GHR) model (Chandler et al. 1958, Gazis et al. 1959) was the first class developed, and according to this model, the follower's acceleration depends on the follower's speed, the driver's response time, relative speed and spacing. Chandler et al. (1958) argued that GHR model is stable only in high-density traffic conditions where vehicles have to follow each other very closely. Besides, this model is based on the assumption that sensitivity to stimuli in both acceleration and deceleration is identical, which they regard that as a true assumption in low-speed traffic operation. Considering the mentioned assumptions, it becomes clear that GHR models have their own behavioral limitations (Leutzbach, 1988), such as the fact that drivers react to arbitrary small changes in the stimulus, such as relative speed, and that the driver following the lead vehicle is still influenced by the leader's actions even when the distance between the two vehicles is considerable.

The second car-following class is the safety-distance model, first developed by Gipps (1981), which ensures that a following vehicle always maintains a safe distance from its leader. While robust and computationally efficient, the model is limited by its simplification of driver behavior, as it assumes fixed parameters for each driver (e.g., acceleration, braking capacity, and reaction time).

Finally, the psychophysical car-following models, the last category present in Table

1, incorporate the driver's perception using "perceptual thresholds". When the threshold values are reached, the drivers begin to respond to changes in spacing or relative velocity. One of the most famous models is the Wiedemann car-following model, which was first proposed by German engineer and traffic specialist Dietrich Wiedemann (1974). The model is based on the assumption that drivers follow a lead vehicle with a particular time headway, or gap, which depends on the relative speed of the two vehicles. The Wiedemann model considers the driver's perception-reaction time, their maximum acceleration and deceleration capabilities, and their desired speed. The model has been widely used in traffic simulation and analysis and has been modified and extended over the years to incorporate more advanced driving behaviors and conditions.

Besides the car-following models highlighted by Olstam and Tapani (2004), which have been used mainly to represent human drivers, it is essential to mention the most recently developed car-following models, such as the Intelligent Driver Model (IDM). The IDM car-following has been introduced by Treiber (2000) and it describes how each vehicle's positions and speeds change over time. Similarly to any car-following model, IMD aims to balance two different aspects, the necessity to keep a safe distance from the vehicle in front and the desire to achieve "free flow" speed.

2.2.2 CAVs microsimulation

Concerning connected and autonomous vehicles car-following models, it is known that they are still having their technology improved, and there are still no established universal standards for building them. Therefore vehicle companies and researchers test different approaches and various algorithms, consequently, there are also no established mathematical models for simulating traffic with CAVs (GORA *et al.*, 2020). This section presents how recent studies focused on CAVs microsimulation are representing their behavior.

Available microsimulators usually adopt specific models to represent traffic behavior and allow users to calibrate and validate its parameters. Recent studies are focused mainly on the longitudinal representation of CAVs, therefore car-following models are highlighted in this section. Table 2 presents a summary of some main microsimulators available and their respective car-following models, which are mainly models previously mentioned focused on conventional vehicle representation. However, even when a microsimulator already has an implemented car-following, it allows its user to overwrite it with different types of representation, which also is represented in Table 2.

Table 2 – Details of microsimulation platforms.

Platform	Country	Car following (CF) models	External module	External module interface
Paramics	UK	Fritzsche	External DLLs	C++, MATLAB
VISSIM	DE	Wiedemann 74, Wiedemann 99	COM interface, External DLLs	C++,MATLAB, Python
MITSIM	USA	Gazis–Herman–Rothery (GHR)	Source code can be scripted	-
AIMSUN	ES	Gipps CF	AIMSUN MicroApi	C++, Python, Delphi, C#
SUMO	DE	IDM, Wiedemann ACC, CACC [...]	Traci	Python, MATLAB
OpenTrafficSim	NL	IDM+	Source code can be scripted	-

Source: Adapted from Raju e Farah (2021)

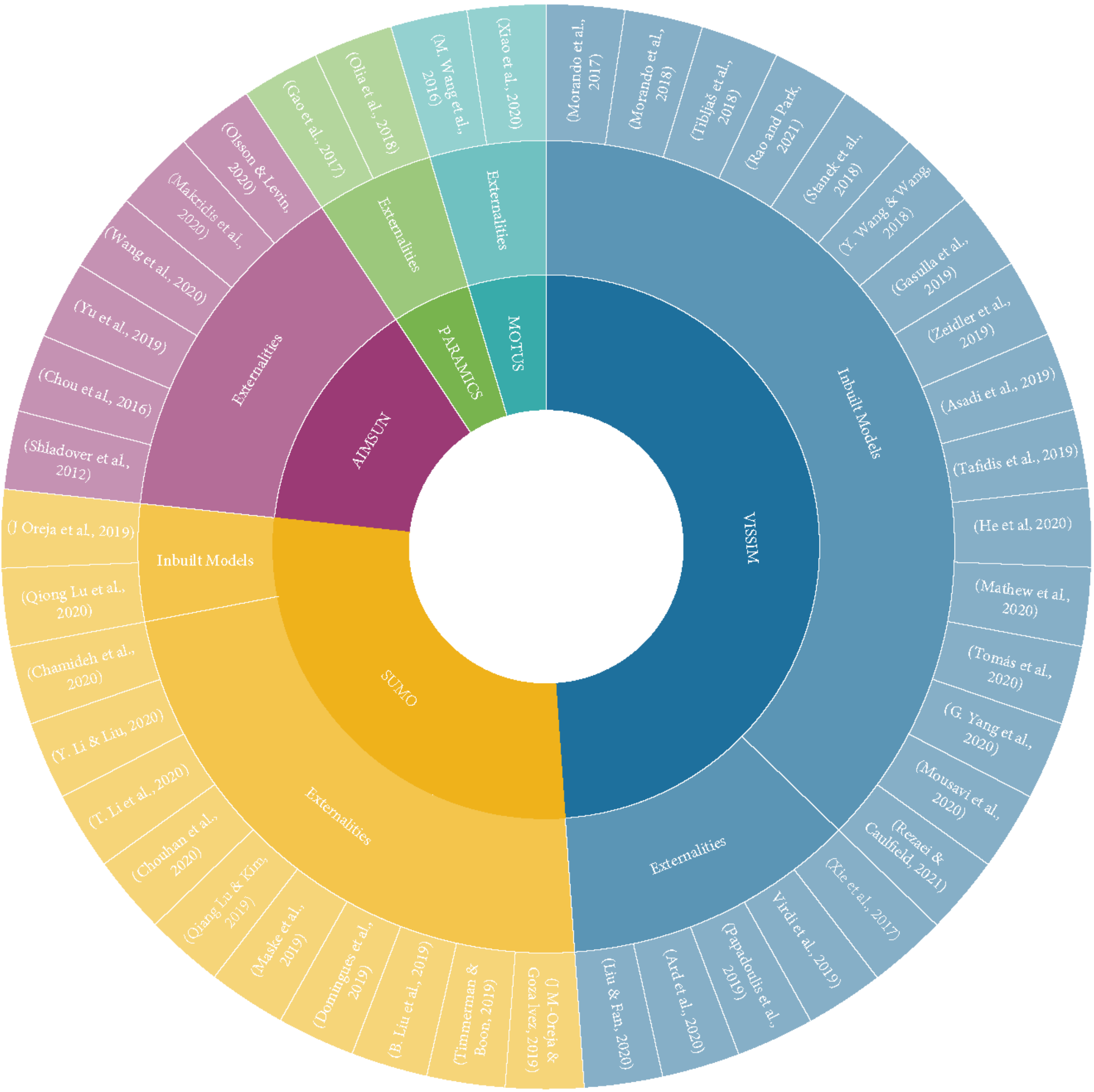
Recent studies that focus on CAVs impacts evaluation still don't have a similar methodology, which means that different CAVs' protocols are being modeled and simulated, and this variability limits the scope of their comparability and applicability. The vast amount of literature sources results in a wide range of applied tools and datasets, assumed methodology to investigate the potential impacts of future CAVs traffic, and, consequently, differences in the main findings (GORA *et al.*, 2020). Figure 2 summarises different studies focused on CAVs assessment on road safety and traffic operation, considering simulation software used and the method implemented to represent CAVs.

In addition to nearly half of the studies in Figure 2 using VISSIM as the microsimulator—demonstrating its adaptability for simulations—the type of CAV simulation is also highlighted in Figure 2. These studies differ in their approach to simulating CAVs, using either internal or external models. The following sections of this chapter will explore the distinctions and specificities of these approaches.

2.2.2.1 *Inbuilt models to represent CAVs*

There is expressive participation of internal models in CAV modeling, as shown in Figure 2. Researchers modeled CAVs by modifying the settings of the built-in car following models in microsimulation platforms in order to properly weight inbuilt behavioral models (RAJU; FARAH, 2021). Since using a real vehicle with levels of connectivity and automation to calibrate microsimulation models is an expensive and complex method to implement, many studies are based on a project named CoExist as a basis for representing CAVs in their simulations. CoExist project was a European research project that aimed to explore and develop new approaches to managing urban traffic in order to reduce congestion, increase efficiency, and improve the quality of life in urban areas.

Figure 2 – CAV microsimulation studies over different platforms.



Source: Raju e Farah (2021)

The project was funded by the European Union's Horizon 2020 research and innovation program and ran from 2016 to 2019. CoExist focused on developing and testing new technologies and strategies for managing urban traffic, including the use of intelligent transport systems (ITS), connected and autonomous vehicles (CAVs), and cooperative mobility services. It was based on tests carried out with CAVs in four European cities (Helmond – Holland, Milton Keynes – United Kingdom, Gothenburg – Switzerland and Stuttgart – Germany), with different urban structures and traffic compositions, in order to analyze their effects on infrastructure in mixed traffic (DAHL *et al.*, 2018).

CoEXist offers four different configurations of the navigation system for autonomous vehicles, which users can choose based on their aggressive requirements, from cautious to aggressive, and since its version 11, VISSIM includes driving behavior parameters for each of these modes. The parameters were established using a combination of empirical studies, co-simulation assumptions, and data gathered from the CoEXist study (SUKENNIK, P., 2018).

Besides, various studies have been conducted to understand the impacts of CAVs on different test scenarios, using VISSIM and adapting the psychophysical Wiedemann 74 and 99 car-following models. These scenarios include congested networks (STANEK *et al.*, 2018), traffic signals (WANG; WANG, 2017), roadway capacity (MARTIN-GASULLA *et al.*, 2019), traffic stream characteristics (ASADI *et al.*, 2019), free speeds (HE *et al.*, 2020), operational performance (MATHEW *et al.*, 2020), emission impacts (TOMáS *et al.*, 2020), safety performance (YANG *et al.*, 2020), unsignalized intersections (MOUSAVI *et al.*, 2020; TAFIDIS *et al.*, 2019), and transitional impacts (REZAEI; CAULFIELD, 2021).

In summary, while many CAV simulation studies have used VISSIM and its car-following models, the critical parameters used to mimic CAV behavior can vary among studies and may not include important lane-changing and communication parameters. The behavior of simulated AVs may also be less realistic compared to real-world CAV behavior. Additionally, there is a need for more attention to be paid to modeling the communication aspects of CAVs (RAJU; FARAH, 2021).

2.2.2.2 External models implementation to represent CAVs

Microsimulation platforms provide the opportunity to script external logic through APIs. Consequently, researchers can override the inbuilt models and utilize data feeds to control vehicle motion during the simulation process, offering a significant advantage in testing their models and frameworks (RAJU; FARAH, 2021). This section specifically concentrates on VISSIM external models, as this study employs it as the simulation platform for representing CAVs.

The behavior of the CAVs can be governed by various models including the Gipps model (GIPPS, 1981), Intelligent Driver Model (IDM) (TREIBER *et al.*, 2000), Optimum Velocity Model (OVM) (BANDO *et al.*, 1995), Adaptive Cruise Control (ACC) (AREM *et al.*, 2006), Cooperative Adaptive Cruise Control CACC (MILANéS; SHLADOVER, 2014), and Cooperative Longitudinal Following Behavior.

In order to represent these models, some algorithms have been applied on simulation, such as adaptive dynamic programming, optimization-based ramp control, Virdi CAV Control Protocol, decision-making CAV control algorithm, Model Predictive Control, Autonomous intersection management, Platooning Extension Plexe, cooperative scheduling mechanism for CAVs, discrete-time occupancies trajectory-based intersection traffic coordination algorithm, lane sorting, matrix-based intersection management logic, and Cooperative Controller and Distributed Algorithm.

VISSIM enables users to control vehicles externally using two different approaches: Component Object Model (COM) Application Programming Interface (API) or External Driver Model (EDM) with DriverModel.dll "dynamic link library"function. Each method, COM API and EDM, has its strengths and weaknesses, both related to the capacity to read and write vehicles' parameters in the simulation.

The COM API does not depend on a certain programming language, and it can be used in a wide range of programming and scripting languages, including VBA, VBS, Python, C, C++, C, Delphi, and MATLAB. Its main advantage is to be able to access any data contained in VISSIM.

Regarding longitudinal movement, COM API can read and modify three parameters: desired speed, operating speed, and position. However, after a comparison between a realistic trajectory and simulations modifying speed, desired speed, and position with COM API, Manjunatha et al. (2022) found that the "change desired speed"method results in lag time issues, which means that the vehicles' simulated trajectory does not follow a realistic trajectory. Nevertheless, the COM API does not offer direct control over lateral movements. Its sole option is to set a desired lane, and the vehicle will transition to the specified lane when it becomes feasible.

The EDM approach enables users to replace the internal driving behavior by a fully-developed user-defined behavior for some or all vehicles in a simulation run. During a simulation, VISSIM communicates with the DLL code in every time step, so VISSIM passes the current state of each vehicle and its surroundings to the DLL, and the DLL code computes the acceleration/deceleration of the vehicle and its lateral behavior.

Table 3 summarizes various research papers that utilized VISSIM as a microsimulator to conduct their analysis on Connected and Autonomous Vehicles (CAVs). Manjunatha et al. (2022) results indicate that CAVs improve travel time and speed. Nonetheless, the emissions did not exhibit a similar pattern. While increasing the penetration rate of Autonomous Vehicles (AVs) led to emissions reductions, increasing the penetration rates of Connected Vehicles (CVs) and Connected and Autonomous Vehicles (CAVs) resulted in higher emissions. The selected CV logic, designed to maximize the likelihood of vehicles arriving at green signals, might cause increased variations in second-by-second accelerations, ultimately leading to higher overall emissions.

Table 3 – Details of CAV microsimulation studies with external control.

STUDY	FOCUS	ENVIRONMENT	ALGORITHM/MODEL	MOVEMENTS
Manjunatha et al. (2022)	Traffic Operation and Emissions	Isolated signalized intersection	Talebpour & Mahmassani car-following (modified version of the IDM)	Longitudinal
Ard et al. (2020)	Traffic Operation and Energy Efficiency	Road segment between entry and exit ramps	Model Predictive Control (MPC)	Longitudinal
Liu and Fan (2020)	Traffic Operation	Four-lane basic freeway segment	Revised Intelligent Driver Model (IDM)	Longitudinal
Virdi et al. (2019)	Road Safety	Highway environment and a residential urban endowment	Talebpour & Mahmassani car-following to lead vehicle	Longitudinal and gap acceptance
Papadoulis et al. (2019)	Road Safety	Motorway segment + on and off ramp	Own model	Longitudinal and lateral
Xie et al. (2017)	Traffic Operation	Freeway on-ramp	Optimal control (nonlinear optimization problem)	Longitudinal

Source: The author.

Ard et al. (2020) found that AVs perform at a 10%–20% higher energy efficiency than human-driven vehicles, and simulated human-driven vehicles were found to drive up to 10% more energy-efficiently than they did in the baseline.

Liu and Fan (2020) found that when it is increased CAV penetration rate, freeway capacity increases, and further the capacity increases significantly with the increase in speed limits.

Virdi et al. (2019), on the other hand, found that at low penetration rates of CAV, the conflicts will increase, and their results demonstrated that CAV operation seems to show a significant overall improvement in safety at midblock road sections. Besides, with the increase in CAV penetration rates, the conflicts are reduced. The greater the priority, the more the reduction in conflicts.

Papadoulis et al. (2019) results also indicated that CAVs bring about compelling benefits to road safety as traffic conflicts significantly reduce even at relatively low market penetration rates.

Xie et al. (2017) key findings was that the optimal control strategy was successful in coordinating the merging of vehicles and will enhance safety and mobility in situations where there is less traffic than the capacity of the roadway.

Accordingly, Table 3 indicates that the car-following model developed by Talebpour & Mahmassani, which is an adaptation of the Intelligent Driver Model, is the most commonly employed approach to represent the longitudinal behavior of Connected and Autonomous

Vehicles (CAVs) in simulations using VISSIM. Additionally, the longitudinal movement appears to be the most prevalent aspect represented in VISSIM simulations involving CAVs.

In light of the studies analyzed and the distinctive aspects of this research, one particular article stands out: Manjunatha et al. (2022) have already assessed their algorithm in terms of traffic operation, but its safety aspects have not been explored yet. This aligns perfectly with the primary objective of the current study, which aims to focus on safety. Furthermore, their algorithm was specifically designed for urban scenarios, making it a highly relevant and suitable choice for the intended simulation scenario in this research.

2.2.2.3 Co-simulation to represent CAVs

Advanced simulations are increasingly employed to conduct accelerated tests of connected and automated vehicles (CAVs) in virtual environments. While traditional vehicle simulation has concentrated on high-fidelity models of vehicle components, recent advancements and stricter regulations have shifted the focus towards understanding how vehicles interact with their surroundings. However, most existing simulators are designed for conventional traffic and human-driving scenarios and do not fully exploit the core functionalities of CAVs, such as sensing and communication. Co-simulation, which combines various models like vehicle dynamics, traffic flow, and wireless communication, is essential for creating realistic testing environments for these advanced vehicles (VARGA *et al.*, 2023).

The study by Niewerth et al. (2024) highlights that the co-simulation approach used involves substantial computational demands, especially when analyzing large-scale traffic systems with a high prevalence of autonomous vehicles (AVs). It notes that limitations in hardware resources, such as CPU, GPU, and memory, can affect the scalability of the simulation. The study emphasizes the need for future research to optimize the co-simulation framework and utilize more advanced hardware to enable a more thorough examination of AV impacts in larger-scale scenarios.

2.3 CAVs impact on road safety

Connected and autonomous vehicles are expected to improve many transportation aspects, such as traffic efficiency and road safety, due to their deterministic and coordinated behavior and to the fact that most crashes are related to human errors such as fatigue, alcohol, or drug consumption (SINGH, 2015). However, as CAVs are still in the testing period, it is not possible to say for sure what are their impacts, and how they behave interacting with conventional vehicles as there are not enough data available on road crashes with CAVs worldwide.

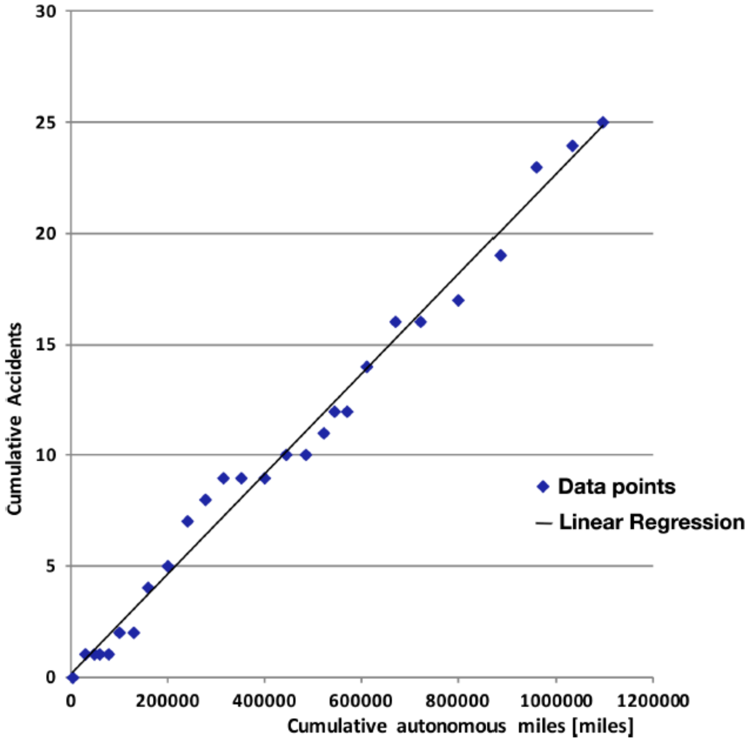
2.3.1 CAVs crash data

There were a total of 779 crashes involving connected and autonomous vehicles (CAVs), around the world, from January/2014 to June/2024 (CRASHES, 2024). Of these crashes, 84.98% resulted in no injuries, 14.76% resulted in injury to a person, and 0.26% were unknown or not specified. The distribution of these crashes by country shows that the majority occurred in the United States (748 crashes), with smaller numbers reported in Japan (8 crashes), Russia Federation (7 crashes), Finland (3 crashes), China (3 crashes), Austria (2 crashes), and Estonia (2 crashes).

