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Microscopic Behavioral Modelling, and Simulation-based Evaluation of Autonomous Vehicles Deployment Scenarios

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Abstract

Autonomous vehicles (AVs) have the potential to transform transportation systems by significantly improving road safety, reduce congestion, optimize traffic flow, and contributing to environmental sustainability. Assessing the potential impacts of AVs requires robust quantification methods that encompass both macroscopic and microscopic effects. Given that conducting large-scale real-world tests of AVs is impractical due to the costs, safety concerns, and regulatory hurdles involved in deploying fleets of AVs on public roads, researchers conduct simulation-based assessments. Especially many studies utilizes microscopic traffic models (MTMs) to conduct experiments and assess the impacts of AVs deployment scenarios. However, accurately replicating AV driving behavior in MTMs and understanding their impacts on traffic systems remain significant challenges. The main aim of this doctoral dissertation is to develop advanced models for simulating the driving behavior of AVs and assessing their impacts on traffic efficiency and safety in urban networks. This includes the creation of an optimization framework for AV behavioral modeling, the development of a deep learning-based trajectory prediction model, and the evaluation of AV deployment scenarios in urban traffic networks to understand their effects on overall traffic performance and safety.

A comprehensive review of existing AV modeling techniques is conducted to evaluate current CF models and identify gaps in the literature. The review paper, presented in this dissertation, categorizes CF models into mathematical and data-driven approaches, assessing their strengths and weaknesses. It was found that most mathematical CF models, originally designed for human-driven vehicles, are insufficient for accurately capturing AV behavior, particularly in mixed traffic scenarios. On the other hands, data-driven approaches, although promising, face challenges in terms of interpretability and integration into simulation tools. This review highlights the need for modeling techniques that can more effectively and accurately capture AV dynamics.

To address these limitations, an optimization framework is proposed. This framework extracts optimized parameter values for commonly used CF models, such as the Intelligent Driver Model (IDM), Krauss model, and Adaptive Cruise Control (ACC) model to better replicate AV driving behavior. By fine-tuning parameters such as time headway, reaction time, and minimum gap, the optimized models achieve a more accurate representation of AVs in simulations. The results indicate that the optimized CF models significantly improve the replication of AV driving dynamics, leading to reductions in traffic conflicts in the network.

In the next phase, a novel deep learning-based trajectory prediction model is introduced to capture the complex driving behaviors of AVs. The model utilizes a dynamic spatio-temporal graph convolutional network (STGCN) to predict future AV trajectories. By integrating reciprocal distance and angular encoding into a weighted adjacency matrix, the model effectively captures spatial dependencies between vehicles in the traffic scene. Temporal dependencies are learned through a temporal convolutional network (TCN), which processes historical vehicle trajectories to forecast future movements. The proposed model, tested on real-world traffic datasets, achieves a 34% reduction in prediction errors over a 5-second prediction horizon compared to existing models. This improved prediction accuracy provides critical insights into AV decision-making and navigation in complex traffic environments.

The final section of the dissertation presents a simulation-based impact assessment that evaluates the effects of varying AV penetration rates on traffic efficiency and safety in urban networks. Using the optimized CF models for AVs, multiple deployment scenarios were simulated within a detailed model of Munich's urban traffic network, with AV penetration rates ranging from 0% to 100%. The findings reveal that while AVs have a substantial potential to improve road safety at higher penetration rates—resulting in a 25% reduction in traffic conflicts in fully AV environments—their impact on traffic efficiency is more limited. Modest improvements in travel time and vehicle throughput were observed, especially under existing infrastructure constraints. These findings highlight the importance of further adjustments to urban infrastructure, such as adaptive traffic signal controls and dedicated AV lanes, to maximize the benefits of AV deployment.