One of the main technological hubs in the world, Silicon Valley, in California, offers a reliable base for early CAVs testing on public roadways. The California Department of Motor Vehicles (CDMV) has required manufacturers to report any collision resulting in property damage, bodily injury, or death within 10 days of the incident. This information needs to be written and made public in an effort to increase consumer safety and transparency. From 2015 to 2022 the number of road crashes involving CAVs increased, with a 96% average annual growth rate (CALIFORNIA DEPARTMENT OF MOTOR VEHICLES, 2023), and this data has a significantly high correlation with the autonomous miles traveled (i.e., the more cumulative miles traveled, the more cumulative crashes) (DIXIT *et al.*, 2016). This statement about the relation between CAVs miles traveled and the number of road crashes is obvious, once the CAVs miles traveled captures the exposure of the CAV to being involved in a road crash. However, it is conceivable for the cumulative accident trend to plateau as a function of cumulative miles, indicating that CAV technology is improving and becoming more accident-free as more miles are logged (FAVARò *et al.*, 2017). However, the current stage of CAVs implementation is still far from this relation stability as can be seen in Figure 3.

Dixit et al. (2016) developed a benchmark for the crash exposure of AVs with normal vehicles, using the mentioned CDMV database of CAVs crashes, from September 2014 to November 2015, with the California Highway Patrol (CHP) Safety Database from 2014. With the available data in 2016, their study pointed out that approximately 1 crash is expected every 2.07 million miles, however, based on data released by Google on their trials 1 crash was

Figure 3 – Correlation between cumulative crashes and cumulative autonomous miles.



Source: Favarò *et al.* (2017)

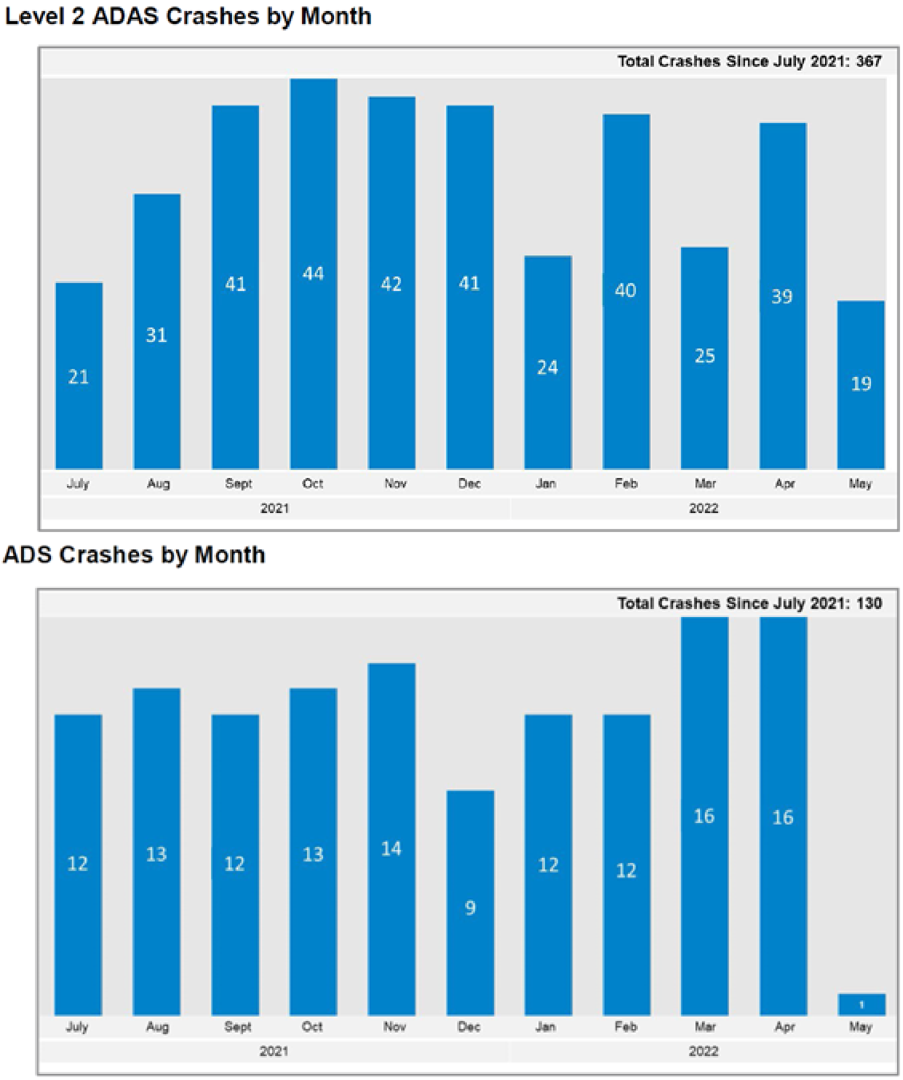
expected every 47,148 miles traveled by Google AVs. Yet, no fatalities occurred as compared to 1 death for every 108 million miles in California. Although Google AVs have a higher crash rate than traditional vehicles, it is important to consider that AVs were still in the early stages of development when they were first introduced, and even now they are still in the process of being refined. As a result, it is important to take into account certain limitations, such as the fact that the sample size of crashes involving Google AVs is small.

The low availability of CAV crash data characterizes the current major limitation of applying conventional methods of road safety analysis with this new technology. Nevertheless, the available data gives important insights, as point Dixit et al. (2016): the major number of crashes involved the conventional vehicle being at fault, not the AV. One possible reason for the problem is that the other vehicle's driver may have had different expectations for how the autonomous vehicle would behave compared to what they were used to. This suggests that there is a need to gain a deeper understanding of how drivers interact with one another and what kind of behavior they anticipate from the vehicles they are sharing the road with.

The National Highway Traffic Safety Administration (NHTSA) has issued a Standing General Order (the General Order) requiring manufacturers and operators to report certain crashes involving vehicles with autonomous driving systems. The data is categorized into two groups:

the first includes vehicles classified as Levels 3 through 5 according to SAE standards, known as advanced driver systems (ADS), which operate independently of driver input; the second group consists of Level 2 vehicles, referred to as advanced driver assistance systems (ADAS). This order ensures that NHTSA receives timely and transparent notifications of real-world crashes involving both ADS and Level 2 ADAS vehicles.

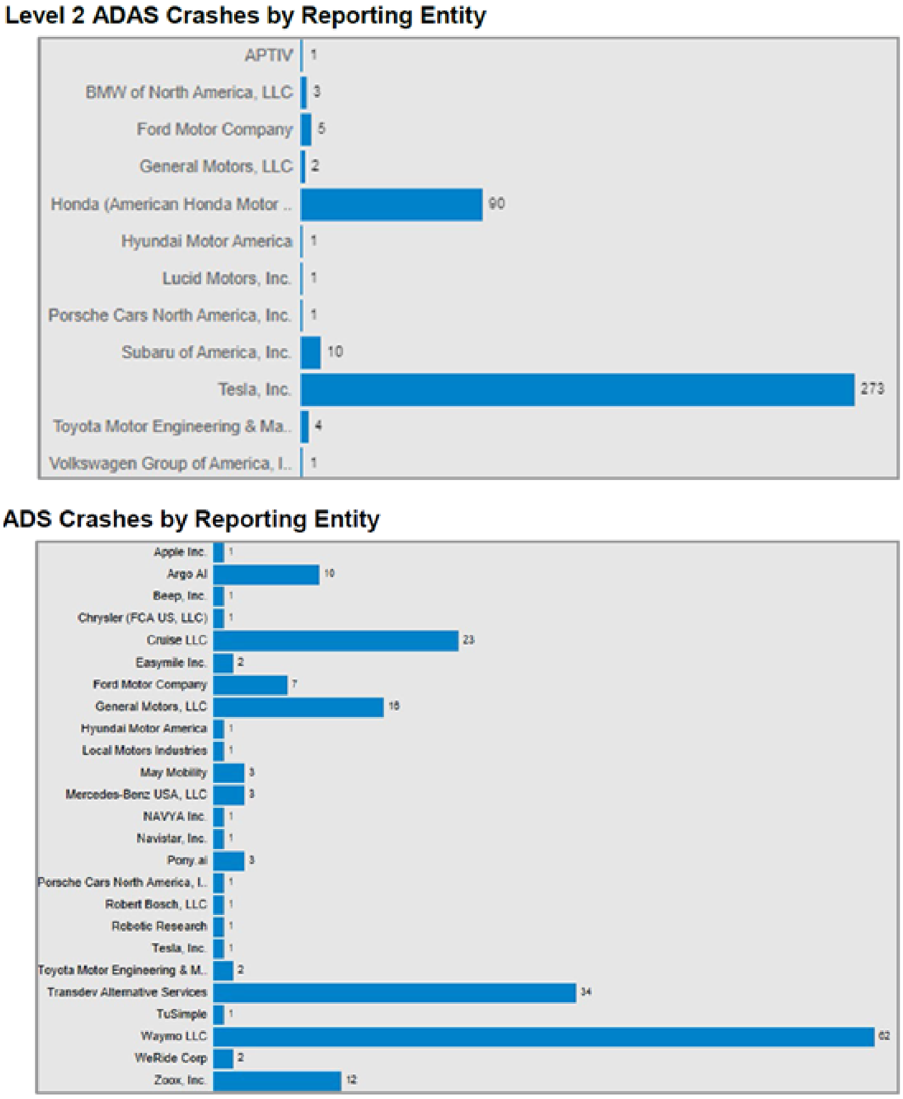
Figure 4 – Road crashes by month



Source: Administration (2021)

The reported data from NHTSA has several limitations. One limitation is that the data is not normalized or adjusted by any measure of exposure, including the operational driving domain or vehicle miles traveled. This means that the number of crashes reported for any given manufacturer or operator may not be directly comparable to other manufacturers or operators. Despite the mentioned limitation, Figure 5 highlights Tesla and Waymo as principal crash reporters. Additionally, a single crash may have multiple reports from multiple entities, which means that the overall number of reports submitted does not equate to the total number of incidents and is not a meaningful safety metric.

Figure 5 – Road crashes by entity

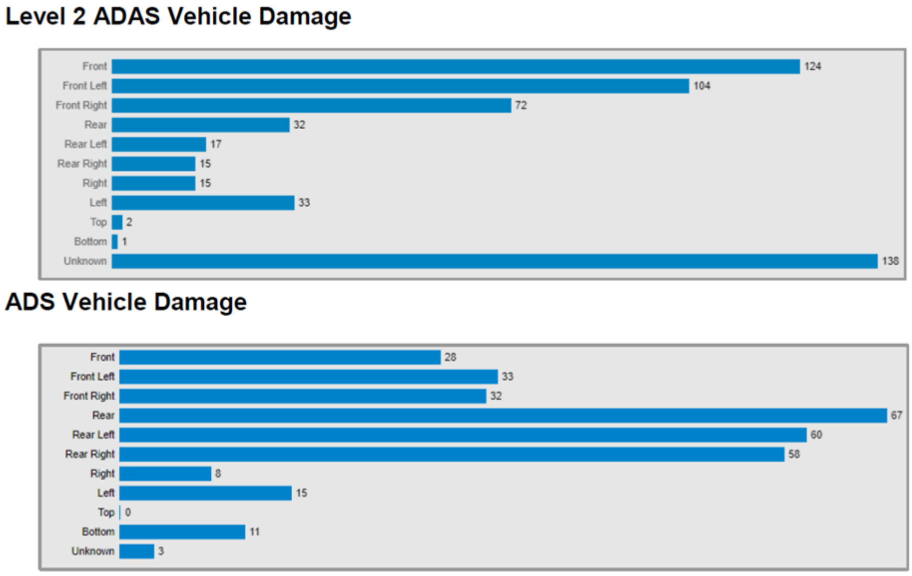


Source: Administration (2021)

Figure 6 shows a contrasting tendency in crashes between Level 2 and Level 3 forward: the former type tends to damage their fronts, while Level 3 forward tends to cause damage to the rear.

Although there is an apparent connection between road safety and actual crashes, it is important to consider the events leading up to a crash to develop effective engineering solutions to prevent future crashes. Moreover, relying solely on observational studies based on reported crashes is a reactive approach to safety issues, as countermeasures are often only implemented after a significant number of collisions have already occurred (PERKINS; HARRIS,

Figure 6 – Vehicle damage in road crashes



Source: Administration (2021)

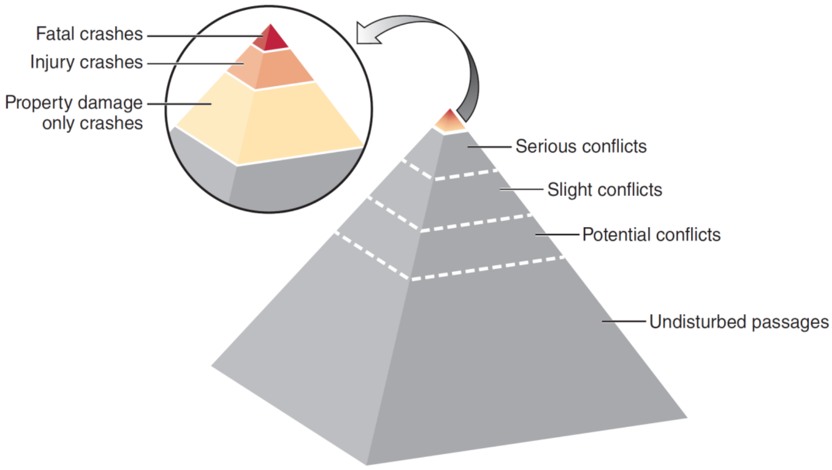
1968; SAUNIER; SAYED, 2007). Considering both the lack of road crash data involving CAVs and the importance of proactive safety analysis, the safety continuum theory is characterized as a possible strategy to be implemented for assessing the road safety performance of CAVs, and this theory is discussed in the following section.

2.3.2 Road safety assessment with traffic conflicts

Safety continuum theory was first introduced as an alternative to the use of crashes in safety studies, in the late 1960s, by Perkins and Harris (1968). Their work used risky situations between vehicles that did not lead to crashes, i.e. traffic conflicts. Like crashes, traffic conflicts are affected by traffic patterns, road users, road geometry, and other factors. Amundsen and Hydén (1977) provided the most accepted definition of traffic conflict as "an observable situation in which two or more road users approach each other in space and time to such an extent that there is a risk of collision if their movements remain unchanged". The Swedish technique of Traffic Conflict Analysis ((HYDÉN, 1987)) considers traffic safety as a sequence of chronologically dependent events ranging from undisturbed passages to crashes. This concept is the safety continuum, represented by the Hydén pyramid, as shown in Figure 7.

The traffic conflict technique has many benefits as a safety surrogate in road traffic safety research, beyond being a proactive approach, there is the fact that traffic conflicts occur more frequently than road crashes, so it can produce statistically reliable results without the need for historical crash data. This difference is noticeable in the pyramid volume corresponding to

Figure 7 – Road safety continuum



Source: Hydén (1987)

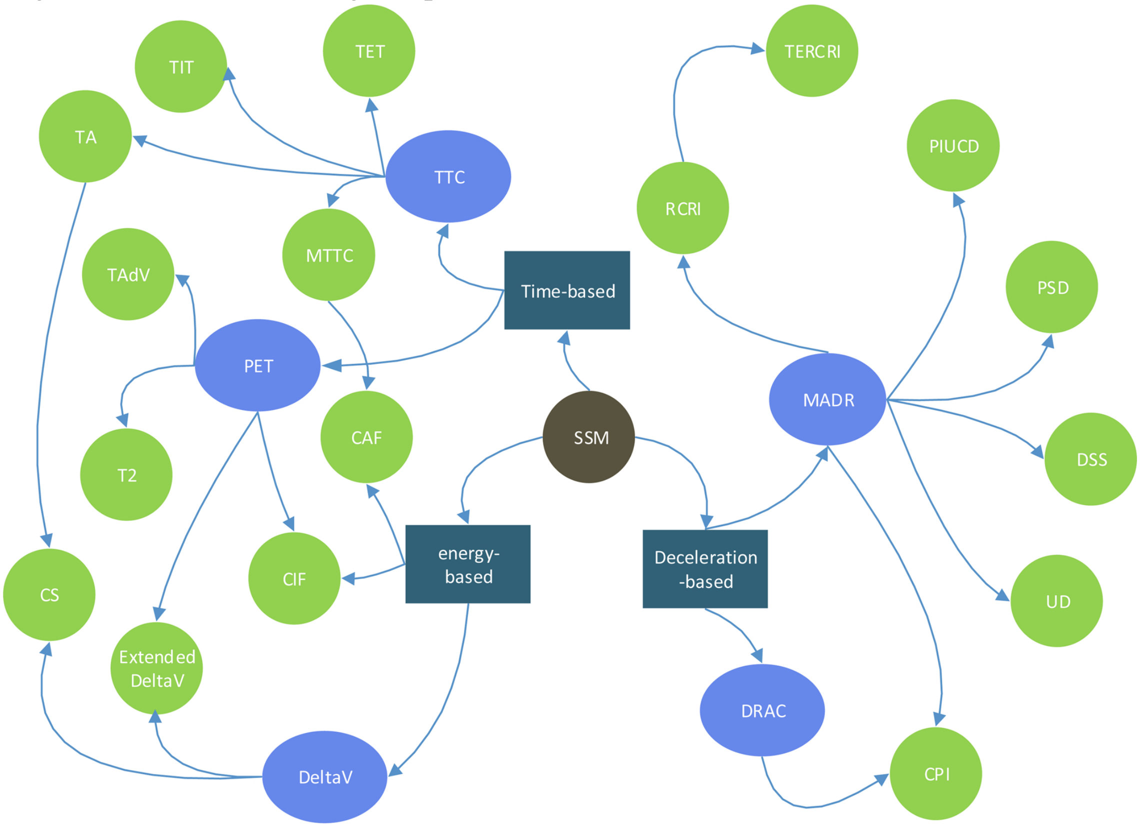
each category, Figure 7, which is directly related to the occurrence rate. However, in opposition to the upper and lower portions of the pyramid, which are readily recognizable, there is no clear or objective method for identifying the intermediate categories (CUNTO, 2008), thus, the Surrogate Measures of Safety (SMoS) are defined to reflect high-risk events that may occur leading up to a projected point of collision.

Cunto (2008) classify SMoS into three categories, which are illustrated in Figure 8: time-based SMoS, deceleration-based SMoS, and energy-based SMoS. Time-based SMoS are designed to measure the risk of an interaction concerning the amount of time remaining before a potential collision occurs. The most commonly used time-based SMoS is Time-to-Collision (TTC), which was first introduced by Hayward (1971). TTC is defined as the amount of time remaining before a collision between two vehicles would occur if they maintain their current course and speed difference. The key assumption behind TTC is that the speeds and directions of the vehicles involved remain constant, and it has the main advantages of being frequently used and being easy to measure. However, TTC has limitations such as constant velocity assumption (no evasive actions considered), and it requires a threshold to determine interaction severity (CUNTO, 2008).

Another significant time-based SMoS is Post-Encroachment Time (PET), first proposed by Allen et al. (1978), which measures the amount of time between when the first vehicle leaves a conflict point and when the second vehicle approaches that same point. Unlike TTC, PET does not require any assumptions about the speeds, directions, or collision course of the vehicles involved, but it is also threshold sensitive.

SMoS that are based on deceleration focus on how vehicles' ability to slow down can

Figure 8 – SMoS knowledge map.



Source: Wang *et al.* (2021)

prevent collisions from occurring, rather than measuring time proximity. Cooper and Ferguson (1976) proposed DRAC (Deceleration Rate to Avoid the Crash) to assess the severity of an interaction. DRAC is calculated as the minimum braking rate needed for a vehicle to avoid colliding with another vehicle. The calculation of DRAC assumes that one vehicle takes evasive action while the other maintains its speed and direction. Thresholds are also required to determine the risk of collision using DRAC.

Cunto (2008) further extended DRAC and developed a Crash Potential Index (CPI) by considering a vehicle's braking capability or maximum deceleration rate (MADR). CPI represents the probability that DRAC exceeds the maximum deceleration rate (MADR) at a moment. CPI's aim is to encompass three key elements of vehicle interactions, which are the braking needed to avoid a crash during an interaction, the maximum braking power that can be applied based on vehicle type and environmental conditions, and the time exposed to the interaction.

Energy-based SMoS differ from time- and deceleration-based SMoS by focusing on the severity of a collision rather than its proximity. DeltaV is a particularly important energy-based SMoS that measures the change in velocity that occurs during a collision. It takes into account the speed, mass, and angle of approach of each vehicle involved in the collision. Shelby (2011) highlights the significance of DeltaV as an important indicator of collision severity. Besides, CFI (Conflict Index) is a safety performance measure that integrates PET, as well as the speeds, masses, and angles of the road users involved, to estimate the amount of kinetic energy that would be released in a potential collision. The CFI takes into account both the likelihood of a crash and its severity, making it a comprehensive safety performance measure.

As the previous paragraphs mention, the development of SMoS has focused on two primary goals: firstly, to calculate the probability of a collision occurring, also known as collision risk, and secondly, to determine the potential outcomes of a collision, referred to as collision severity (BEHBAHANI; NADIMI, 2015). Table 4 presents an SMoS summary indicating each measure's aim of development.

Table 4 – Surrogate Measures of Safety Review.