Zusammenfassung

Autonome Fahrzeuge (AVs) haben das Potenzial, Transportsysteme zu transformieren, indem sie die Verkehrssicherheit erheblich verbessern, Staus reduzieren, den Verkehrsfluss optimieren und zur ökologischen Nachhaltigkeit beitragen. Die Bewertung der potenziellen Auswirkungen von AVs erfordert robuste Quantifizierungsmethoden, die sowohl makroskopische als auch mikroskopische Effekte umfassen. Da groß angelegte Tests von AVs in der realen Welt aufgrund der damit verbundenen Kosten, Sicherheitsbedenken und regulatorischen Hürden unpraktisch sind, greifen Forscher auf simulationsbasierte Bewertungen zurück. Insbesondere nutzen viele Studien mikroskopische Verkehrsmodelle (MTMs), um Experimente durchzuführen und die Auswirkungen von AV-Einsatzszenarien zu bewerten. Allerdings bleibt die genaue Nachbildung des Fahrverhaltens von AVs in MTMs und das Verständnis ihrer Auswirkungen auf Verkehrssysteme eine bedeutende Herausforderung. Das Hauptziel dieser Doktorarbeit ist die Entwicklung fortschrittlicher Modelle zur Simulation des Fahrverhaltens von AVs und die Bewertung ihrer Auswirkungen auf die Verkehrseffizienz und -sicherheit in städtischen Netzwerken. Dies umfasst die Entwicklung eines Optimierungsrahmens für die Modellierung des AV-Verhaltens, die Entwicklung eines auf Deep Learning basierenden Trajektorienvorhersagemodells und die Bewertung von AV-Einsatzszenarien in städtischen Verkehrsnetzen, um deren Auswirkungen auf die allgemeine Verkehrseffizienz und -sicherheit zu verstehen.

Eine umfassende Überprüfung bestehender AV-Modellierungstechniken wird durchgeführt, um aktuelle CF-Modelle zu bewerten und Lücken in der Literatur zu identifizieren. Das in dieser Dissertation vorgestellte Übersichtsartikel kategorisiert CF-Modelle in mathematische und datengetriebene Ansätze und bewertet deren Stärken und Schwächen. Es wurde festgestellt, dass die meisten mathematischen CF-Modelle, die ursprünglich für menschgesteuerte Fahrzeuge entwickelt wurden, nicht ausreichen, um das Verhalten von AVs, insbesondere in gemischten Verkehrsszenarien, genau zu erfassen. Datengetriebene Ansätze hingegen sind zwar vielversprechend, stehen jedoch vor Herausforderungen in Bezug auf Interpretierbarkeit und Integration in Simulationstools. Diese Übersicht hebt die Notwendigkeit von Modellierungstechniken hervor, die die Dynamik von AVs effektiver und genauer erfassen können.

Um diese Einschränkungen zu überwinden, wird ein Optimierungsrahmen vorgeschlagen. Dieser Rahmen ermittelt optimierte Parameterwerte für häufig verwendete CF-Modelle wie das Intelligent Driver Model (IDM), das Krauss-Modell und das Adaptive Cruise Control (ACC)-Modell, um das Fahrverhalten von AVs besser nachzubilden. Durch die Feinabstimmung von Parametern wie Zeitabstand, Reaktionszeit und Mindestabstand erzielen die optimierten Modelle eine genauere Darstellung von AVs in Sim-

ulationen. Die Ergebnisse zeigen, dass die optimierten CF-Modelle die Nachbildung der Fahrdynamik von AVs erheblich verbessern und zu einer Reduzierung von Verkehrskonflikten im Netzwerk führen.

In der nächsten Phase wird ein neuartiges, auf Deep Learning basierendes Trajektorienvorhersagemodell eingeführt, um das komplexe Fahrverhalten von AVs zu erfassen. Das Modell verwendet ein dynamisches spatio-temporales Graph Convolutional Network (STGCN), um zukünftige AV-Trajektorien vorherzusagen. Durch die Integration von reziproker Distanz und Winkelkodierung in eine gewichtete Adjazenzmatrix erfasst das Modell effektiv räumliche Abhängigkeiten zwischen Fahrzeugen in der Verkehrsszene. Zeitliche Abhängigkeiten werden durch ein Temporal Convolutional Network (TCN) gelernt, das historische Fahrzeugtrajektorien verarbeitet, um zukünftige Bewegungen vorherzusagen. Das vorgeschlagene Modell, getestet an realen Verkehrsdaten, erreicht eine Reduzierung der Vorhersagefehler um 34 % über einen Vorhersagehorizont von fünf Sekunden im Vergleich zu bestehenden Modellen. Diese verbesserte Vorhersagegenauigkeit liefert wichtige Erkenntnisse über die Entscheidungsfindung und Navigation von AVs in komplexen Verkehrsumgebungen.