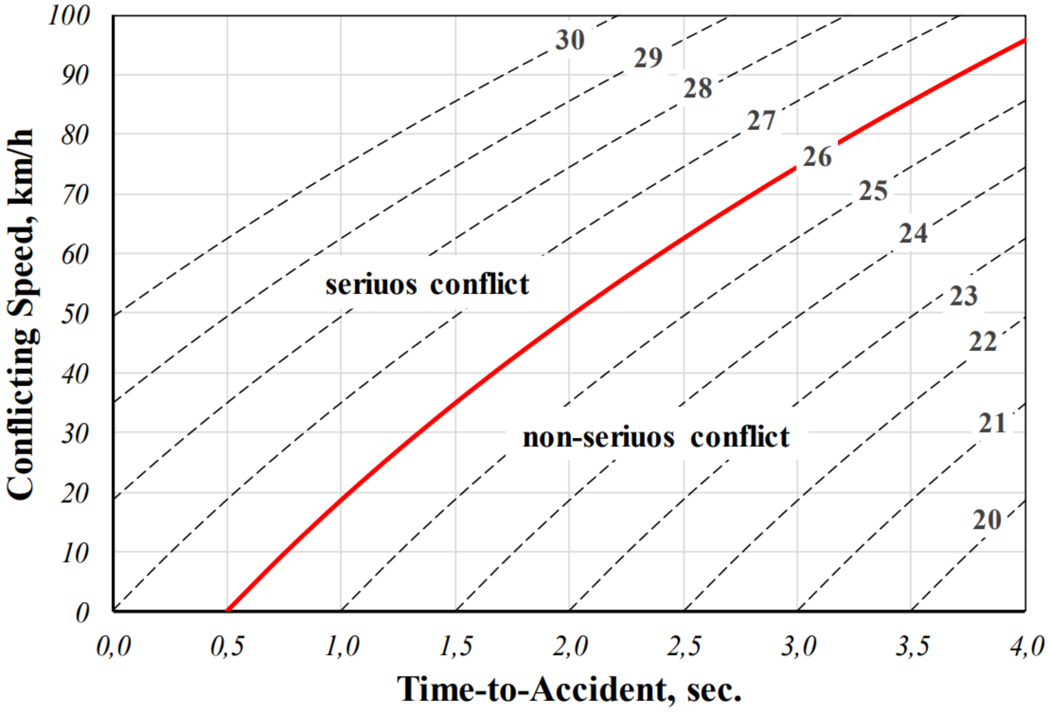
Surrogate Measures of Safety Aims of Development	
Collision Risk	Time-to-collision (TTC)
Collision Risk	Post-encroachment time (PET)
Collision Risk	Deceleration rate to Avoid Collision (DRAC)
Collision Risk	Crash Potential Index (CPI)
Collision Severity	DeltaV
Collision Severity	Conflict Index (CFI)

Source: Adapted from Behbahani H. et al. (2015)

In traffic severity evaluation, the Swedish Traffic Conflict Technique utilizes Time-to-Accident (TA) and Conflict Speed (CS) to assess the likelihood of severe crashes. TA measures how long road users have to avoid a collision, with shorter times indicating greater severity. CS reflects both the difficulty in avoiding a collision and the potential impact severity, with higher speeds suggesting more severe outcomes. The severity levels, as shown in Figure 9, are determined by combining TA and CS. If both road users take evasive actions, the conflict's severity is based on the user with the lower severity rating. Conflicts with severity levels above 26 are considered serious, a category that strongly correlates with police-reported accidents and helps estimate the expected number of accidents accurately (SVENSSON, 1992).

SMoS were created based on field safety studies(i.e., conflict studies). However, these types of field observations can be time-consuming and resource-intensive. Additionally, there is a risk of errors being introduced due to human observation, which can have an impact on the reliability of these field-based safety studies (WANG *et al.*, 2021). In addition to these limitations, evaluating the impact of CAVs on road safety is also hindered by the low penetration

Figure 9 – Conflict severity diagram: TA vs CS.



Source: Hydén (1987)

rate of CAVs in urban settings. The lack of sufficient field data makes it difficult to apply traditional methods for safety assessment. Therefore, with existing technology, CAV's impact investigation is mainly dependent on simulated data.

2.3.3 CAVs assessment on road safety using SSAM

Do et al. (2024) examine the adequacy of conventional SMoS for CAVs, highlighting that CAVs, which rely on computer algorithms for driving decisions, may exhibit behavior that differs significantly from CNVs. This study suggests that traditional indicators such as TTC, PET, and DRAC may be inadequate for assessing the safety of CAVs, particularly when CAVs and CNVs operate at similar speeds. The conventional measures may fail to accurately capture the safety implications of CAV-specific car-following behaviors, potentially misinterpreting these behaviors as hazardous.

Despite the limitations of traditional safety measures for CAVs, recent studies assessing CAV safety performance heavily rely on these indicators. Wang et al. (2021) reviewed recent CAV safety impact studies (Table 5) and how they assess safety using SSM. The evaluation of CAVs safety effects has mainly utilized time-based and deceleration-based safety performance measures, with Time-to-Collision (TTC) being the most widely used measure. It is relevant to

Table 5 – Summary of SMoS and other safety indicators used for CAV safety evaluation.

Indicator	Reference	Simulation Tool	Threshold
TTC	Virdi et al., 2019	VISSIM + SSAM	1.5 s
	Papadoulis et al., 2019	VISSIM + SSAM	1.5 s
	Li et al., 2018	General-Purpose (GP) simulation tools	2 s
	Morando et al., 2018	VISSIM + SSAM	1.5 s
TET, TIT	Jeong et al., 2017	General-Purpose (GP) simulation tools	2 s (TTC)
	Rahman and Aty 2018	VISSIM + SSAM	1-3 s (TTC)
	Rahman et al., 2019a, 2019b	VISSIM + SSAM	1-3 s (TTC)
	Li et al., 2017a, 2017b, 2017c	VISSIM	2 s (TTC)
RCRI	Rahman and Aty, 2018 Rahman et al., 2019a, 2019b	VISSIM + SSAM	3.42 m/s for PC 2.42 m/s for HGV
	Li et al., 2018	General-Purpose (GP) simulation tools	3.4
TA	Wu et al., 2019	VISSIM + SSAM	2 s
DRAC	Zhong et al., 2019	VISSIM	-3 m/s²
Standard deviation of speed	Fu et al., 2019	PreScan	-
	Rahman and Aty, 2018	VISSIM + SSAM	-

Source: Adapted from Wang et al. (2021)

highlight that many studies have evaluated the safety of both CAVs and conventional vehicles using the same SSM, such as TTC with a threshold value of 1.5 or 2 seconds.

Safety studies utilizing traffic simulation tools require significant efforts for model development and calibration. While specialized simulation tools generate more detailed and precise results for safety impact evaluation, general-purpose simulation tools are computationally less demanding and can be integrated with optimization algorithms to identify promising safety strategies for further analysis using specialized simulation models. However, general-purpose simulation tools may oversimplify vehicle/traffic characteristics and interactions, potentially ignoring important aspects. Hence, selecting the appropriate simulation tool involves balancing accuracy and efficiency (WANG *et al.*, 2021).

Wang et al. (2021) also highlight that when it comes to modeling safety in mixed autonomy traffic or fully autonomous traffic, it's uncertain whether the SMoS that have been validated in traditional traffic environments can still be applicable. This is because the behavior of CAVs can be significantly different from that of conventional vehicles, and even among CAVs with different automation/connectivity levels, their behaviors are likely to differ. Additionally, it is also pointed out by the authors that the presence of CAVs can change the behaviors of conventional vehicles. Therefore, conventional SMoS or SSM-based models may need to be revised. For instance, according to them, the thresholds used in SMoS may need to be adjusted, and it's unclear whether TTC = 1.5 s can still be a suitable choice for both conventional vehicles and CAVs.

Despite the methodological limitations of using conventional SMoS to analyze the impacts of CAVs on road safety, most recent studies listed in Table 5 that employ microsimulation traffic models, particularly VISSIM, combine simulations with Safety Surrogate Analysis Method (SSAM) to assess CAV safety. In Virdi et al. (2019) study, CAVs were gradually introduced into the traffic environment in increments of 10%, and their findings indicate that at low penetration rates, CAVs can lead to an increase in conflicts at signalised intersections, but a decrease in conflicts at priority-controlled intersections. For example, when CAV penetration was at 20%, there was a +22%, -87%, -62%, and +33% change in conflicts at signalised, priority, roundabout, and DDI intersections, respectively. However, as CAV penetration rates increased, there was a global reduction in conflicts. At a 90% CAV penetration rate, there was a -48%, -100%, -98%, and -81% change in conflicts at signalised, priority, roundabout, and DDI intersections, respectively.

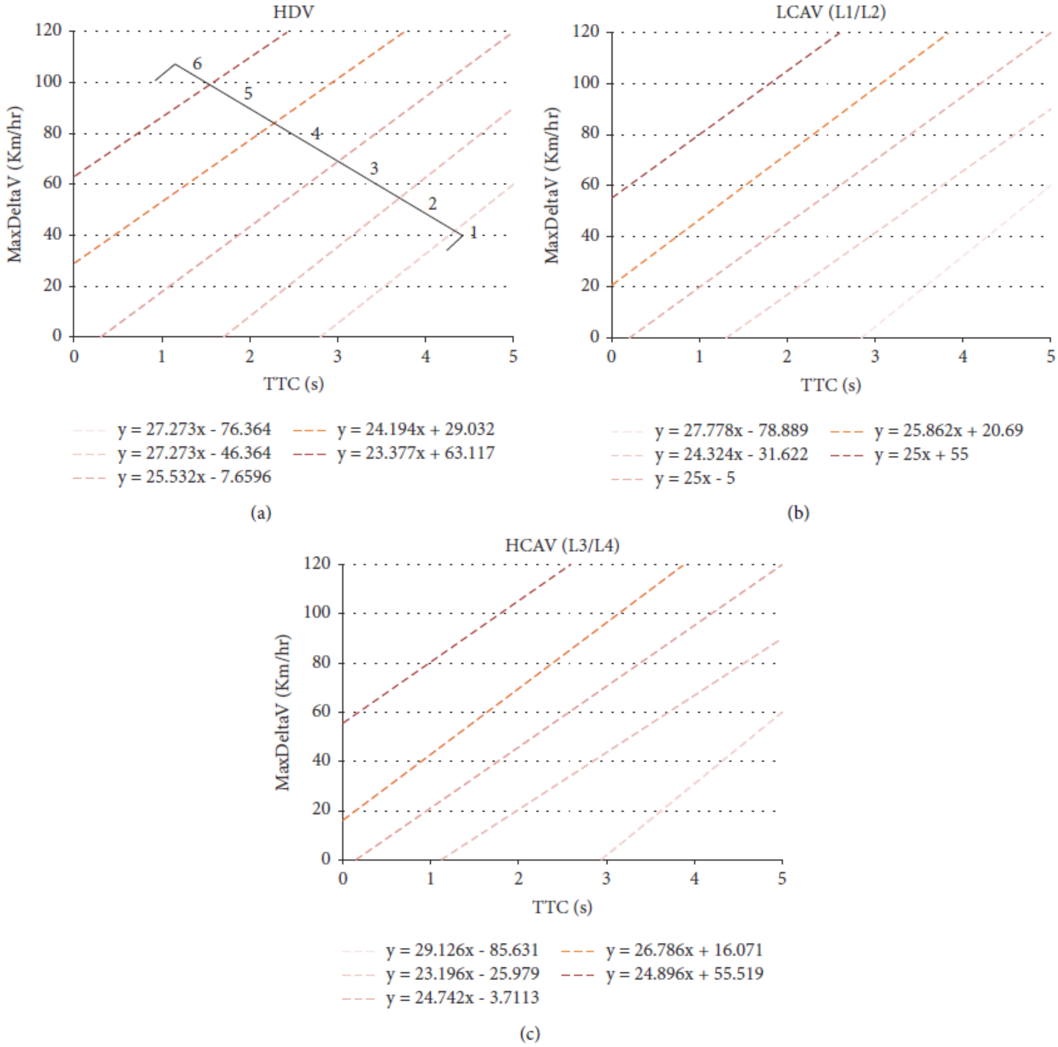
Furthermore, Papadoulis et al. (2019) also found that the introduction of CAVs has a significant positive impact on road safety, even at low market penetration rates. The estimated traffic conflicts decreased by 12-47% for a 25% CAV penetration rate, 50-80% for a 50% penetration rate, 82-92% for a 75% penetration rate, and 90-94% for a 100% penetration rate. Furthermore, the study suggests that the presence of CAVs promotes efficient traffic operation.

Miqdady et al. (2023) does a different safety assessment approach, by assessing the proximity/consequence (TTC/MaxDeltaV) charts for various vehicle types, presented in Figure 10. The findings reveal that as the percentage of CAVs on the road increases, there is a significant reduction in the number of high-severity conflicts. With nearly 100% of vehicles being CAVs, severe conditions are expected to vanish, and conflicts with lower severity are also reduced.

Morando et al. (2018) findings of the study suggest that when AVs are widely adopted, they can significantly improve road safety, even when they travel closer together to improve traffic operation and reduce delays. Specifically, for signalised intersections, the number of conflicts is reduced by 20% to 65% when AV penetration rates are between 50% and 100%. Similarly, for roundabouts, the number of conflicts is reduced by 29% to 64% with 100% AV penetration rate.

Finally, Rahman et al. (2018) study suggests that a minimum market penetration rate (MPR) of 30% is necessary to observe significant improvements in surrogate measures of safety

Figure 10 – Conflict severity diagram: TTC vs MaxDeltaV.



Source: Miqdady *et al.* (2023)

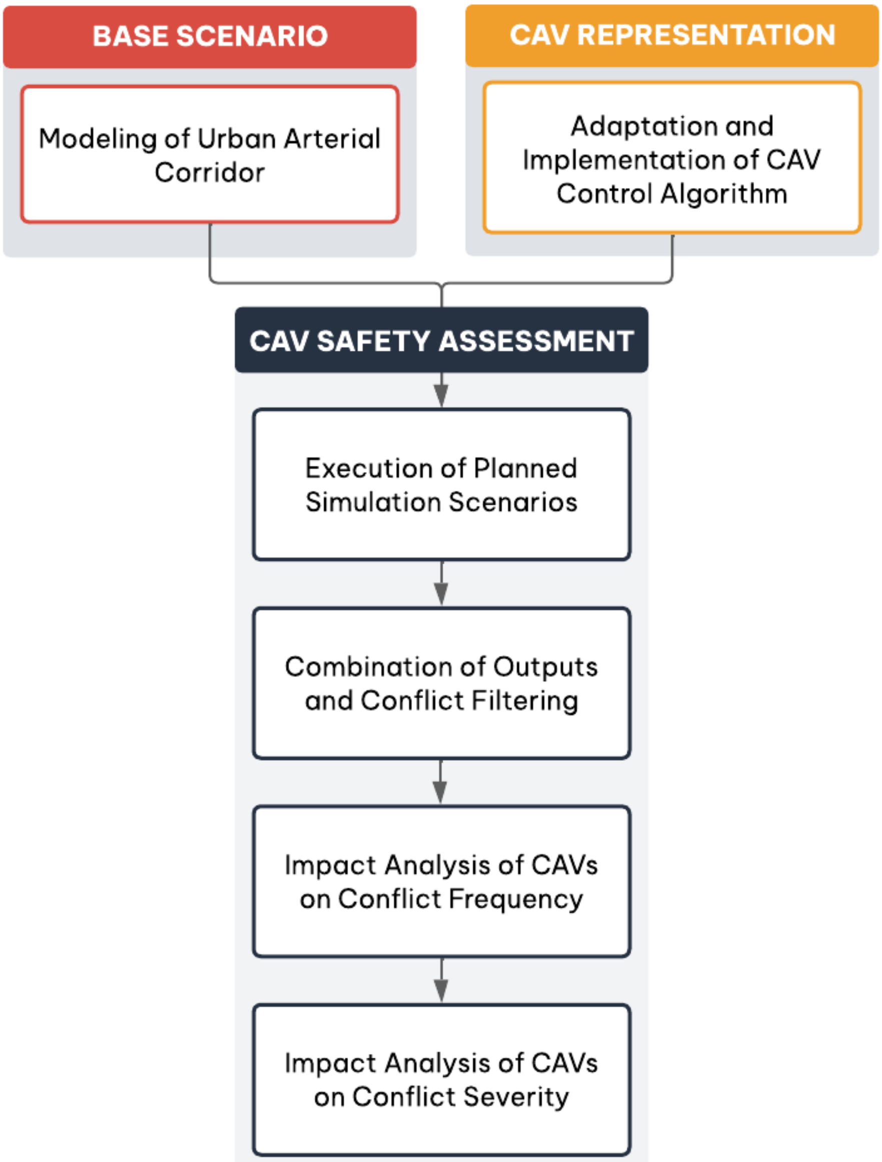
for both CAV approaches compared to the base scenario without CAVs. Additionally, the CAV approach using connected vehicles with platooning (CVPL) outperformed the approach using only connected vehicles without platooning (CVWPL) in terms of surrogate safety measures, especially when the MPR was 50% or higher. The study also found improvements in traffic operation characteristics, such as average speed.

Each one of mentioned studies used a different way of representing automation or connectivity in vehicles. Therefore, it is clear that there is still great difficulty in standardizing the characterization of CAVs in microsimulation. However, even with this variability in representations, there is a trend in all the works toward improving road safety as CAVs gain greater participation on the roads.

3 RESEARCH METHODOLOGY

In this chapter, the methodology employed to assess the safety of CAVs using microsimulation and conflict analysis is presented. Figure 11 summarizes this study's three main stages: base scenario modeling, CAV's behavior algorithm implementation, and CAV safety assessment.

Figure 11 – Description of the method used in this study.



Source: The author.

The chapter begins with an overview of the base scenario modeling, detailing the network's location, dimensions, behavior, and traffic demand. It then introduces the methodology used to model the behavior of Connected and Autonomous Vehicles (CAVs), addressing the limitations of inbuilt models in microsimulation platforms, particularly in terms of connectivity, as discussed in Chapter 2. Despite the potential of co-simulation for evaluating CAV impacts on urban traffic, it was not used in this study due to computational constraints. This study focuses on a urban segment with significant vehicular demand, which poses challenges that exceed the capabilities of current computational resources. Consequently, the methodology adopted involves using microsimulation combined with external algorithms to control CAV behavior. The chapter concludes with a detailed discussion of the adaptation and implementation of these algorithms. The final step of this work assesses the safety aspects of the chosen model within a calibrated network, fulfilling the primary objective of this study.

3.1 Modeling of Urban Arterial Corridor - Base scenario

The objective of this research is to simulate Connected and Automated Vehicles (CAVs) within an urban corridor network. To construct the base scenario, it was essential to incorporate urban road characteristics, including interrupted traffic flows with signal-controlled intersections, stop-sign-controlled intersections, and public transit lines with designated stops.

Data for constructing the base network were obtained through drone flights conducted during peak hours on two business days. This data provided valuable insights into vehicle directional flow volumes and compositions. Additionally, mean traffic volume data was sourced from electronic surveillance equipment provided by the State Traffic Department of Ceará (DETRAN-CE) and integrated into the network.

Geometric characteristics of the corridor, including lane widths, were acquired through satellite images. Signal programming for the simulated period was derived from the DETRAN-CE database and verified through on-site observations to ensure accuracy and reliability.

Following the establishment of the geometry, flow direction, and composition data in the base scenario, the network calibration process commenced, a critical stage in any modeling effort. Calibrating the VISSIM model can be complex due to the large number of parameters involved, each with default values that represent general behaviors. Accurate calibration requires adjusting these parameters to reflect the specific conditions of the modeled environment.

Since the primary aim of this research is to assess road safety within the simulation network, traffic operations are given less emphasis. Given the substantial effort required for calibration—VISSIM provides up to 50 parameters for adjustment—this study chose to use reference values rather than conducting extensive manual calibration. Accordingly, the study relied on a previously calibrated urban corridor model in Fortaleza, where driver behavior is expected to be similar to the current simulation's.

Lacerda (2016) calibrated VISSIM's parameters for two urban corridors in Fortaleza, Ceará, using mean speed as the target measure. Through a sensitivity analysis of 50 parameters across the four available models, seven were identified as relevant: three from the Wiedemann 74 (W74) car-following model, two additional car-following parameters (duration and frequency of temporary lack of attention), and two lane-changing parameters (minimum headway front/rear and safety distance reduction factor).

Within the W74 model (WIEDEMANN, 1974), the parameters *desired speed*—the average free-flow speed drivers seek to maintain under unconstrained conditions—and *ax*—the standstill distance, i.e., the average gap between a stopped vehicle and the one ahead—were obtained directly from field data due to their ease of measurement. In contrast, *bx_add* and *bx_mult*, which define the distribution of desired following distances at higher speeds by adding and multiplying components to the standstill distance, were calibrated using saturation flow as the target measure. The remaining parameters—Dur. TLA, Prob. TLA, minimum headways (front/rear), and the safety distance reduction factor—were optimized using Genetic Algorithms.

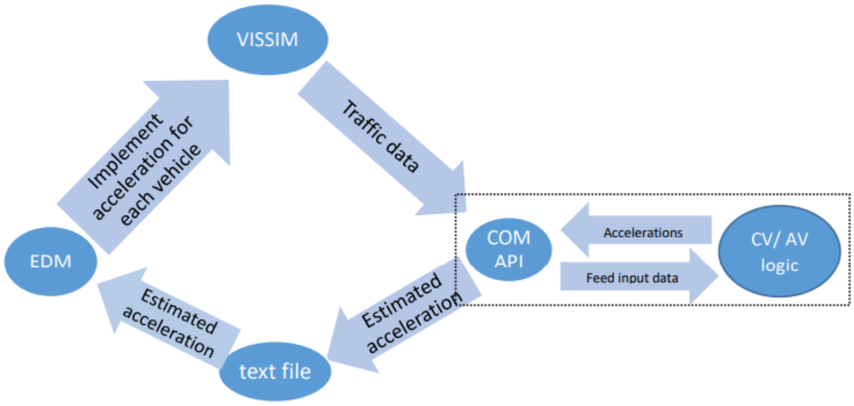
The calibration process, conducted through a combination of manual adjustments and sequential optimization, yielded a *desired speed* of 50 km/h, an *ax* of 2.2 m, and values of 5.0 for both *bx_add* and *bx_mult* across the two analyzed corridors. Default settings were retained for the other parameters.

3.2 CAVs external model: algorithm adaptation

As previously discussed, this study aims to analyze Connected and Automated Vehicles (CAVs) using VISSIM's external control models. The core methodology for representing CAVs in this work is adapted from the approach of Manjunatha et al. (2022). Their algorithm includes various components, such as implementing the CACC (Cooperative Adaptive Cruise Control) to manage the following behavior of CAVs.

The algorithm developed by Manjunatha et al. (2022) implements both VISSIM interfaces, COM API and EDM, to overcome their negative points. Therefore this method is able to read and write almost any desired parameter to each vehicle in the simulation step. Figure 12 represents how Manjunatha et al. (2022) model modifies CAVs' parameters in each step. For each time step, all data from all vehicles in the network are read by COM API, and the vehicles defined as CAVs will have their accelerations calculated following the associated logic. All the calculated parameters are saved in a .txt file, then, also for each time step, the EDM interface reads this file, and using the vehicle's ID as a key, changes, in real-time, the parameters of acceleration and lane change if needed, based on the python output. The following subsections describe AVs and CVs algorithm developed by Manjunatha et al. (2022).

Figure 12 – Longitudinal Control Framework.



Source: Manjunatha et al. (2022).

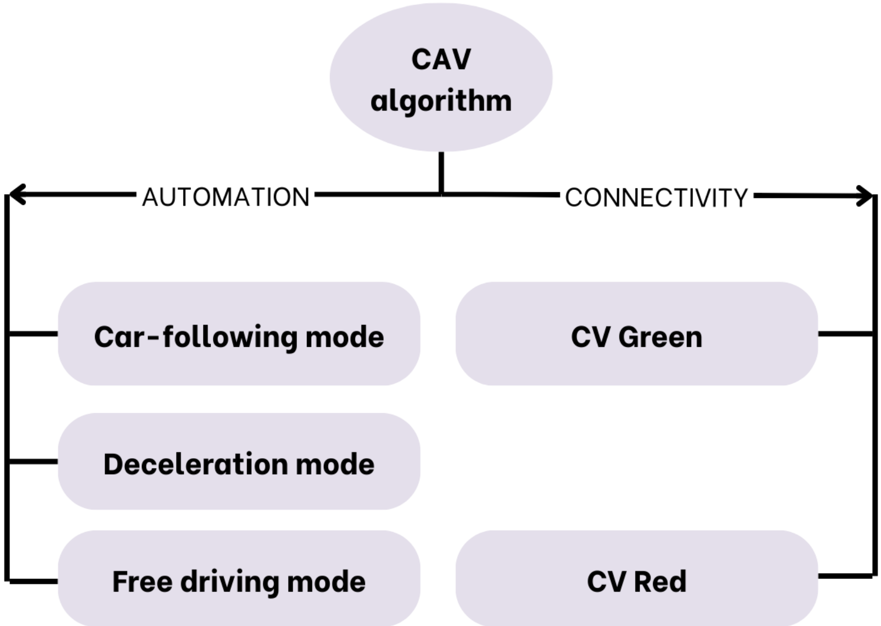
The code utilizes two behaviors to predict a CAV's motion: automation and connectivity. Each behavior has different control modes, resulting in a total of five different codes, as presented in Figure 13. The automation framework has three types of scenarios for a CAV, while the connectivity framework has only two. The following sections provide a detailed explanation of these behaviors and their corresponding scenarios.

Since this algorithm focuses on the longitudinal behavior of CAVs, acceleration is the primary attribute governed by the control modes. Although outputs are generated for both automated and conventional control mode, only one is ultimately selected for application, as discussed in the following section.

3.2.1 Automation algorithm

The autonomous functionality of the code operates under three distinct regimes, each overriding Vissim's default calculations as needed. In Car Following Mode, the system ensures vehicles maintain proper following distances when trailing another vehicle. Deceleration Mode activates when the vehicle needs to reduce speed due to obstacles ahead, such as a red traffic signal. Lastly, Free Driving Mode is applied when no immediate constraints or obstacles are detected, allowing for standard driving behavior. The complete algorithm, which governs these

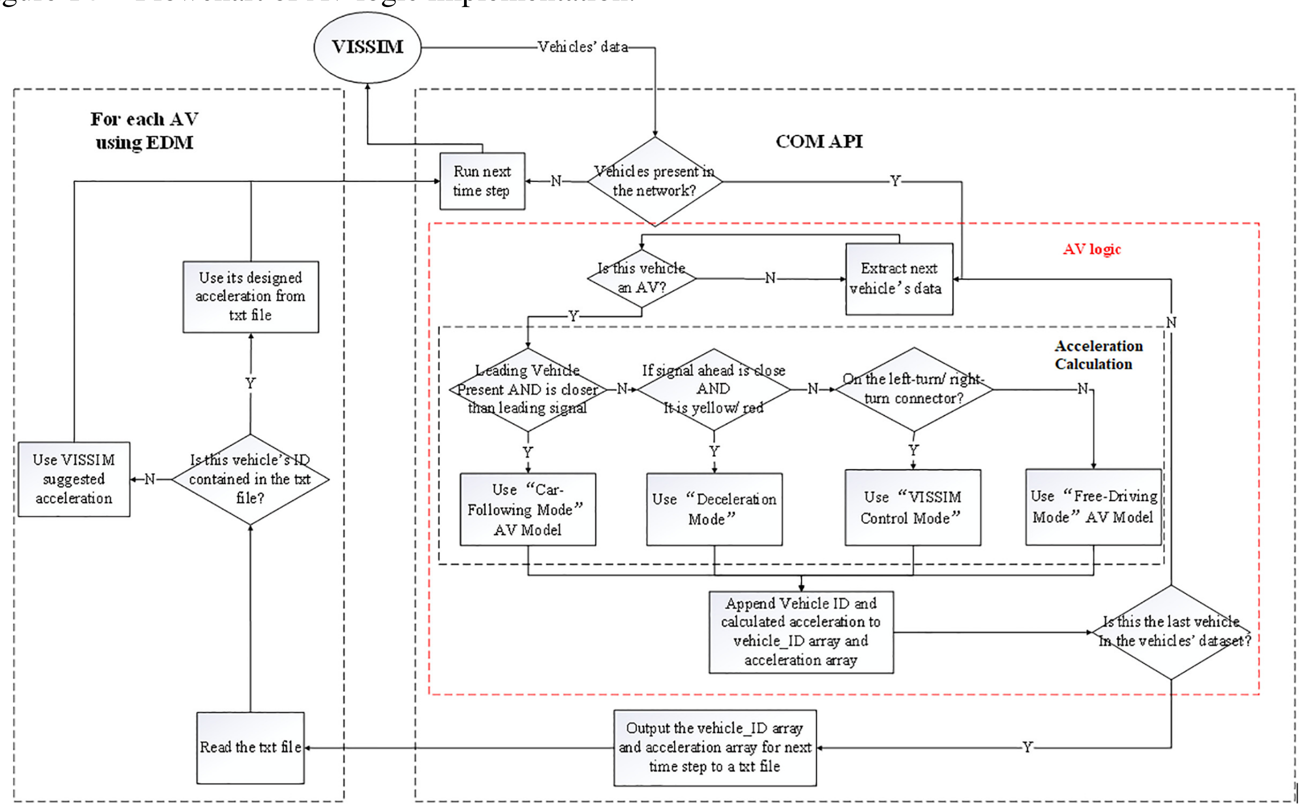
Figure 13 – Possible control modes implemented in CAVs' algorithm.



Source: Adapted from Manjunatha et al. (2022).

modes, is detailed in Figure 14, and it is designed to evaluate each vehicle's situation at every time step to determine the appropriate mode of operation.

Figure 14 – Flowchart of AV logic implementation.



Source: Manjunatha et al. (2022).

The first regime occurs when the CAV is in a car-following stage, where its closest leading target within a 300-meter buffer is another vehicle that may influence its behavior. During this phase, the acceleration value is computed using the Cooperative Adaptive Cruise Control (CACC) formulas, with parameters adapted from the study by Van Arem et al. (2006) to accurately represent the response characteristics of an autonomous vehicle.

Before describing the formulation of car-following AV mode, is important to highlight that its acceleration calculation primarily considers two factors: safety constraints and vehicle movement. The first parameter calculated is named safe distance, defined as the distance the automated vehicle (AV) should maintain from the leading vehicle in the event that the leading vehicle decelerates at its maximum rate, presented in equation 3.1.

$$\Delta x_n = (x_{n-1} - x_n - l_{n-1}) + v_n \tau + \frac{v_{n-1}^2}{2\overset{decc}{a_{n-1}}} \tag{3.1}$$

Where:

- Subscript n and $n-1$ represent the Autonomous Vehicle (AV) and its leader.
- x_n is the location of vehicle n.
- l_n is the length of vehicle n.
- v_n is the speed of vehicle n.
- τ is the reaction time of vehicle n, assumed here as 0.1 second.
- $\overset{decc}{a_n}$ is the maximum deceleration of vehicle n, assumed here as -6m/s².

A vehicle always adopts as the safe space headway the minimum value between safe distance, presented in 3.1, and sensor detection range, here considered as 300 meters. This algorithm considers that there is a vehicle stopped outside of the sensors' detection range, which cannot be detected by the sensors at the time of decision-making.

Then, the maximum safe speed is adopted as the minimum value between v_{limit}, equal to 50 km/h, and the Torricelli's formula applied with the maximum deceleration of vehicle and the safe space headway.

$$a_n^{(d)}(t) = k_a \cdot a_{n-1}(t-\tau) + k_v\,(v_{n-1}(t-\tau) - v_n(t-\tau)) + k_d\,(S_n(t-\tau) - S_{\text{ref}}) \tag{3.2}$$

$$S_{\text{ref}} = \frac{v_{n-1}^2}{2}\left(\frac{1}{a_n^{\text{decc}}} - \frac{1}{a_{n-1}^{\text{decc}}}\right) \tag{3.3}$$

$$a_n(t) = \min\left(a_n^{(d)}(t), k\left(v_{\max} - v_n(t)\right), a_{\text{comf}}\right) \tag{3.4}$$

Where:

- S_n is the spacing.
- S_{ref} is the minimum of:
  - Minimum distance (S_{min}), set as 2 meters,
  - Following distance based on the reaction time (S_{system}), calculated by $v_n\tau$,
  - Safe following distance (S_{safe}).
- a_n is the acceleration of vehicle n.
- k_a, k_v, and k_d are model parameters used as 1.0, 0.58 and 0.1 respectively.
- k is a model parameter set as 1.0.
- a_{comf} is the comfortable acceleration level, assumed as 2.5 m/s².

The "deceleration mode"is activated when the CAV is approaching a signal head displaying a red or yellow indication, and this object is the nearest. In this mode, the vehicle will slow down or decelerate in response to the traffic signal's status. The equation 3.5 calculates the distance required for the vehicle to come to a complete stop if it decelerates at a comfortable deceleration, here adopted as -3.5 m/s².

$$S_{\text{d}} = \frac{1}{2}\left(\frac{v_n^2(t)}{a_{\text{comf}}^{\text{decc}}}\right) \tag{3.5}$$

When the vehicle is not influenced by a leading vehicle or a traffic signal, and it's executing a linear trajectory, in other words, it's not planning to execute a lane change or a turning movement, the "free driving"mode is activated. In this mode, the vehicle's objective is to either maintain its current speed or reach the desired speed set for that specific situation.

In all situations not previously specified, the CAV's control is reverted to VISSIM's standard gap acceptance or lane change models. However, this study adapted the algorithm from Manjunatha et al. (2022) due to issues identified in the initial code, particularly during lane changes. For instance, a problematic scenario was observed where a CAV in lane 1 of link 1 failed to detect vehicles in lane 2 of the same link beginning to change lanes into its path. VISSIM's models account for adjacent lanes, which is a parameter in the lateral movement model, preventing such conflicts with vehicles controlled by VISSIM. To resolve this issue, the adapted algorithm not only transfers control of the vehicle executing the lane change to VISSIM but also extends control to all vehicles within a 20-meter radius of the specific vehicle.

3.2.2 Connectivity algorithm

An Infrastructure-to-Vehicle (I2V) model was used to represent CV in this study, so the signal timing data was used to replicate its behavior. It is important to note that in the VISSIM application example, the "Connected Vehicles"(CVs) always follow the advice given to them, whereas, in reality, a true CV might make a choice depending on the driver's decision.

The flowchart presented in Figure 15 is related to CV algorithm control. When the signal ahead is green, the COM API first calculates if the vehicle can reach the intersection within the current green phase. This is done by comparing the desired speed with the minimum speed required to reach the end of the green phase.

If the desired speed is greater than or equal to the minimum speed required to reach the end of the green phase, then the desired speed remains unchanged, and the vehicle can pass through the intersection during the current green phase at its desired speed.

If the desired speed is less than the minimum speed required to reach the end of the green phase, or if the signal ahead is red, then the COM API compares the desired speed with the maximum speed allowed to reach the start of the next green phase. This step checks whether the vehicle needs to decelerate to arrive after the start of the next green phase.

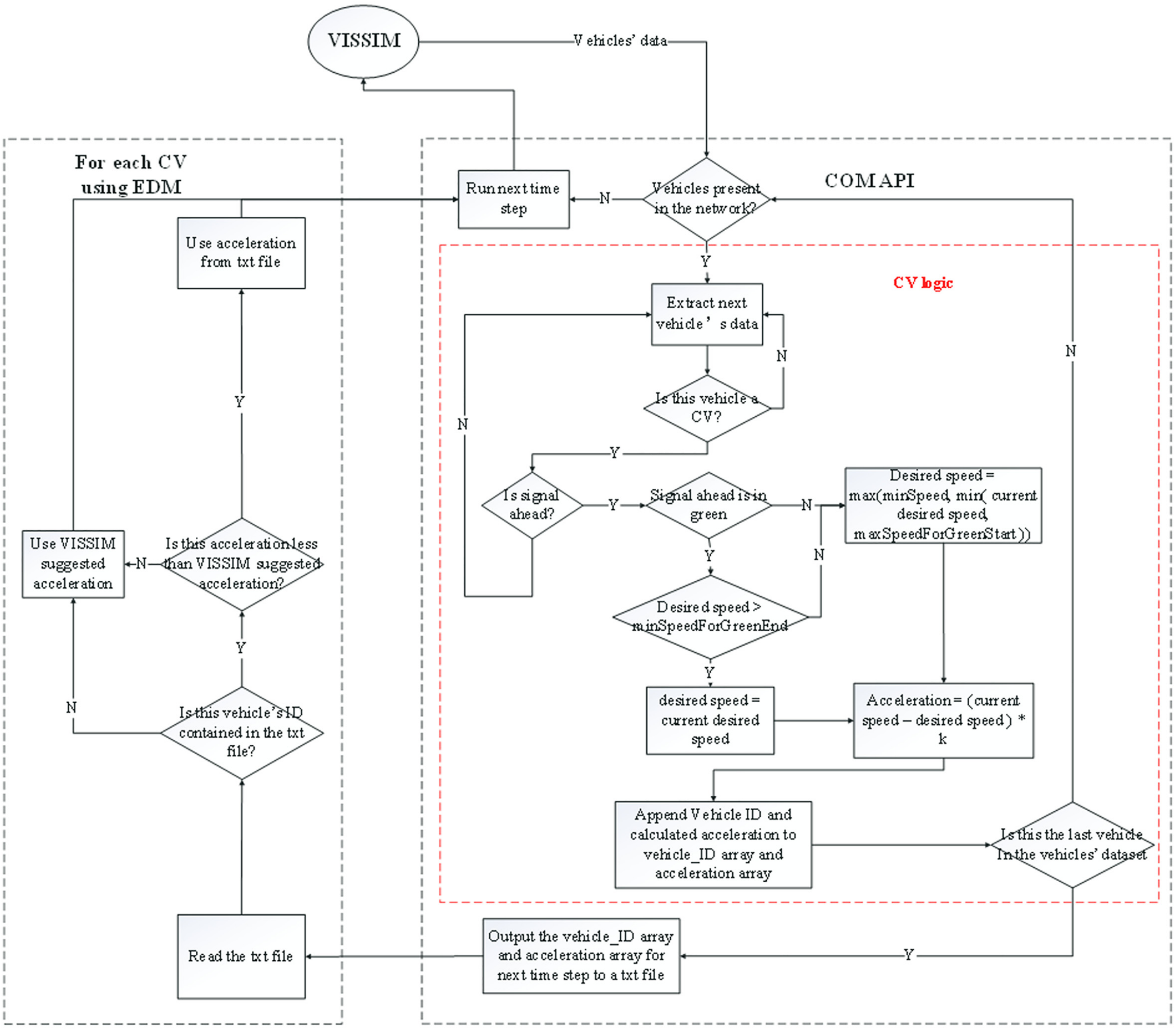
The desired speed is then updated to be the minimum of its original value and maximum speed allowed to reach the start of the next green phase.

When the External Driver Model (EDM) locates the vehicle ID in the acceleration ".txt"file, it compares the estimated acceleration to the VISSIM suggested acceleration and selects the lower value. In other words, the vehicle's acceleration is limited by both the VISSIM car-following model and the Connected Vehicle (CV) logic, with the lower acceleration being implemented. This ensures that the vehicle's behavior adheres to the constraints imposed by both the base VISSIM simulation and the additional CV logic.

3.3 CAV safety assessment

The final aim of this study is to analyze the impact of varying penetration levels of Connected and Autonomous Vehicles (CAVs) within the conventional vehicle fleet on road safety,

Figure 15 – Flowchart of CV logic implementation.



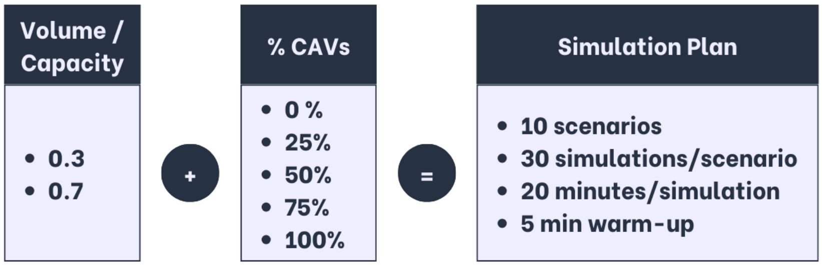
Source: Manjunatha et al. (2022).

considering different vehicle demands. It begins with implementing the simulation plan, which includes varying the volume-to-capacity ratios and CAV market penetration levels. Following the simulation, the conflict data is processed and filtered to isolate the situations of interest. Finally, the safety analysis is conducted, focusing on both conflict frequency and severity.

3.3.1 Simulation Plan for Scenario Analysis

To achieve the final objective of this study, simulations were performed with CAV market penetration levels ranging from 0% to 100% in 25% increments, as shown in Figure 16, resulting in five distinct penetration scenarios. In addition to analyzing the effect of CAV share, the study also examined safety impacts under different traffic volumes. Two traffic volume scenarios were considered, corresponding to volume-to-capacity ratios of 30% and 70%. The capacity value was empirically derived from the all-CNV scenario and kept constant for all penetration levels. Combining vehicle composition and demand produced a total of ten unique scenarios. Each scenario was simulated 30 times, with 5 minutes of warm-up and 15 minutes of valid simulation.

Figure 16 – Simulation Plan: Scenario Configuration, Duration, and Warm-Up Time.



Source: The author.

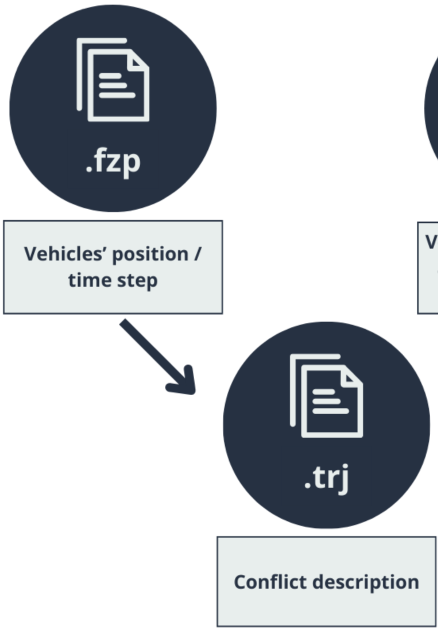
3.3.2 Simulation Data Processing

In this stage of the study, combining outputs from the simulation is crucial for a thorough analysis of vehicle behavior and conflict detection. The primary file, containing trajectory data, enables the Surrogate Safety Assessment Model (SSAM) software—developed by the Federal Highway Administration (FHWA) and the US Department of Transportation—to identify conflicts occurring during the simulation. However, this file does not include critical details about the control modes of the vehicles at the time of each conflict. These details are recorded in the '.txt' log file, which documents the specific control modes utilized. Additionally, the '.fzp' file provides the capability to track each vehicle's behavior at any timestep throughout the simulation. By integrating these data (Figure 17) sources—trajectory data for conflict detection, control mode logs for contextual information, and the '.fzp' file for detailed vehicle tracking—an assessment of vehicle interactions and conflict scenarios can be achieved.