Der letzte Abschnitt der Dissertation präsentiert eine simulationsbasierte Wirkungsbewertung, die die Auswirkungen variierender AV-Durchdringungsraten auf die Verkehrseffizienz und -sicherheit in städtischen Netzwerken bewertet. Mithilfe der optimierten CF-Modelle für AVs wurden mehrere Einsatzszenarien in einem detaillierten Modell des städtischen Verkehrsnetzes von München simuliert, wobei die AV-Durchdringungsraten von 0% bis 100% reichten. Die Ergebnisse zeigen, dass AVs bei höheren Durchdringungsraten ein erhebliches Potenzial zur Verbesserung der Verkehrssicherheit haben – mit einer Reduzierung von Verkehrskonflikten um 25% in vollständig von AVs dominierten Umgebungen. Ihre Auswirkungen auf die Verkehrseffizienz sind jedoch begrenzter. Es wurden nur moderate Verbesserungen bei Reisezeit und Fahrzeugdurchsatz festgestellt, insbesondere unter den bestehenden Infrastrukturbedingungen. Diese Ergebnisse verdeutlichen die Bedeutung weiterer Anpassungen der städtischen Infrastruktur, wie z. B. adaptive Verkehrssteuerungssysteme und dedizierte AV-Fahrspuren, um die Vorteile des AV-Einsatzes zu maximieren.

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Science is vast and ever-evolving, a boundless ocean of discovery and understanding. Through this dissertation, I have endeavored to make a small contribution to this immense collective endeavor. While the journey has been challenging, it has also been deeply rewarding, and I could not have completed it without the support and encouragement of many remarkable individuals.

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Contents

List of Figures

Acronyms

ACC	Adaptive Cruise Control.
ADE	Average Displacement Error.
ANN	Artificial Neural Network.
AV	Autonomous Vehicle.
CACC	Cooperative Adaptive Cruise Control.
CAV	Connected Autonomous Vehicle.
CF	Car-Following.
DQN	Deep Q-Networks.
DRL	Deep Reinforcement Learning.
GCN	Graph Convolutional Network.
GRU	Gated Recurrent Unit.
IDM	Intelligent Driver Model.
KPI	Key Performance Indicator.
LC	Lane-Changing.
LSTM	Long Short-Term Memory.
PR	Penetration Rate.
RL	Reinforcement Learning.
RMSE	Root Mean Square Error.
STGCN	Spatio-Temporal Graph Convolutional Network.
TCN	Temporal Convolutional Network.
TTC	Time-to-Collision.

1 Introduction

1.1 Motivation

Autonomous vehicles (AVs), also known as self-driving cars, represent a transformative shift in transportation technology [1]. Equipped with advanced sensing technologies such as lidar, radar, ultrasonic sensors, and high-resolution cameras, alongside machine learning algorithms and artificial intelligence, these vehicles can navigate roads, detect obstacles, and make real-time decisions without human intervention [2]. Optimistic views predict the mass deployment of AVs in our transportation system in the near future. However, their widespread adoption faces challenges, including regulatory hurdles, ethical considerations [3], costs [4], induced traffic demand [5] and the need for further technological refinement [6, 7] to ensure safety and reliability in all driving conditions.

AVs are gaining prominence not just for their self-driving capabilities but also for their ability to generate vast amounts of data through Information and Communication Technology (ICT). When these capabilities are combined, they form Connected Autonomous Vehicles (CAVs), collectively known as Autonomous and Connected Transport (ACT) [8–10]. This evolution opens new opportunities for stakeholders, particularly ICT firms and SMEs, to collaborate in developing traffic sensors and communication systems. In Europe, the EU has heavily invested in ACT-related projects like 5G-MOBIX [11,12], Drive2TheFuture [13], CoExist [14], and Autodrive to address the deployment barriers, foster economic growth, and enhance job creation and training opportunities across Europe.

The advent of AVs is expected to have broad societal and economic impacts, including the creation of new business models and industries. For instance, AVs could revolutionize the logistics and transportation sectors by enabling fully automated delivery services, reducing costs, and increasing efficiency [15]. Additionally, ride-sharing services like Waymo [16], Uber [17], and Lyft [18] are already exploring or deploying AVs, making these services more accessible and affordable by eliminating labor costs. The rise of AVs is also likely to spur innovation in related sectors such as insurance, urban planning, and infrastructure development [19–21]. Moreover, AVs could contribute to the growth of smart cities, where transportation systems are integrated with digital infrastructure, enhancing overall urban efficiency [19, 22].

AVs are expected to have significant impacts on transportation systems. The most immediate effect could be on traffic safety, as AVs have the potential to reduce accidents caused by human error, which is responsible for over 90% of road accidents [23–25]. Meanwhile, AVs hold the potential to increase fuel efficiency [26–28], and improve mobility for those unable to drive [25, 29]. Additionally, AVs could improve traffic flow and reduce congestion [30] through more efficient driving patterns and coordination between vehicles, however, their effects are not yet quantitatively confirmed [31, 32].