SSAM requires input threshold for Time-to-Collision (TTC) to define a traffic conflict. The TTC threshold default value of 1.5 seconds is grounded in the findings of Van der Horst (1993), who, through driving simulator experiments on a closed-course road, observed that the likelihood of a crash becomes significant when TTC falls below this value.

However, specifying thresholds to TTC becomes challenging in environments where conventional vehicles and CAVs interact. The behavior of CAVs differs significantly from that of conventional vehicles and can influence conventional vehicle behavior as well. CAVs have much

Figure 17 – Types of Outputs Generated Per Simulation and Their Content.



Source: The author.

shorter reaction times—potentially approaching zero depending on the system design—and can exchange detailed and real-time information, such as maneuvers, with other CAVs and infrastructure. Consequently, while conventional Surrogate Safety Measures (SSMs) may still be relevant for evaluating CAV safety, their accuracy is questionable and may not fully capture the complexities of CAV behavior (WANG *et al.*, 2021).

Addressing this limitation, Das et al. (2023) highlighted two significant approaches to defining conflicts differently for CAVs compared to conventional vehicles. The first approach, developed by Virdi et al. (2019), proposed reducing the TTC and PET threshold values for CAVs to one-third of the conventional vehicle values, reflecting CAVs' shorter reaction times and closer following distances. The second approach, by Sinha et al. (2020), assumed no traffic conflicts when CAVs were the following vehicles, maintaining the TTC threshold of 1.5 seconds only when a conventional vehicle was the follower.

In this context, the present study first examines whether these varying thresholds impact conflict frequency when CAVs are the following vehicles. A t-test is conducted to assess this impact. If the results show a statistically significant difference, it would justify implementing these differing thresholds. Conversely, if no significant difference is found, the filtering will not be implemented.

Another important filter to be applied relates to the network's warm-up time, which corresponds to the first five minutes of the simulation. Additionally, to ensure the analysis is relevant to the specific algorithm implemented for CAVs in this study, it is essential to filter by conflict type. Since the focus of this study is solely on controlling the longitudinal behavior of CAVs, the analysis will be restricted to 'rear end' conflicts. This filtering step ensures that only the most pertinent data is considered for evaluating the performance of the CAV algorithm.

3.3.3 Impact analysis of CAVs on conflict frequency and severity

To assess conflict frequency across different simulated scenarios, various approaches are implemented to visualize the impact of Connected and Autonomous Vehicles (CAVs) on conflict numbers. It is important to note that even if a vehicle is labeled as a CAV in the simulation, the control mode during the conflict timestep significantly influences the analysis. This is because CAVs can be controlled by VISSIM in specific situations, as explained in 3.2.1 . Consequently, the control mode of the vehicle at the moment of the conflict is the primary parameter used to segment the data.

Mean conflict values across different scenarios are compared to identify trends in conflict frequency, with t-tests employed where appropriate to validate the statistical significance of any changes. Following this, conflict locations are mapped to gain insights into how the CAV algorithm performs relative to VISSIM's control mode.

Furthermore, this study enhances the safety assessment of simulation outputs by examining conflict severity. The analysis begins by segregating the data into distinct severity groups based on the relationship between TTC and MaxDeltaV. MaxDeltaV represents the maximum change in speed during a conflict and serves as an indicator of the conflict's intensity. The methodology follows the approach outlined by Miqdady et al. (2023), which provides specific grouping equations for CNVs and CAVs.

After segregating the data into severity groups, the probability of encountering a severe conflict is estimated using a categorical model. When the dependent variable has more than two categories, a categorical model with multiple responses is used. These models can be of two types: ordered models, which take into account the order of the response categories, and unordered models, which ignore this order. Since the levels of injury severity are naturally ordered, ordered categorical models are commonly employed to measure the relationship between risk factors and injury severity in traffic accidents.

Models that do not consider the ordered nature of severity are also frequently used in the analysis of traffic accident injury severity, and the traditional unordered response model, the Multinomial Logit Model (MLM), is used in this study to develop the comparison between scenarios.

The model to estimate the impact of multiple CAV aspects on safery incorporates the following explanatory variables: CAV penetration, the v/c ratio, and whether the conflict involves a CAV as the follower vehicle. By analyzing these variables, the study aims to provide a understanding of how CAVs affect the severity of traffic conflicts across different scenarios.

4 RESULTS AND DISCUSSIONS

The objective of this chapter is to present and discuss the results obtained from applying the method described in Chapter 3, along with the identified limitations. The discussion begins with the base scenario, focusing on modeling and adjustments. Following this, scenarios involving Connected and Autonomous Vehicles (CAVs) are analyzed in terms of road safety, specifically regarding the frequency and severity of the conflicts generated.

4.1 Modeling of the urban arterial corridor

The selected urban corridor, Washington Soares Ave., is one of the main arterial streets in Fortaleza, and it consists of three lanes per direction. The selected segment spans 675 meters between two signalized intersections, as shown in Figure 18, namely Edilson Brasil Ave. to the north and Oliveira Paiva Ave. to the south. Furthermore, as it can be noticed, beyond the intersections, the network also includes three bus stops.

To understand the daily corridor flow behavior, electronic surveillance equipment data was used to know the peak hours in this location. It was found that 5 p.m. is the most congested situation in this area, with over 3,100 standard car units per hour, on a standard business day, in Washington Soares Avenue. After collecting the peak hour information, drone flights were executed over the two signalized intersections, and the flight videos provided each

Figure 18 – Urban corridor simulated.

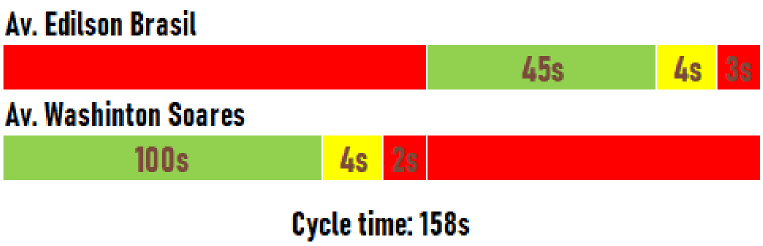
Source: The author.

area's directional flow and traffic composition. The flow data for the other intersection points were collected on-site using manual surveys.

The simulated urban corridor segment includes two signalized intersections, with traffic light programming provided by DETRAN-CE. At peak hour (5 p.m.), the cycle length for the intersection on Edilson Brasil Ave. is 158 seconds, while for the intersection on Oliveira Paiva, it is 163 seconds. Figures 19 and 20 detail green and inter-green times for each signal.

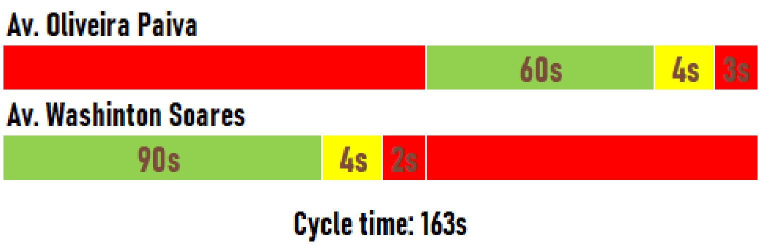
There are three public transit stops represented in the base network. During the peak hour, approximately 12 different transit lines use these bus stops, with different types of vehicle characteristics implying different bus service times at stops. This study did not focus on calibrating the use of public transit to match the characteristics of the simulated urban corridor, therefore default values of bus service times were used as inputs to represent the presence of public transport in the simulation.

Figure 19 – Cycle time for intersection Washington Soares x Edilson Brasil.



Source: The author.

Figure 20 – Cycle time for intersection Washington Soares x Oliveira Paiva.



Source: The author.

As discussed in the previous chapter, this study adopted the VISSIM car-following parameter values calibrated by Lacerda (2016), based on two urban corridors with characteristics similar to Washington Soares Avenue. For longitudinal parameters, the calibration yielded final values of "ax"at 2.2 m, and both "bx_add"and "bx_mult"at 5.0. These settings indicate slightly cautious behavior in conventional vehicles (CNV), resulting in vehicles maintaining larger spacing. Furthermore, desired speed was calibrated as 50 km/h, and default values were used for the remaining parameters.

4.2 Execution of Planned Simulation Scenarios

The first challenge, before executing the simulation plan, was adapting the CAV algorithm for any network type, extending its use to urban corridors. This was achieved by enabling the automatic collection of network information, removing the need for manual input.

The entire code structure was also revised to optimize simulation time, involving the removal of unnecessary operations (such as redundant logical tests and the export of non-essential text files), the adoption of more efficient functions like those provided by the Pandas library, and the use of Jupyter Notebook.

As a result, the optimization of the implemented algorithm significantly reduced the time required to process a network containing CAVs. The initial test conducted with the original code, using the simulation network from this study, estimated up to four days to complete a single simulation of 100% CAVs with a 0.7 v/c ratio lasting 60 minutes. With the optimization, this estimate was reduced by up to 50%. However, given the high number of simulations required (240 simulations involving CAVs) and the extended time needed to complete the entire simulation plan, it was necessary to reduce the simulation duration due to these computational constraints. Therefore, each scenario was simulated lasting 20 minutes.

After modeling the base scenario, the simulation plan was executed with CAV market penetration levels ranging from 0% to 100% in 25% increments, resulting in five distinct scenarios based on CAV penetration, as illustrated in Figure 16. The study also investigated the safety impacts of CAVs under different traffic volume conditions, including volume-to-capacity ratios of 30% and 70%. This combination of vehicle composition and demand produced a total of ten unique scenarios.

Each scenario was simulated 30 times, with each simulation running for 20 minutes, including a 5-minute warm-up period. Thus, the valid simulation period for each run was 15 minutes. The outputs from these simulations included .trj, .fzp, and .txt files, which were compiled for each scenario. The following discussions are based on the results obtained from this simulation plan.

4.3 Behavior of connected and autonomous vehicles algorithm

As explained in the last chapter, the implemented algorithm has five different control modes: related to automation, there are the 'car-following' mode, 'free driving' mode, and 'deceleration' mode, and related to connectivity, there are two modes, 'Signal Green' and 'Signal Red'. In situations where a CAV is performing a lane change or a conversion, or if the vehicle is classified as conventional, the control mode is categorized as CNV.

Figure 21 shows the exposure of CAVs to each of the six control modes across the simulated scenarios. The top section displays the low vehicular demand scenario, while the bottom section shows the high volume demand scenario. A notable observation from this figure is that there is no significant change in the percentage of CAVs exposed to each control mode as market penetration levels increase. CAVs are predominantly controlled by the 'AV - car-following' mode in all scenarios, with this proportion increasing as network demand rises. The 'VISSIM' control mode is the next most significant, indicating that CAVs often spend a considerable amount of time executing lane changes, undergoing conversions, or being near other vehicles involved in lane changes.

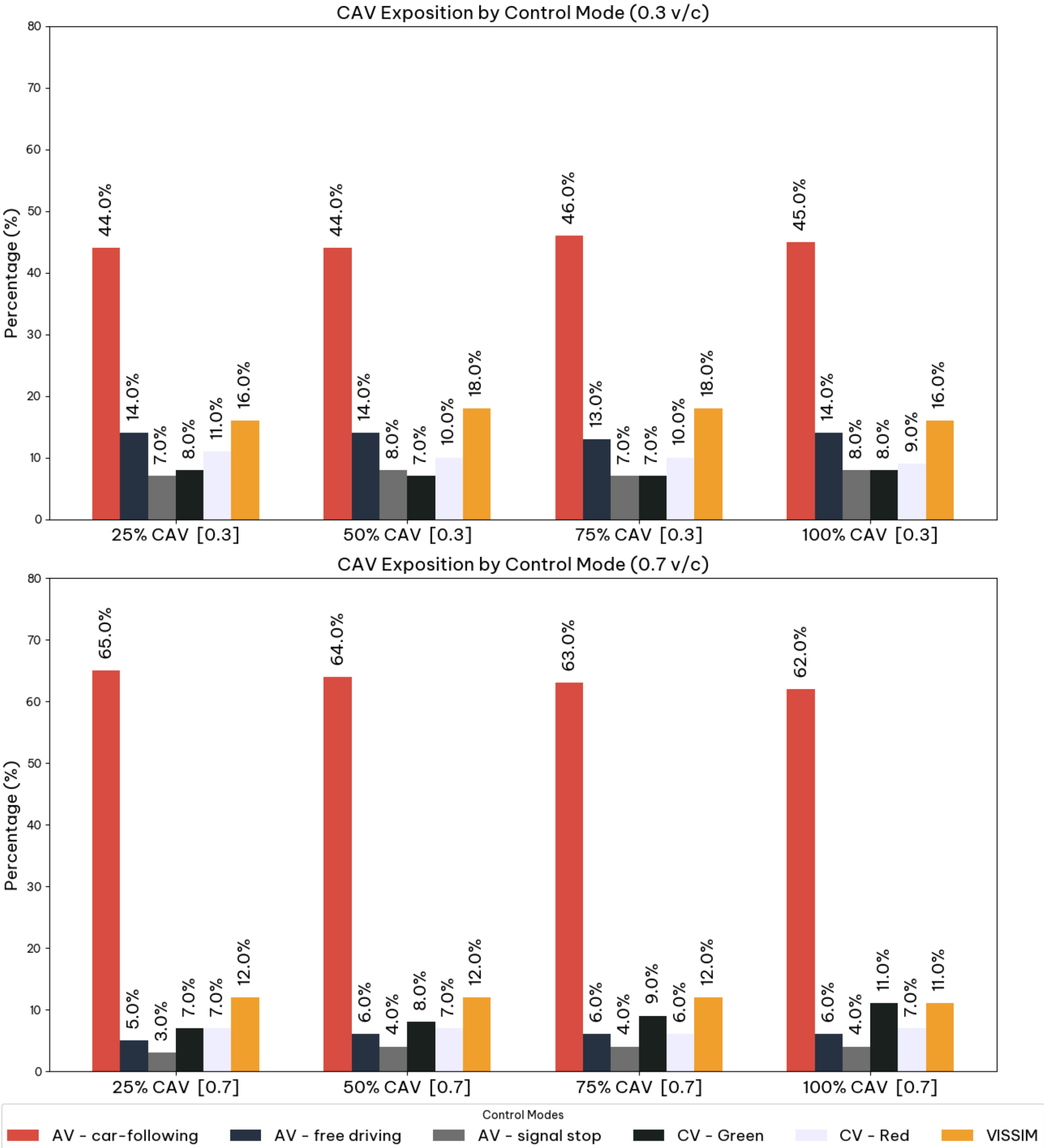
Since the proposed CAV control modes focus on longitudinal behavior, it is crucial to understand the longitudinal configuration of individual conflict situations by the leader and follower vehicle types according to the control mode at the conflict time step. There are four potential leader-follower configurations to consider: two with CNV as the follower and two with CAV as the follower.

Figure 22 illustrates the first scenario, where a CNV is the follower with varying leaders. It can be observed that the spacing maintained by the follower from the leader at the moment of conflict is consistently around 10.5 meters. While in motion, this spacing increases to approximately 50 meters.

Figure 23 shows the scenarios when a CAV is a follower. In these cases, the spacing maintained by the follower from the leader, in the conflict moment, is approximately 9 meters, similar to the spacing while in motion. The abrupt drop in vehicle position values in the figure simply reflects a link change, where the link distance restarts from zero.

The difference in spacing between CAVs and CNVs, especially in car-following situations, reveals a significant variation in longitudinal behavior. CAVs tend to exhibit more aggressive behavior by maintaining shorter spacing, even while in motion. This suggests that CAVs are likely to generate more conflicts, as conflicts are time-space indicators, and the

Figure 21 – Exposure of CAVs to each of the six control modes in different scenarios.



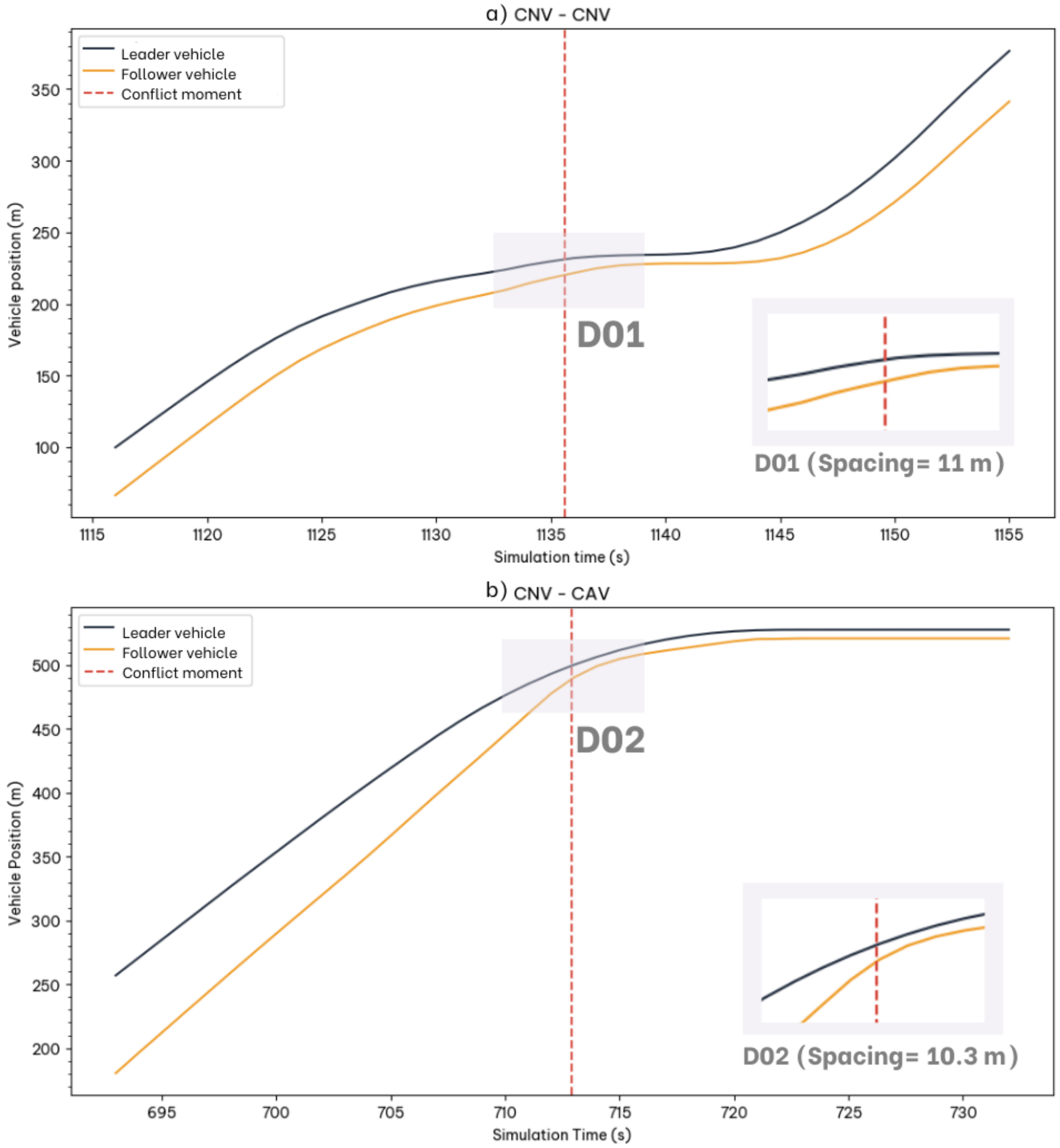
Source: The author.

aggressive behavior of these vehicles increases the likelihood of such conflicts.

4.4 Simulated traffic conflicts filtering

As explained in Chapter 3, after calibrating the base scenario and executing the simulation plan, the next step involves extracting vehicular conflicts. The present work labels as

Figure 22 – Longitudinal behavior before and after a conflict of CNVs as followers of (a) CNV and (b) CAV.