Assessing the potential impacts of AVs requires robust quantification methods that encompass both macroscopic and microscopic impacts. Macroscopic impacts refer to large-scale effects such as overall changes in traffic flow, congestion levels, and emissions on a regional or national scale. These are typically evaluated using traffic simulation models, economic analysis, and environmental impact assessments. On the other hand, microscopic impacts focus on the behavioral changes at the individual or vehicle level, such as changes in driving patterns, route choices, and vehicle interactions. Behavioral models and detailed simulation tools are often employed to study these microscopic impacts, which can provide insights into how AVs might influence driving behavior, road safety, and vehicle dynamics. Given that the current technology and infrastructure are not yet capable of supporting extensive, real-world testing of large fleets, primarily due to regulatory constraints, safety concerns, and the high costs associated with such large-scale trials, researchers conduct simulation-based evaluations of AVs and CAVs using traffic models.

Traffic models are categorized into microscopic, mesoscopic, and macroscopic models, each distinguished by their complexity and network scale [2, 31, 33]. Microscopic models offer high detail, simulating individual vehicle behaviors like lane changes and interactions. Macroscopic models treat vehicles as continuous flow patterns across large networks, focusing on flow, velocity, and density, with less complexity and detail. Mesoscopic models combine aspects of both, capturing individual vehicle behaviors while considering overall traffic flow, offering a balanced approach that is detailed yet less complex than microscopic models.

Microscopic traffic models (MTMs) are increasingly utilized in impact assessment studies of AVs [34–42]. These models simulate the detailed movements and interactions of individual vehicles within a traffic network, allowing researchers to analyze the potential effects of AVs on traffic dynamics, safety, and efficiency. By incorporating various driving behaviors (car-following and lane-changing), vehicle types, and traffic conditions, microscopic simulation models can provide a comprehensive understanding of how AVs might perform in real-world scenarios. They are particularly valuable for evaluating scenarios such as mixed traffic conditions, where both AVs and human-driven vehicles coexist.

1.2 Problem Definition and Dissertation Objectives

The driving behavior of AVs might differ significantly from that of human-driven vehicles [39, 43]. These behaviors are represented in MTMs through car-following (CF), and lane-changing (LC) configurations. In recent researches, considerable efforts have been made to accurately model these behaviors, particularly the CF behavior, for AVs and CAVs within MTMs [37, 39, 40, 42, 44–48]. The CF behavior is a sequence of decisions made by a vehicle to safely follow a leading vehicle, and there are various state-of-the-art methods, including both mathematical [49–53] and data-driven models [54–60], designed to replicate this behavior for AVs and CAVs.

Mathematical CF models consist of modifiable parameters that replicate vehicle driving behavior under different traffic conditions. These parameters are often calibrated using extensive field driving data. Conversely, data-driven models leverage various algorithms and trajectory datasets to establish relationships between a following vehicle's driving decisions and influencing factors such as the speed and gap of the leading vehicle. Although data-driven models often outperform mathematical models in replicating vehicle CF behavior, they are not widely used in impact assessment studies.

In simulation-based impact assessment studies, the selection of a CF model is influenced by two main factors: the model's ability to accurately replicate driving behavior and its integration into widely used simulation tools. Due to the complexity of traffic flow and the high computational demands of microsimulation tools, simpler and well-established mathematical models are typically integrated into these tools. Researchers distinguish AVs' driving behavior from that of human-driven vehicles based on factors such as time gap, reaction time, headway, and driving imperfection. However, due to the lack of extensive field data for AVs, researchers often make assumptions about AVs' driving capabilities, leading to varying and sometimes questionable conclusions regarding their potential impacts.

Data-driven models are particularly powerful in capturing AV driving behavior within a traffic scene, which has drawn attention to the trajectory prediction problem in recent years. In the context of AVs, predicting the future motion and trajectory of surrounding vehicles is crucial for safe and efficient driving decisions. This prediction involves both the CF and LC configurations of nearby vehicles. Despite several proposed methods in the literature for AV trajectory prediction, the interpretability of these models remains a significant challenge [60–67].

Given that accurate impact assessment of AVs relies on the ability to replicate their driving behavior accurately, this dissertation aims to achieve two primary goals: First, to develop methods (mathematical and data-driven) for replicating the driving behavior of AVs under varying traffic conditions; and second, to conduct a network-wide simulation based impact assessment to systematically evaluate the effects of AV deployment scenarios under different traffic demand conditions using the developed methods.