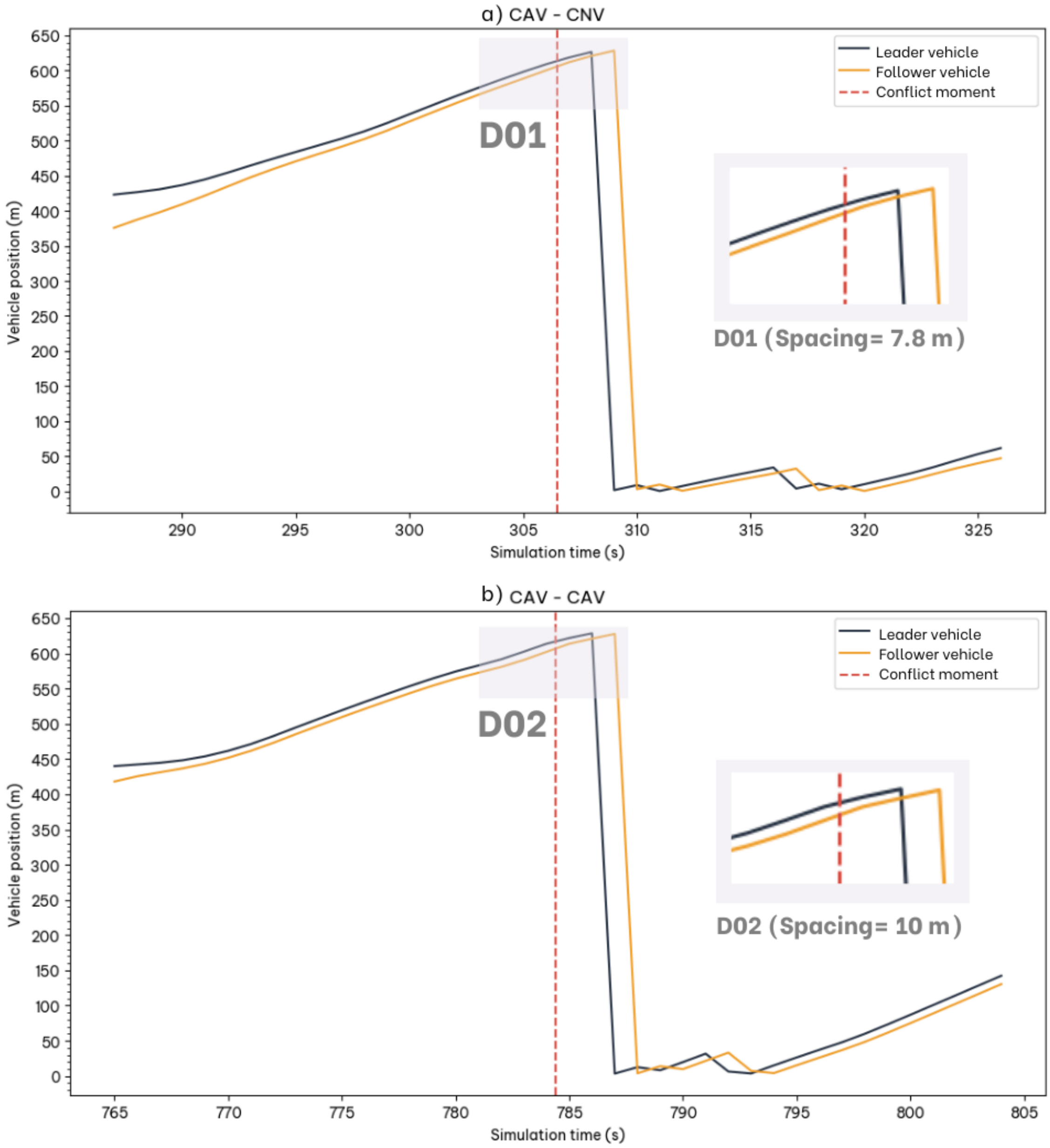


Source: The author.

a conflict any vehicular interaction that the time-to-collision is less or equal to 1.5 seconds.

After extracting conflicts using the specified threshold, the conflict filters applied are detailed in Figure 24. The initial filter removes conflicts occurring during the first five minutes of warm-up time, ensuring that the analyzed data pertains to the final fifteen minutes of each simulation. Furthermore, the analysis selects only rear-end conflicts. Although default angles in SSAM were used, modifications on the conflict type label were made based on the control mode at the time of the conflict. Specifically, if either the leader or follower (or both) were controlled by the 'VISSIM lane change mode,' the conflict was reclassified as 'lane change,' regardless of

Figure 23 – Longitudinal behavior before and after a conflict of CAVs as followers of (a) CNV and (b) CAV.

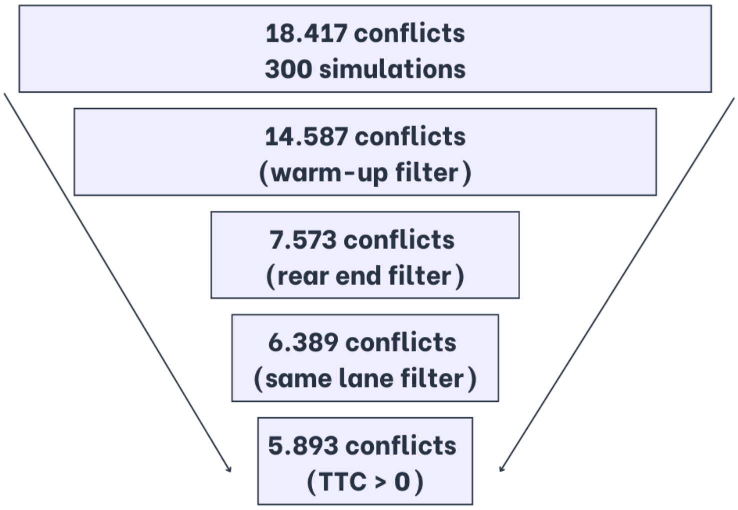


Source: The author.

the angle suggesting a 'rear-end' conflict. Additionally, the evaluation considered the link and lanes where the vehicles were located at the time of the conflict, assessing only those where both vehicles interacted exclusively longitudinally—i.e., within the same link and lane.

The final filter addresses a limitation in the simulator concerning the accurate representation of crash events. Situations where Time to Collision (TTC) values are zero indicate that a collision between the two objects is imminent. In these cases, the current positions and velocities of the objects suggest that they are either already in contact or will come into contact at the very next moment, given their trajectories.

Figure 24 – Conflict filtering process and the number of conflicts after each filter.



Source: The author.

However, a TTC of zero does not accurately represent real crash scenarios. Instead, these situations might expose issues related to the vehicular representation within the simulation. Specifically, zero TTC values could arise when vehicles are unable to detect the presence of a lead vehicle due to the lead vehicle undergoing maneuvers such as lane changes or conversions. Consequently, conflicts with TTC = 0 are considered a simulator limitation and are filtered out of the data, as they do not precisely reflect actual crash dynamics or their impact on traffic flow.

Finally, it has been mentioned in Section 2.3.3 that Wang et al. (2021) highlighted the potential need for different TTC thresholds for Connected and Autonomous Vehicles (CAVs) compared to Conventional Non-Autonomous Vehicles (CNVs), due to the smaller reaction times of CAVs. To explore this, a t-test was conducted on the simulation results to compare the average number of conflicts between scenarios with and without adjustments to the TTC limit: 1.5 seconds for CNVs as followers and 1.0 seconds for CAVs as followers.

The analysis yielded a p-value of 0.684, which is significantly above the standard significance level of 0.05. This indicates that altering the TTC limit does not result in a statistically significant change in the number of conflicts, even when accounting for different traffic capacities. Consequently, the data suggest that modifying the TTC limit does not substantially impact conflict frequency. Therefore, based on the current experimental conditions, it can be concluded that implementing a different TTC limit for CAVs does not offer clear benefits and does not warrant the added complexity of such changes.

4.5 Impact of CAVs on conflict frequency

In this section, it is examined the influence of CAVs on the frequency of traffic conflicts. Traffic conflicts provide insights into the potential risks and safety benefits associated with varying levels of CAV penetration in traffic flow. The analysis is carried out by comparing scenarios with different combinations of CAV penetration percentages and v/c ratios. Table 6 presents a summary of the average number of conflicts, as well as the minimum and maximum conflict numbers observed across 30 simulation runs for each scenario. Additionally, the table lists the estimated hourly flow rates for CAVs and CNVs under each scenario, providing a comprehensive view of how CAV integration impacts overall traffic dynamics.

From the data presented in Table 6 it can be noticed, as expected, the more vehicles simulated, more frequent are the conflicts frequency. For instance, compared to the lightly loaded scenarios (v/c = 0.3), the conflict frequency in scenarios v/c = 0.7 increases dramatically—by over 1000% when CAV penetration is low.

Moreover, it is observed that in scenarios with a v/c ratio of 0.3, increasing CAV penetration from 0% to 100% does not necessarily lead to a reduction in average conflicts, suggesting that CAVs alone may not mitigate conflicts in less congested conditions. However, in more heavily loaded scenarios (v/c = 0.7), the 100% autonomous scenario, when compared to the base scenario, shows that a higher CAV presence appears to reduce the number of conflicts, indicating that CAVs can play a more significant role in enhancing traffic safety under congested conditions.

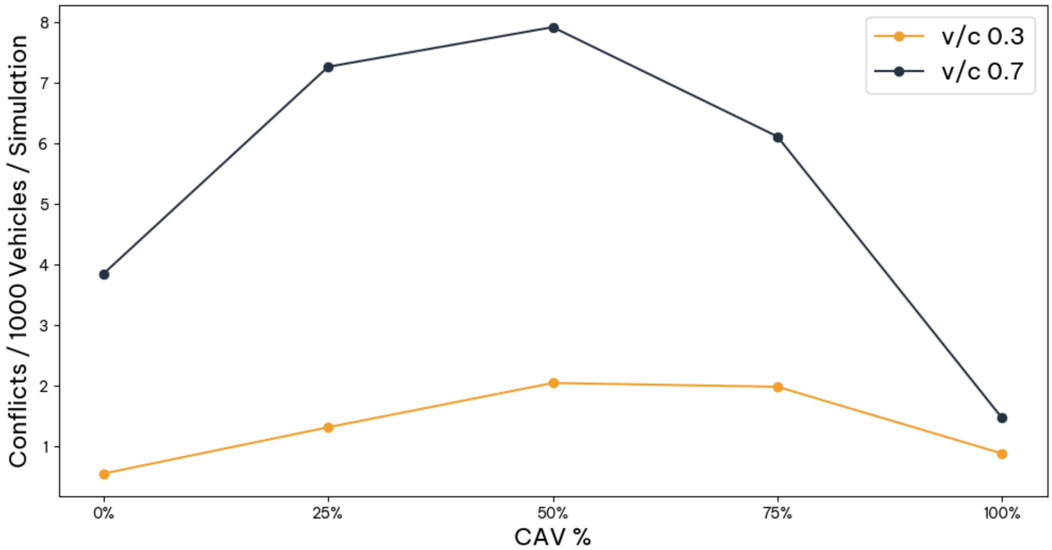
Table 6 – Summary of average vehicular flow per vehicle type and conflict number results scenarios simulations.

No	Scenario (vc + CAV%)	CAV (vehic/h)	CNV (vehic/h)	Average Conflicts Number	Min Conflicts Number	Max Conflicts Number
1	**0.3 + 0%**	0	2688	1	0	3
2	**0.3 + 25%**	672	2016	4	1	7
3	**0.3 + 50%**	1344	1344	6	1	14
4	**0.3 + 75%**	2016	672	5	2	11
5	**0.3 + 100%**	2688	0	2	0	6
6	**0.7 + 0%**	0	6717	26	10	46
7	**0.7 + 25%**	1679	5038	49	25	92
8	**0.7 + 50%**	3359	3358	53	32	82
9	**0.7 + 75%**	5038	1679	41	26	63
10	**0.7 + 100%**	6717	0	10	4	17

Source: The author.

To visualize the conflict data presented in Table 6, especially how it fluctuates across different scenarios of CAV market penetration and varying v/c ratios, the average numbers are plotted in Figure 25. To enhance the comparison between scenarios with low and high vehicular demands, the average number of conflicts is normalized by the total vehicle volume for each v/c scenario in Figure 25. For scenarios with low vehicular demand (v/c = 0.3), the average number of conflicts doubles as CAV penetration increases, peaking at the scenario with 50% CAV and 50% CNV. In the final two scenarios, the conflict number first stabilizes and then decreases to a level close to that of the base scenario (0% CAV). In high vehicular demand scenarios (v/c = 0.7), the average number of conflicts continues to increase with rising CAV penetration, up to the 50% CAV and 50% CNV scenario. However, in the last two cases, the conflict number decreases, eventually falling below the level observed in the base scenario (0% CAV).

Figure 25 – Average Number of Conflicts per Scenario per 1000 vehicles.



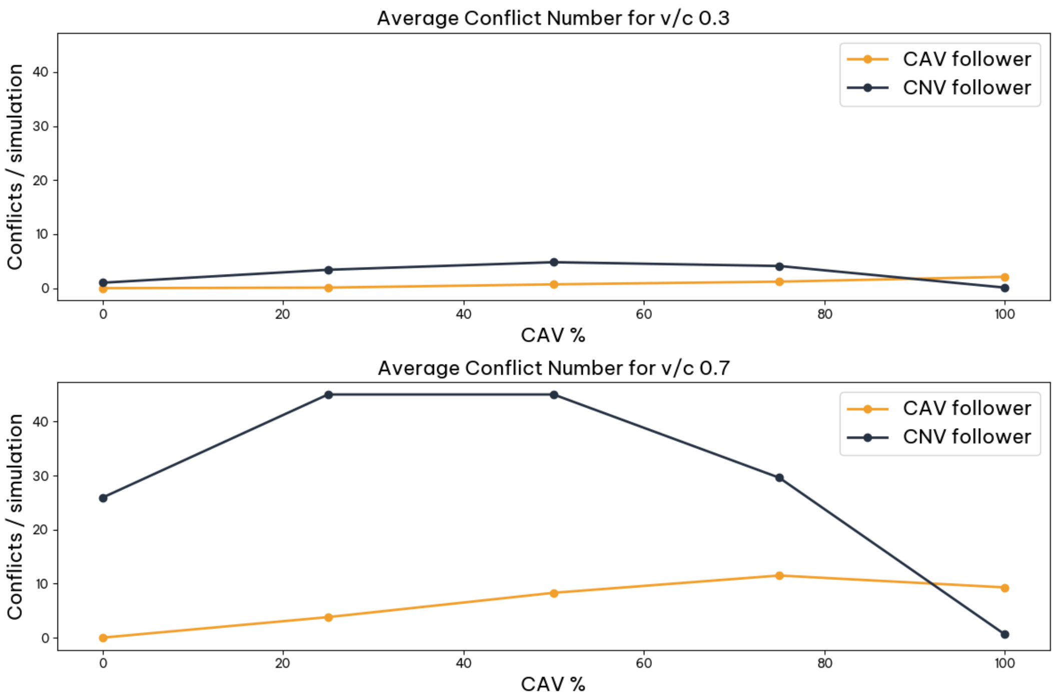
Source: The author.

The information presented in Figure 25 might suggest that the introduction of CAVs could negatively impact road safety performance. However, the increase in conflicts with the increments of CAVs market penetration is counter-intuitive and warrants further investigation. The first step in this investigation involves understanding the nature of these conflicts, particularly identifying which types of vehicles are involved.

It's important to note that the CAV algorithm implemented in this study focuses solely on longitudinal behavior. Therefore, during certain maneuvers, such as lane changes or merges, CAVs may temporarily operate under VISSIM's control instead of their autonomous system. As a result, even if a vehicle is classified as a CAV in the simulation, its behavior during conflicts is evaluated based on its control mode at that moment. If a CAV is under VISSIM's control during a conflict, it is considered a CNV for the purposes of this analysis. This distinction is essential for accurately interpreting the conflict data and understanding the impact of CAVs on road safety without misinterpretation.

The analysis of Figure 26 reveals that CNVs experience a higher number of conflicts compared to CAVs across both v/c ratios. In a low vehicular demand scenario with a v/c ratio of 0.3, CNVs show an average conflict range from 1 to 5, whereas CAVs display a lower and less variable range, from 0 to 2. In a higher vehicular demand scenario with a v/c ratio of 0.7, CNVs continue to have a higher number of conflicts, averaging 29 across all CAV penetration levels, with individual counts ranging from 1 to 45. In contrast, CAVs show a more moderate range, from 4 to 12, with an average of 8 conflicts per scenario. The ratio of CNV conflicts to CAV conflicts varies with the v/c ratio, but the disparity becomes more pronounced at v/c = 0.7, particularly at higher levels of CAV penetration.

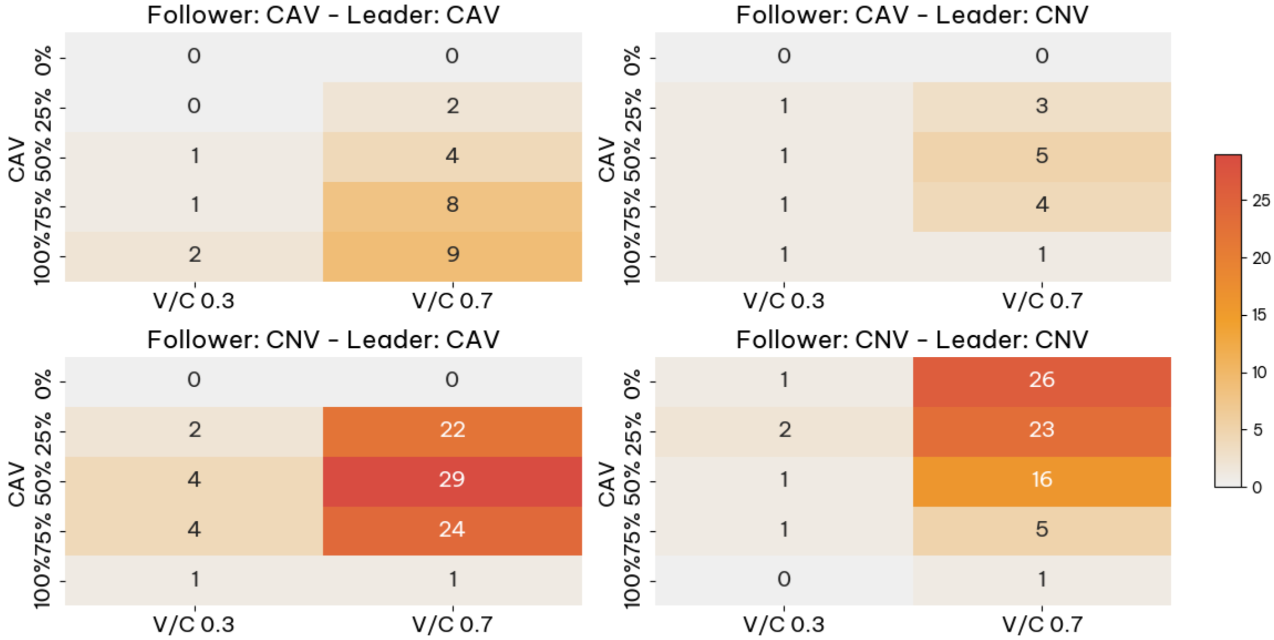
Figure 26 – Average number of conflicts per scenario and combination of follower and leader vehicles.



Source: The author.

Figure 27 details the combinations of follower-leader vehicle types, and it can be noticed that the highest concentration of conflicts across all scenarios is observed when a CNV follows a CAV. This suggests that the abrupt reactions of CAVs, due to their low reaction times, may not be adequately addressed by the Wiedemann model. Since CNVs are unable to predict the behavior of CAVs, they lack the capacity for safe reactions that CAVs possess.

Figure 27 – Heatmap of average number of conflicts per scenario and combination of follower and leader vehicles.



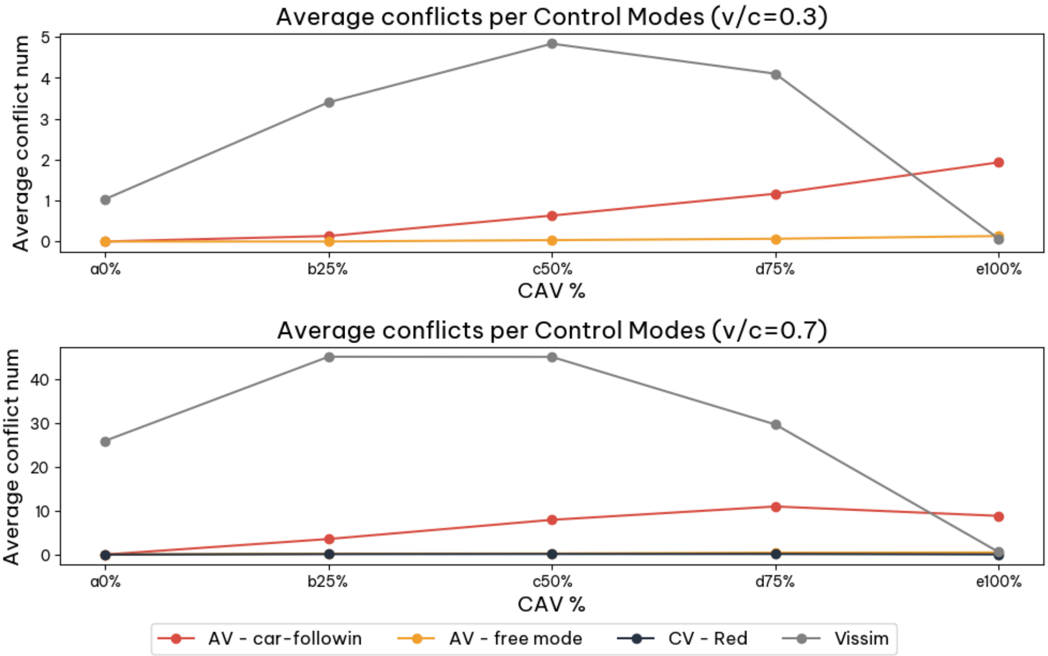
Source: The author.

Furthermore, contrary to expectations—given that CAVs maintain smaller spacing with leader vehicles even in motion—the average number of conflicts with CAVs as followers tends to be lower than with CNVs as followers: 50% fewer in low vehicle demand scenarios and 75% fewer in high vehicle demand scenarios. This can be attributed to the shorter reaction times of CAVs, which allows them to anticipate the leader's next actions and thus avoid unsafe situations.

When conflict data are segmented by the different control modes a vehicle can use, as shown in Figure 28, it becomes evident that nearly all conflicts involving CAVs in the simulation are associated with the car-following mode control. This aligns with the observation that CAVs are predominantly exposed to this control mode.