To support the achievement of these primary objectives, the following sub-objectives are also integral to this dissertation:

- To conduct a systematic review and meta-analysis of the existing state-of-the-art on AVs and CAVs behavioral modelling, and impact assessment.
- To develop a method for replicating the driving behavior of AVs using a mathematical CF model.
- To create a novel deep learning-based approach to accurately predict the trajectory of AVs in a traffic scene.

- To conduct a simulation-based impact assessment of AVs in an urban traffic network.

1.3 Dissertation Contributions

This doctoral dissertation compiles, summarizes, and documents the author's research [1,34,65,68], particularly focused on understanding and modeling the driving behavior of AVs in urban traffic networks and conducting a network-wide impact assessment of AV deployment scenarios. Thus, this doctoral research makes the following contributions at theoretical, methodological, and practical levels:

1. **A systematic review of modelling and simulation of AVs and CAVs longitudinal driving behavior (Sadid and Antoniou (2023) [1], see Appendix A)**: This involves a comprehensive analysis of current methods and models used for simulating AV and CAV driving behaviors, focusing on both mathematical and data-driven approaches. The review identifies the strengths, weaknesses, and gaps in the current literature, providing a foundation for further development. Furthermore, to focus on identifying the set of KPIs that are commonly used in the impact assessment of AVs, such as safety metrics, traffic efficiency, and environmental impacts. It also involves analyzing the impacts revealed through these KPIs in existing studies, thereby providing insights into the broader effects of AV deployment.

2. **Development of an optimization-based model to replicate the driving behavior of AVs (Sadid and Antoniou (2024) [68], see Appendix B)**: Developing a policy-aware optimization framework that finds a set of optimized driving parameters for AVs under various scenarios, aiming to achieve specific objectives such as reducing travel time and improving safety through a well-defined simulation-based objective function.

3. **Development of a dynamic graph-based deep learning method to predict the trajectory of AVs (Sadid and Antoniou (2024) [65], see Appendix C)**: This considers developing a novel dynamic STGCN to predict the trajectories of AVs by capturing both spatial and temporal dependencies among vehicles. This model utilizes a weighted adjacency matrix based on the strategic positions and distances of vehicles, which significantly improves prediction accuracy by better reflecting real-world driving behaviors.

4. **Impact assessment of AVs deployment scenarios in urban networks (Sadid and Antoniou (2024) [34], see Appendix D)**: Conducting a comprehensive simulation-based impact assessment of AVs in urban networks using a SUMO-based simulation platform. The assessment incorporated optimized AV driving behavior, varied penetration rates (PRs), and different demand scenarios.

1.4 Dissertation Structure

This dissertation is structured into nine chapters, each addressing a specific aspect of the research on AVs. The first chapter introduces the research, outlining the motivation, problem definition, and objectives of the study, setting the stage for exploring AV deployment scenarios. Chapter 2 presents the Theoretical Background, providing a review of existing literature and foundational concepts related to behavioral modeling.

Chapter 3 details the Methodology, explaining the research design, the key research questions, and the methodological framework used to achieve the objectives of the study. Chapter 4 presents the summary of the review paper. Chapter 5 addresses the Optimized Driving Behavior of Autonomous Vehicles, introducing the developed optimization framework to enhance AV behavior modeling. In Chapter 6, the dissertation discusses the Deep Learning-based Trajectory Prediction model, which is designed to predict AV movement in complex traffic scenarios using advanced machine learning techniques.

Chapter 7 covers the Impact Assessment of Autonomous Vehicles Deployment Scenarios, where the effects of different AV PRs on traffic efficiency and safety in urban networks are evaluated. Chapter 8 provides a Discussion of the results, highlights the Limitations of the study, and outlines Future Research Directions, summarizing the key findings and proposing avenues for future work. Finally, Chapter 9 presents the conclusion of this dissertation. The schematic diagram in Figure 1.1 shows the overall structure of this dissertation.