To validate the statistical significance of the comparisons made in the preceding discussion—particularly whether CAVs as follower vehicles were responsible for fewer conflicts than CNVs—Table 7 provides a summary of the t-tests conducted across different scenarios. The results consistently show p-values well below the significance threshold of 0.05 when comparing the same scenario with different types of follower vehicles. These findings indicate that CAVs generally generate fewer conflicts compared to CNVs when acting as follower vehicles in similar scenarios, with the notable exception of the 100% CAV scenario, where CAVs were associated

Figure 28 – Average conflict number per control mode per simulation.



Source: The author.

with a higher frequency of conflicts.

Table 7 – Summary of executed t-test for different follower types within the same scenario.

Nº	CAV %	v/c	Avg. Conflicts (CAV)	Avg. Conflicts (CNV)	H0: $\mu_{CAV} = \mu_{CNV}$
1	25%	0.3	0	3	rejected
2	50%	0.3	1	5	rejected
3	75%	0.3	1	4	rejected
4	100%	0.3	2	0	rejected
5	25%	0.7	4	45	rejected
6	50%	0.7	8	45	rejected
7	75%	0.7	12	30	rejected
8	100%	0.7	9	1	rejected

Source: The author.

Regarding the evolution of scenarios (Table 8), it is observed that in almost all increments of 25% CAVs within a scenario, there is a statistically significant change. Exceptions are found in comparisons of scenarios with 50% and 75% CAVs market penetration, in low traffic demand scenarios, and in comparisons of scenarios with 25% and 50% CAVs market penetration, in high traffic demand scenarios.

Therefore, after these statistical evaluations, it can be concluded that the implemented algorithm contributed to an increase in conflicts up to a scenario with 50% CAVs, primarily involving CNVs as follower vehicles. However, when the proportion of CAVs exceeds that of CNVs, the trend reverses, and the number of conflicts decreases, potentially falling below the

Table 8 – Summary of executed t-test between scenarios.

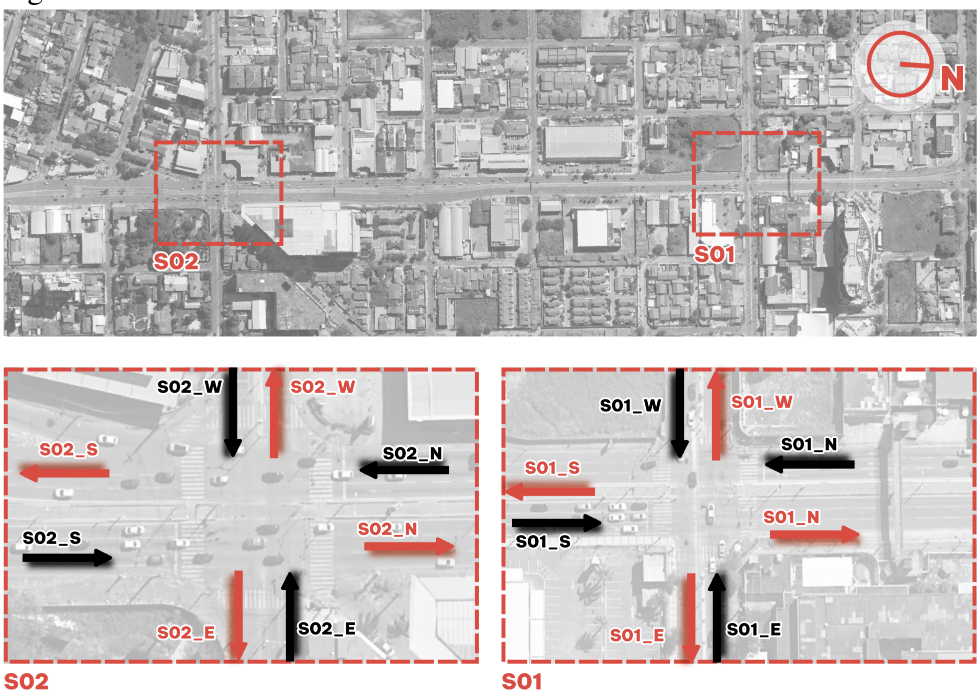
Nº	Scenario 01 (S01)		Scenario 02 (S02)		Average Conflicts (S01)	Average Conflicts (S02)	H0: μ01 = μ02
	CAV %	v/c	CAV %	v/c			
1	0%	0.3	25%	0.3	1	4	rejected
2	25%	0.3	50%	0.3	4	6	rejected
3	50%	0.3	75%	0.3	6	5	not rejected
4	75%	0.3	100%	0.3	5	2	rejected
5	0%	0.7	25%	0.7	26	49	not rejected
6	25%	0.7	50%	0.7	49	53	not rejected
7	50%	0.7	75%	0.7	53	41	rejected
8	75%	0.7	100%	0.7	41	10	rejected

Source: The author.

average values observed in the base scenario.

After assessing the average conflict values for each scenario and control mode pair, it becomes important to examine the spatial distribution of these conflicts. To facilitate this analysis, Figure 29 provides an encoding for all the entry and exit points of the two signalized intersections, wishing to help clarify the spatial context of the conflicts observed. Red arrows are related to exit areas from intersection signal control, and black arrows indicate the entry approaches to each traffic light. The encoding name of each arrow combines the intersection number (S01 or S02) with the corresponding direction (N for North, S for South, E for East, W for West). For example, "S01_N"refers to the entry or exit on the North side of intersection 1, while "S02_W"indicates the entry or exit on the West side of intersection 2.

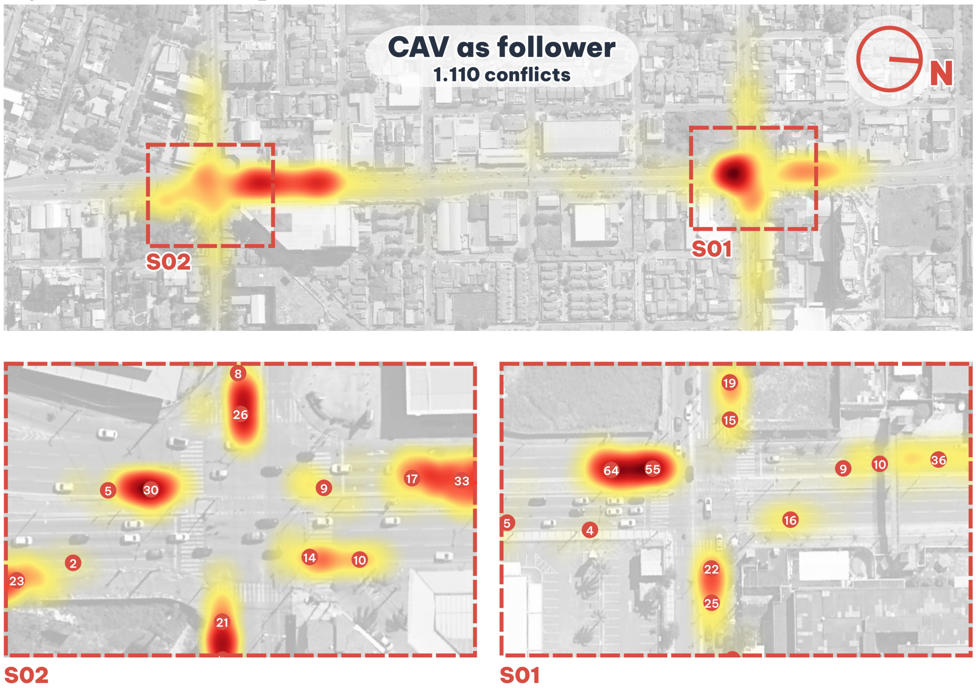
Figure 29 – Studied corridor and intersections.



Source: The author.

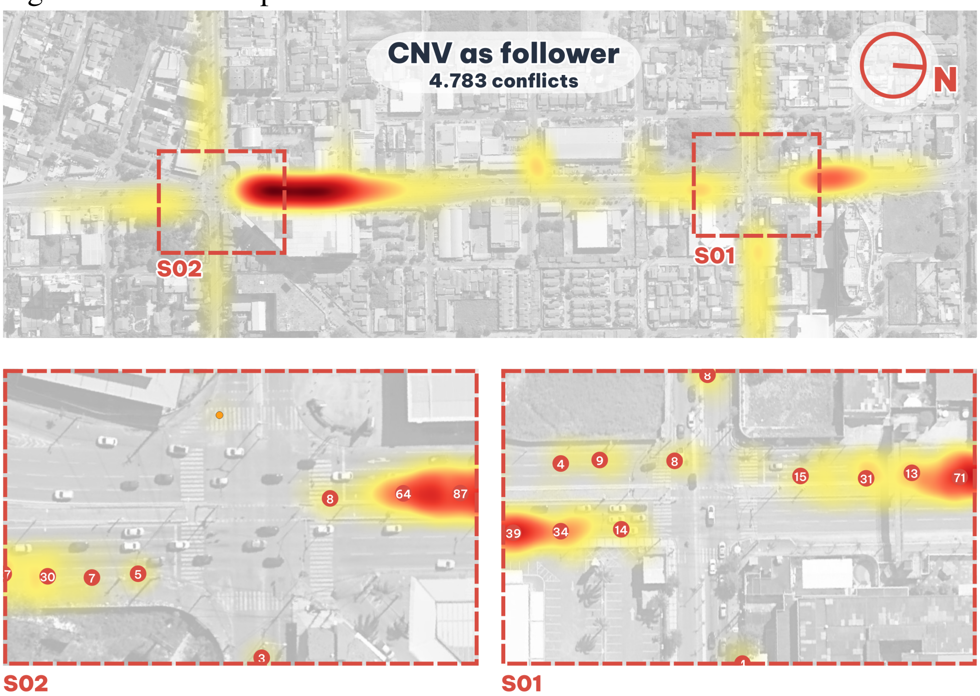
Figures 30 and 31 illustrate the spatial distribution of conflicts. Analysis of these figures reveals that conflicts are concentrated at both signalized intersections across all scenarios. This concentration is expected, given that intersections significantly impact longitudinal vehicle behavior, and the focus of the investigation is on rear-end events.

Figure 30 – Heatmap of total number of conflicts with CAV as follower.



Source: The author.

Figure 31 – Heatmap of total number of conflicts with CNV as follower.



Source: The author.

Conflicts involving a CAV as the follower show a distinct pattern compared to those with a CNV as the follower, specifically a higher concentration downstream the intersections, as illustrated in Figure 30, where all exit areas in both intersections present a conflict concentration. Analysis of the CAV's mode control behavior before and after the conflict time step reveals that, within an intersection, the CAV identifies its lead target as a 'Conflict area' rather than the leader vehicle. Consequently, the mode control defaults to 'AV - free driving' rather than 'AV - car following,' as the leader vehicle is not recognized a few meters ahead. As a result, the CAV accelerates to its desired speed until it exits the conflict area. Once it leaves the intersection and detects the leader vehicle, it then decelerates according to the car-following equations, which leads to the occurrence of the conflict.

Figure 30 highlights a specific exit area, S01_S, which has a higher concentration of conflicts involving CAVs as follower vehicles. This location is notable for its unique characteristic: a transit stop located less than 20 meters from the conflict area, as shown in Figure 32. In contrast, the other two transit stops are situated at least 60 meters away from any conflict zone. The proximity of the transit stop to the conflict area may exacerbate existing issues in conflict frequency.

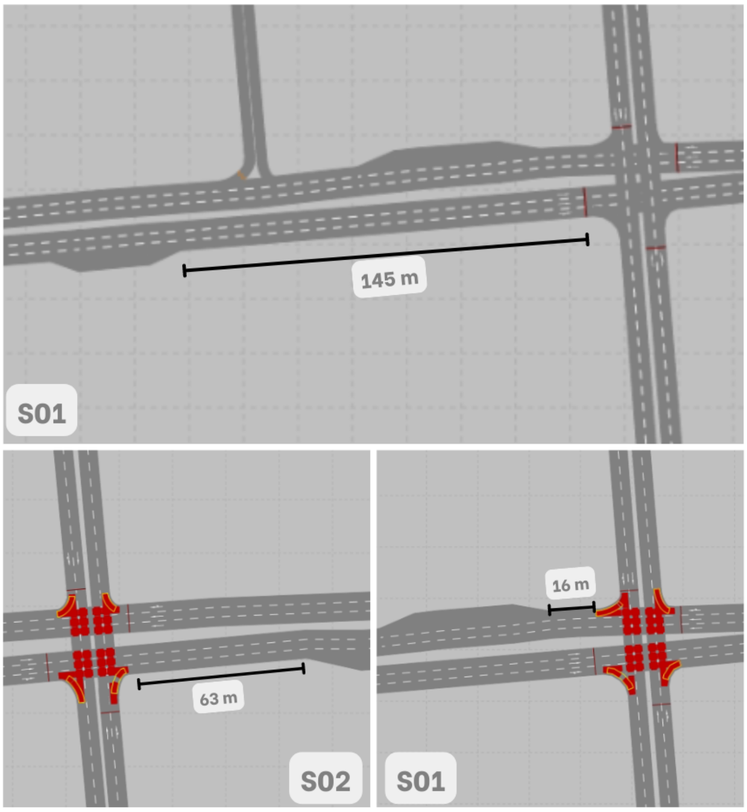
Traffic interruptions caused by transit vehicles stopping to pick up or drop off passengers can lead to abrupt maneuvers by following vehicles, naturally increasing the frequency of conflicts. Additionally, the short distance between the conflict area and the transit stop may further intensify this effect. For instance, a CAV navigating the conflict area in 'AV - free-driving' mode might exit the conflict zone only to encounter a nearly stopped leader vehicle—whether a CNV or another CAV—that has suddenly reduced speed due to a transit vehicle at the stop. This situation implies an abrupt response from the CAV to avoid a collision, creating a conflict.

This section discussed the influence of CAVs on conflict frequency, concluding that the first scenarios of market penetration of CAVs can culminate in an increase of conflict numbers, but with CNVs as the follower vehicle, because the CNV probably won't have the necessary reaction time to respond to CAVs behavior when following one.

4.6 Impact of CAVs on conflict severity

While the previous section focused on the impact of CAVs on the frequency of traffic conflicts, frequency alone does not provide a complete picture of the associated risks. The number of conflicts tells us how often potential collisions occur, but it does not indicate

Figure 32 – Location of transit stops and their distance to intersections.



Source: The author.

how severe those conflicts might be if they escalate into crashes. Understanding the severity of these conflicts is crucial, as not all conflicts carry the same level of risk. This section, therefore, shifts the focus to evaluating how differences in conflict numbers relate to varying levels of severity. Specifically, it examines the effect of the implemented CAV algorithm on the severity of generated conflicts.

To better capture the range of conflict severity, the analysis employs a refined data filter, adjusting the Time-to-Collision (TTC) limit from 1.5 seconds to 3 seconds. While other filters—such as those excluding warm-up time, rear-end conflicts, and instances with TTC equal to zero—remain unchanged, this adjustment significantly increases the number of conflicts under consideration, from 5,893 to 92,732. This approach, aligned with the methodology of Miqdady et al. (2023), expands the conflict sample size, providing a more comprehensive view of severity levels across a broader spectrum of scenarios.

The severity of a traffic conflict is predominantly determined by the kinetic energy that must be dissipated during a collision, which is a function of the vehicle's mass and speed. In typical traffic crashes, most impacts are inelastic, where vehicles deform and absorb energy, rather than bouncing back, converting kinetic energy into damage and heat. Given the homogeneity of vehicle mass in this study, speed emerges as the critical factor influencing the severity of potential collisions. Consequently, higher speeds generally result in more severe conflicts due to the greater amount of kinetic energy involved.

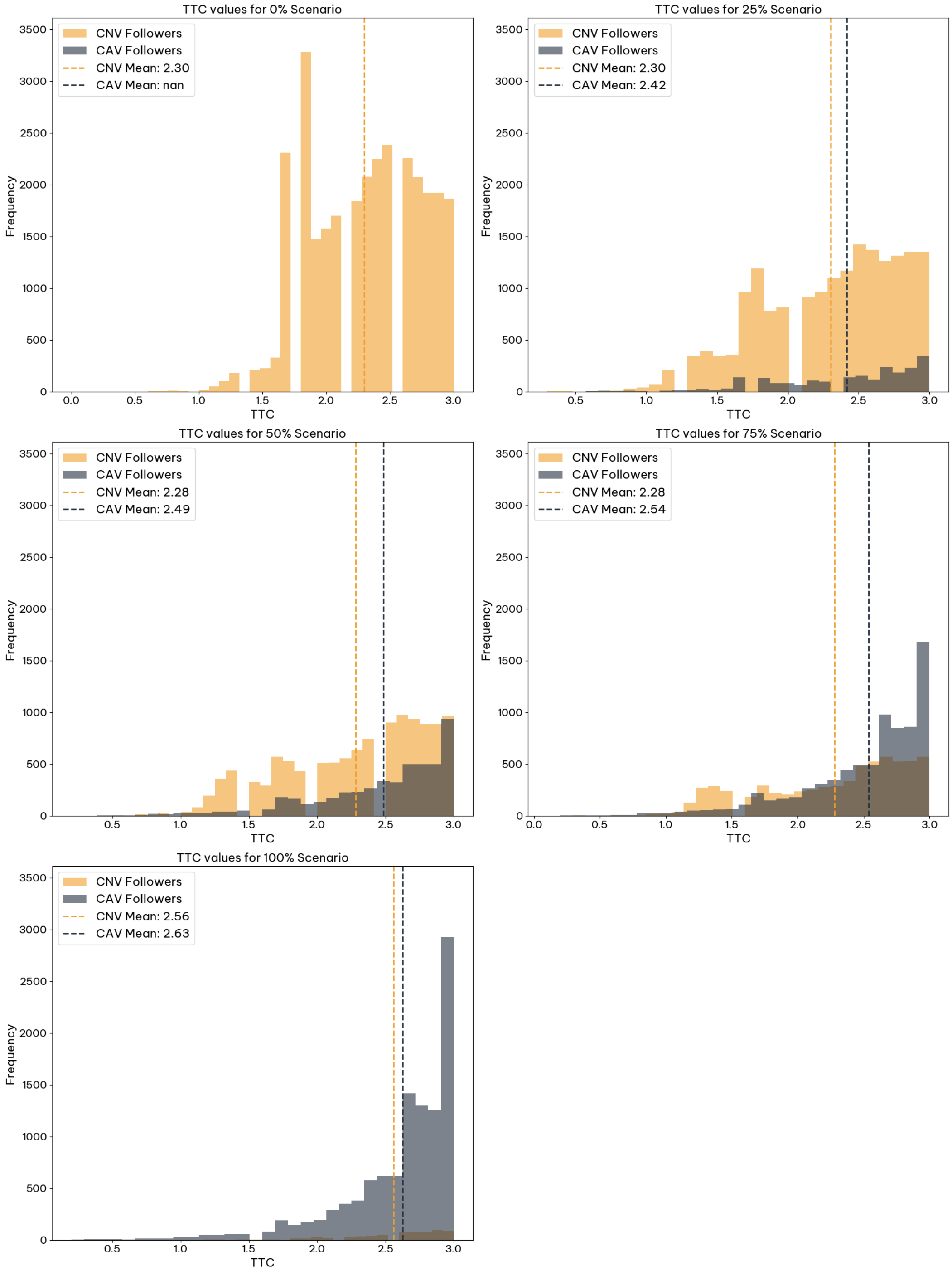
Before delving into the analysis of speed behaviors during the identified conflicts, it is essential to assess how close these interactions came to becoming crashes by examining the TTC. Although TTC is a useful measure of crash proximity, it does not necessarily indicate the severity of a conflict, as different scenarios with varying speeds and proximities can yield the same TTC value. However, the study by Miqdady et al. (2023) effectively utilized TTC to categorize conflicts into different severity groups, complementing it with MaxDeltaV—an approach that will be further explored in the following sections.

TTC distribution is illustrated in Figure 33, each plot corresponding to a CAV market penetration level. Each plot contains two histograms: one for conflicts involving CAVs as followers and another for conflicts with CNVs as followers. The TTC distributions between CAVs and CNVs reveal notable differences. CNVs display a relatively uniform distribution of conflicts across various TTC values, with mean TTC values ranging from 2.28 to 2.56 seconds. In contrast, conflicts involving CAVs are more concentrated towards bigger TTC values, with mean TTC values ranging from 2.42 to 2.63 seconds. These plots highlight that as CAV penetration increases, the average TTC values also tend to rise. However, this isolated information does not provide a complete picture of the severity of the associated crashes.

Severity levels analyzed forward are also influenced by MaxDeltaV values, and their distribution is illustrated in Figure 34. Just like the last figure, the analysis of MaxDeltaV across various CAV market penetration levels is depicted in the five plots provided, each plot containing two histograms: one for conflicts involving CAVs as followers and another for conflicts with CNVs as followers. The MaxDeltaV distributions between CAVs and CNVs show significant differences. CNVs typically exhibit average MaxDeltaV values approximately double those of CAVs, indicating that conflicts involving CAVs generally tend to be less severe. To gain a comprehensive understanding of severity levels, this data will be analyzed in conjunction with the TTC distributions, allowing for the creation of detailed severity classifications.

This section aims to compare the severity of conflicts involving CAVs and CNVs as follower vehicles by aggregating data across all CAV market penetration scenarios, while differentiating only by demand scenarios. As detailed in Chapter 2, the severity levels established

Figure 33 – Histogram of TTC values per scenario and per follower vehicle type.

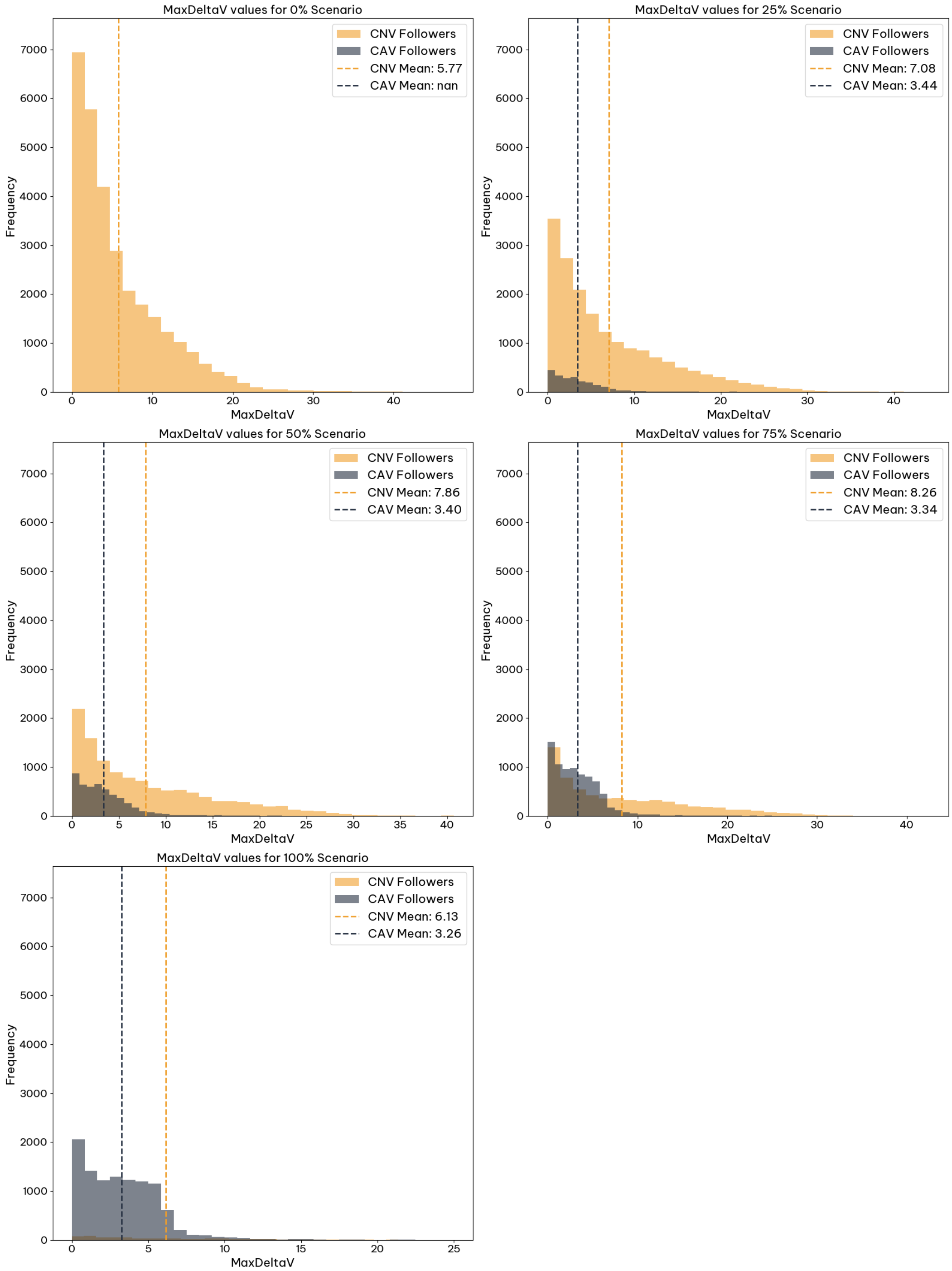


Source: The author.

by Miqdady et al. (2023), which classify conflicts based on TTC and MaxDeltaV values, vary depending on the type of follower involved. This approach has been adopted in the current study.

Figure 35 illustrates a scatter plot of conflicts, organized by v/c ratio scenarios and follower vehicle type, and categorized into six severity groups according to the equations by Miqdady et al. (2023). The plot shows that higher MaxDeltaV values and lower TTC values correspond to more severe potential crashes. It is evident from Figure 35 that CNVs frequently

Figure 34 – Histogram of MaxDeltaV values per scenario and per follower vehicle type.

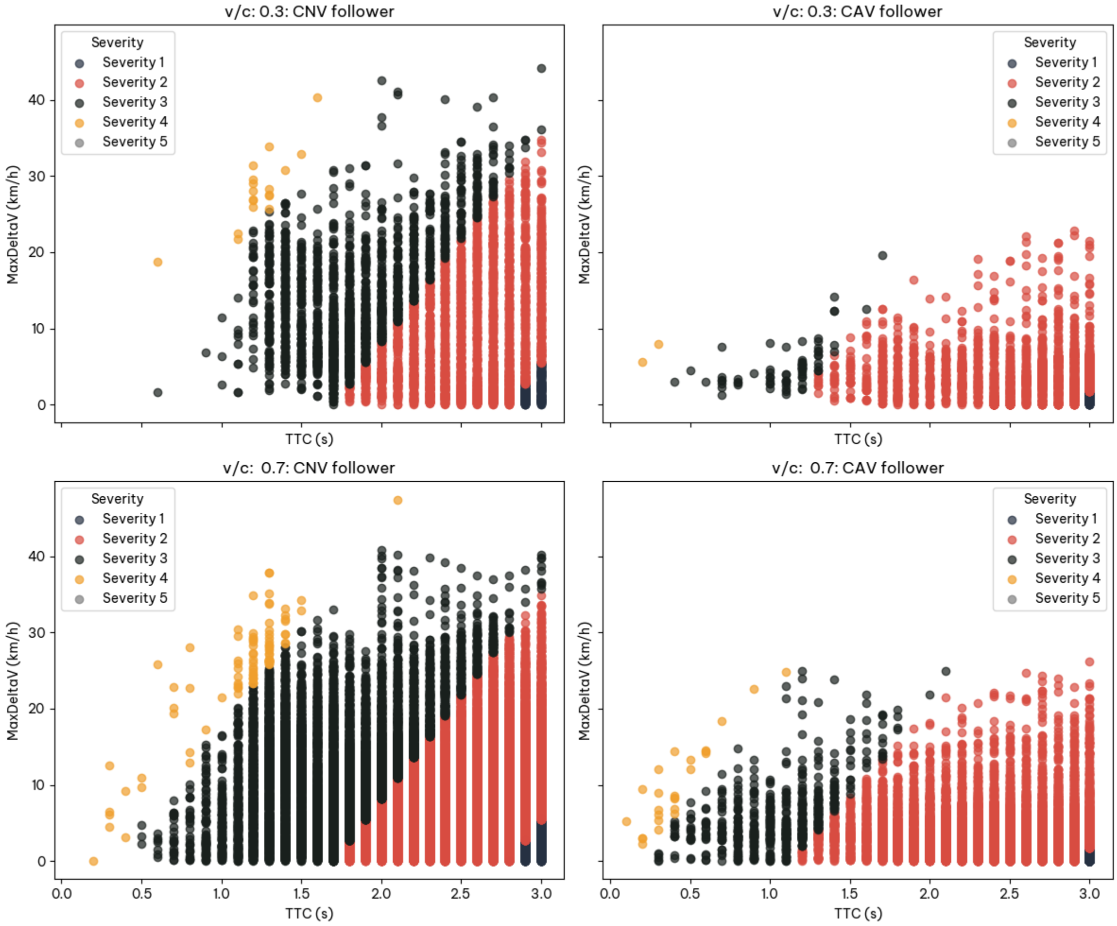


Source: The author.

experience conflicts with higher MaxDeltaV compared to CAVs in both high and low vehicular demand scenarios, with the plots for CAVs appearing relatively flat compared to those for CNVs. However, no additional observations can be discerned visually.

Figure 36 provides an alternative perspective on the conflict data, segmented similarly to the scatter plot by v/c ratio, follower type, and severity level. This figure highlights the

Figure 35 – Scatter plot per severity group.



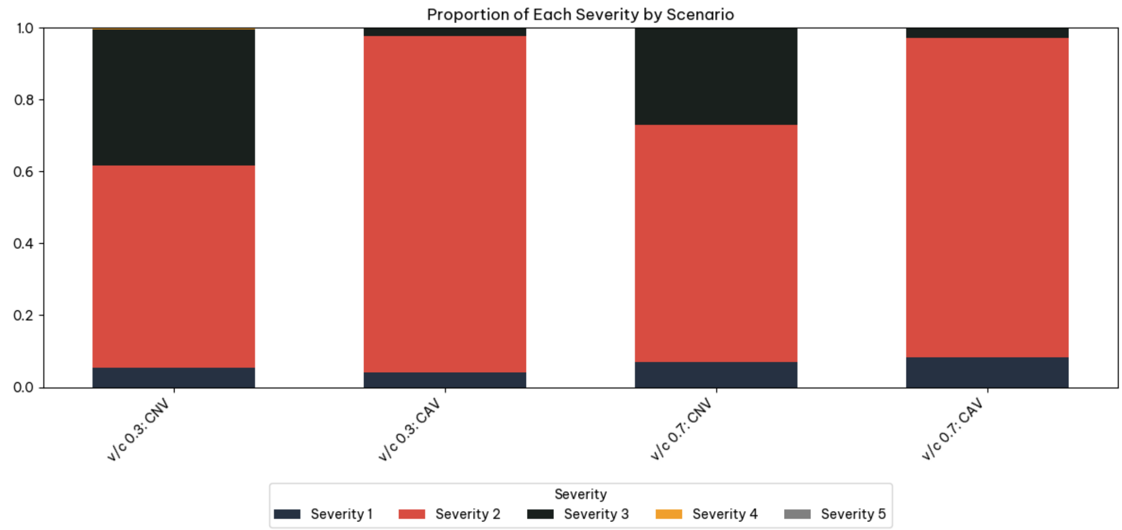
Source: The author.

proportions of each severity level more clearly. It shows that CNVs exhibit a higher concentration of severe level 3 conflicts compared to CAVs in both demand scenarios. Additionally, as network demand increases, vehicle interactions generally tend to be less severe compared to less congested scenarios. In less congested networks, vehicles experience fewer interruptions in car-following situations and can accelerate more frequently to their desired speeds, which often leads to more severe interactions.

Table 9 provides a summary of the number of conflicts categorized by severity level across different v/c scenarios and follower vehicle types. The data reveals that, across all levels of severity, CNVs are associated with a significantly higher number of conflicts compared to CAVs. This pattern holds even in the most severe conflict categories, where CNVs consistently exhibit at least twice as many conflicts as CAVs. This suggests that CNVs are not only more frequently involved in conflicts but also tend to be implicated in more severe scenarios, underscoring the importance of analyzing conflict severity in addition to frequency.

After visualizing the segregation of conflicts into severity levels, it is important to as-

Figure 36 – Proportion of conflicts per severity groups per v/c scenario and follower vehicle type.



Source: The author.

Table 9 – Summary of number of conflicts per v/c scenario per follower vehicle type and severity type.

v/c	Follower Vehicle	Severity 1	Severity 2	Severity 3	Severity 4	Severity 5	Total of Conflicts
0.3	CNV	300	3.203	2.165	18	0	**5.686**
0.3	**CAV**	133	2.988	74	2	0	**3.197**
0.7	**CNV**	4.216	40.404	16.402	93	0	**61.115**
0.7	**CAV**	1.878	20.213	618	25	0	**22.734**

Source: The author.

sess how different scenarios impact the likelihood of varying degrees of severity. To achieve this, a multinomial logit model was utilized to analyze factors influencing event severity, categorized into five distinct levels. This model is particularly well-suited for handling multiple outcome categories, as it facilitates a comprehensive evaluation of how explanatory variables, such as vehicular demand and the type of follower vehicle, affect the probability of an event falling into specific severity levels. By applying this model, insights are gained into the relationships between these variables and the severity outcomes, thereby enhancing the understanding of the factors driving event severity.

Table 10 summarizes the key variables used in the multinomial logit model, which assesses event severity. The explanatory variables include VC_BIN, which denotes vehicular demand, and Involves_CAV, which indicates the type of follower vehicle. The dependent variable, Severity, categorizes the event severity into five levels, ranging from 0 for Level 1 to 4 for Level 5.

The estimated model for explaining conflict severity used Severity Level 1 (0) as the

Table 10 – Description of the variables used to construct the multinomial logit model.

Variable	Description
VC_BIN	1 - v/c equals 0.7; 0 - v/c equals 0.3
Involves_CAV	1 - follower vehicle is CAV; 0 - follower vehicle is CNV
Severity	3 - Level 4; 2 - Level 3; 1 - Level 2; 0 - Level 1

Source: The author.

reference category, with parameters estimated for the remaining categories relative to it, and the results are presented in Table 11. The *VC_BIN* variable is a binary indicator showing whether the v/c is 0.7 (1) or 0.3 (0). The negative coefficient suggests that an increase in *VC_BIN* is associated with a lower probability of higher severity compared to the reference severity level. The p-values for Severity=1 and Severity=2 are less than 0.05, indicating statistical significance. For Severity=3, the p-value is 0.069, suggesting marginal significance, therefore while it may not be statistically significant according to the conventional threshold, it can still be of interest and may warrant further investigation or consideration.

Table 11 – Multinomial logit model results.

Variable	***Severity=1***		***Severity=2***		***Severity=3***	
	Coefficient	**P-Value**	**Coefficient**	**P-Value**	**Coefficient**	**P-Value**
Intercept	2.5059	0.000	2.1117	0.000	-3.1380	0.000
VC_BIN	-0.3556	0.000	-0.7681	0.000	-0.7550	0.069
Involves_CAV	0.3892	0.000	-2.2833	0.000	-0.1801	0.579
Log-Likelihood			-24508.0			
McFadden's R^2			0.07640			

Source: The author.

The *Involves_CAV* variable indicates whether the follower vehicle is a CAV (1) or CNV (0). A positive coefficient for Severity=1 suggests that the presence of a CAV is associated with an increased likelihood of an event being Severity=1 (level 2). However, for Severity=2 (level 3), the negative coefficient suggests a decreased probability of Severity=2 events when the follower is a CAV. The p-values for Severity=1 and Severity=2 are less than 0.05, indicating statistical significance, while for Severity=3 (level 4), the p-value is 0.579, indicating that the variable does not have a significant effect.

The multinomial logit model shows that *VC_BIN* and *Involves_CAV* have significant effects on Severities 1 and 2, with coefficients and p-values suggesting statistically significant relationships. However, the model's ability to explain the variation in the data, as indicated by McFadden's R^2, is limited, suggesting that other variables or models may be explored to improve the fit and explanation of the data.

5 CONCLUSIONS AND FUTURE WORK

The primary goal of this research was to evaluate the impact of connected and automated vehicles (CAVs) on road safety in urban settings through microsimulation. The specific objectives were: first, to identify the most effective models for simulating CAV behavior and their impact on road safety; second, to adapt a CAV algorithm for implementation in a microsimulation model of an urban arterial corridor; and third, to analyze the effects of different levels of CAV penetration in the conventional vehicle fleet on road safety under varying traffic demands.

The first objective, which involved reviewing various algorithms for simulating CAV behavior, was addressed by identifying that CAVs can be represented in simulations using multiple approaches, particularly given their range of automation levels. While co-simulation offers a detailed examination of CAV interactions with road elements such as vehicles, traffic signals, and environmental factors, microsimulation was selected due to the computational constraints of co-simulation networks.

Recent research on CAV impacts has predominantly employed two main strategies for representation in simulations: inbuilt models and external algorithms. The CoExist project, which calibrated CAV behavior using the Wiedemann model, has led to numerous studies utilizing inbuilt models within VISSIM. However, it is important to emphasize that calibrating existing models for car-following, lane changing, and gap acceptance—originally developed based on the behavior of conventional vehicles—may not be the most effective strategy for evaluating the behavior of CAVs in terms of road safety.

Psychophysical models, such as those implemented in the VISSIM microsimulator, do not account for the fact that a CAV has access to information about the speed, acceleration, and intended routes of surrounding vehicles. These models primarily rely on a driver's perception, which varies based on their speed and the distance they maintain from the leading vehicle. As a result, without considering the CAV's ability to access data about other vehicles and even traffic signal programming, the simulated behavior of CAVs may not accurately reflect their real-world behavior, which is deterministic and optimized. This discrepancy highlights the need for a different approach when assessing the behavior and performance of CAVs in traffic simulations.

In this context, VISSIM also allows users to create custom equations for vehicle behavior, providing a more tailored approach. This study opted for an external model within VISSIM, allowing for adaptation to specific regional traffic characteristics.

Given that highly automated vehicles are often involved in rear-end collisions, and most algorithms focus on longitudinal behavior, the chosen algorithm for this study also emphasizes longitudinal behavior. The Cooperative Adaptive Cruise Control (CACC) algorithm, adapted from Manjunatha et al. (2022), was implemented in VISSIM. This algorithm corresponds to SAE Level 3 automation and functions as a traffic jam pilot. It includes Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communications, allowing vehicles to exchange data with other vehicles and traffic signals. However, lane changes and platooning were not included in this study.

In the simulation, CAVs optimize their acceleration based on environmental conditions, using automation and connectivity equations to determine the most appropriate acceleration for each time step (0.1 seconds). The automation formulas controlled the vehicle for over 50% of the simulation time in any scenario, whether low or high vehicular demand or low or high CAV market penetration.

The longitudinal behavior of CAVs, based on the implemented algorithm, resulted in reduced headways even at higher speeds, indicating more aggressive behavior compared to conventional vehicles (CNVs) calibrated for usual drivers in Fortaleza/Ceará. Nevertheless, CAVs exhibited less aggressive acceleration compared to CNVs, with maximum accelerations of -5 m/s² for CAVs versus -8 m/s² for CNVs.

It is important to note that the algorithm does not account for lateral vehicle behavior. Therefore, in situations requiring lane changes or turns, VISSIM's default logic may control the vehicle. An adaptation to the Manjunatha et al. (2022) model was made to manage lane changes: vehicles within a 20-meter buffer of a lane-changing vehicle are controlled by VISSIM's rules to prevent unrealistic simulation outcomes.

The impact of CAV penetration levels on road safety performance was evaluated by examining both the frequency and severity of simulated traffic conflicts, addressing the third objective of this study. To conduct this assessment, 10 unique scenarios were created by combining five CAV market penetration levels (ranging from 0% to 100%, in increments of 25%) with two v/c ratios (0.3 and 0.7). Each scenario was simulated 30 times, with each simulation lasting 20 minutes. The simulated data was then filtered to exclude conflicts occurring during the warm-up period, non-rear-end conflicts, conflicts with a Time-to-Collision (TTC) equal to zero, and conflicts with TTC values exceeding the SSAM threshold of 1.5 seconds.

The analysis of conflict frequency revealed that CAVs could either increase or decrease conflict occurrences, depending on the scenarios compared. In the initial stages of CAV deployment, conflicts were more frequently associated with CNVs as followers, suggesting that CAVs' shorter reaction times may lead to evasive actions by CNVs. This indicates that the initial period of CAV integration in urban environments needs careful management to avoid potential reductions in road safety. However, comparing the base scenario to the full automation scenario showed a 55% decrease in conflicts, suggesting that CAVs have the potential to enhance road safety.

Despite the increase in conflict occurrences in some scenarios, there was no corresponding rise in conflict severity. Conflicts generated in scenarios with CAVs were generally less severe compared to those without CAVs. This observation was supported by calibrating a logit model with explanatory variables including the presence of CAVs as followers and vehicular demand intensity.

To enhance the accuracy and applicability of the model implemented in this dissertation, further refinement is necessary to address the challenges associated with conflict areas, particularly given that conflicts were identified as being concentrated downstream signalized intersections. This refinement could involve integrating advanced algorithms or additional data sources to improve the precision of conflict detection and resolution. However, it is also important to consider the compatibility between the logic used to represent conflict areas in VISSIM and the modeling of CAVs. The limitations may not lie solely in the CAV algorithms but also in how VISSIM represents conflict areas. Therefore, a critical analysis of this compatibility could reveal opportunities for adjustments not only in the CAV model but also in the configuration of conflict areas.

Additionally, incorporating the implemented CACC model with lateral aspects of CAV behavior could provide a more nuanced analysis of conflict frequency and severity. By integrating these dimensions, researchers could achieve a more comprehensive understanding of CAV interactions in various traffic scenarios, leading to more effective safety assessments and mitigation strategies.

It is also important to test this integrated model across diverse network shapes. Such testing will aid in calibrating a robust performance function for road safety, ensuring the model's effectiveness across different traffic conditions and network configurations. This approach will help identify potential limitations and areas requiring further refinement.

Comparative analyses of different models within the same network can illuminate which models offer the highest safety benefits. By evaluating and contrasting various approaches, researchers can determine the most effective strategies for minimizing conflicts and enhancing overall traffic safety.

Lastly, comparing simulated conflict data with actual observations will provide valuable insights into the model's accuracy and reliability. This step is essential for bridging the gap between theoretical predictions and practical outcomes, ensuring that the model reflects real-world conditions and is effectively applicable in practice.

By addressing these areas, future research can significantly advance our understanding of CAV behavior and improve traffic safety measures, ultimately leading to more effective and reliable safety solutions.

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