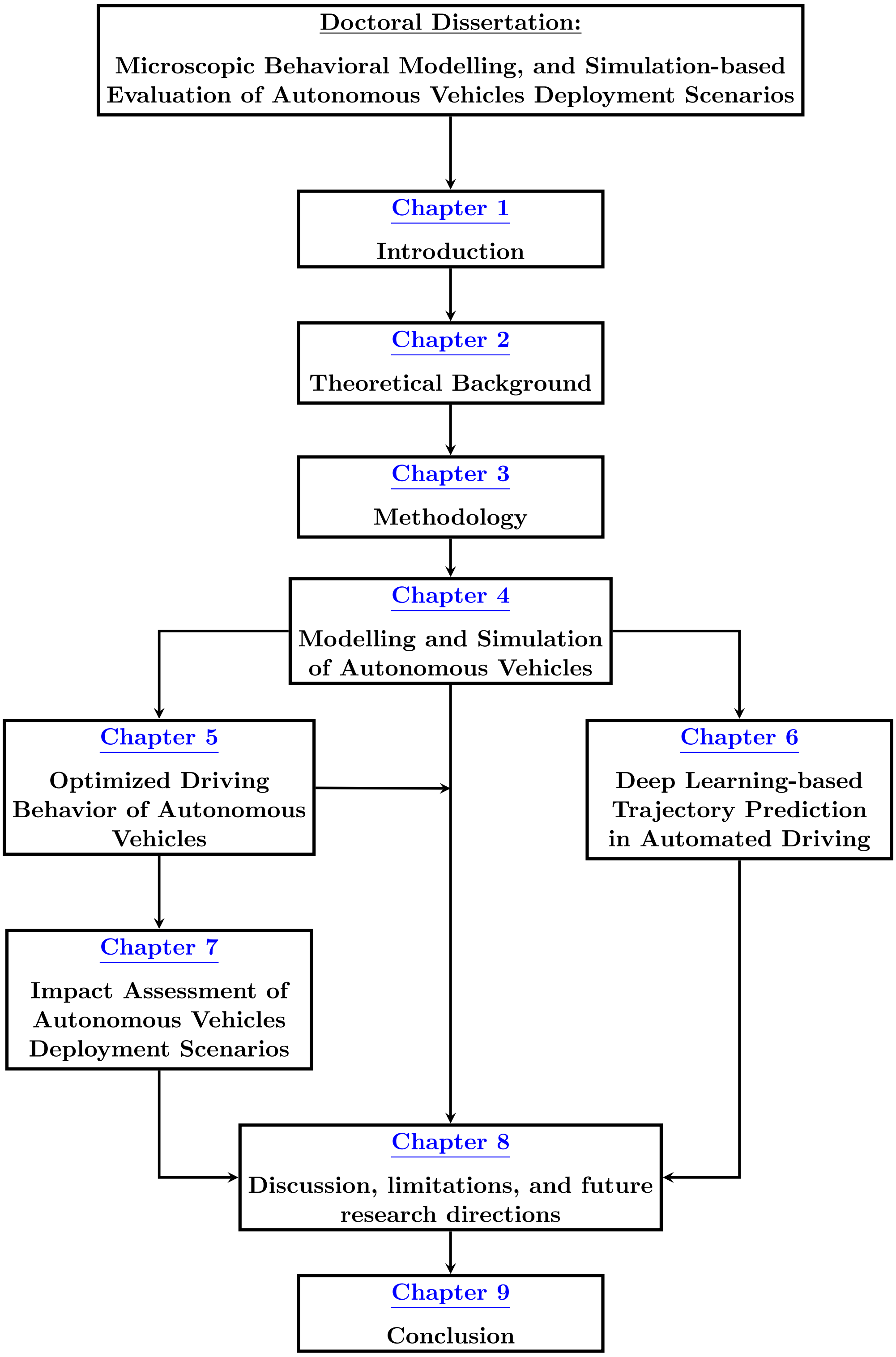

Figure 1.1: Illustration of the overall structure of this dissertation

2 Theoretical Background

Impact assessment of AVs deployment scenarios require the modelling and simulation of their potential driving behavior. The driving behavior of a vehicle could be well described using its CF or LC configurations. A CF model presents a driver's actions to follow a leading vehicle safely and efficiently, whereas a LC model replicate a driver's intention to change its lane in order to achieve strategic, cooperative, tactical or regulatory objectives. Given the scarcity of reliable data on LC dynamics, most researchers focus on CF configurations to capture the overall driving behavior of vehicles and conduct impact assessment. This is also true for AVs, where most simulation-based impact assessment studies are associated with AVs' CF behavior. There are many methods proposed in the literature for modelling of a vehicle's CF behavior. Generally, these methods are categorized into mathematical and data-driven models. In the following sections, we briefly describe each category.

2.1 Mathematical CF Models

Mathematical models are comprised of a set of equations and rules that describe the relationship between parameters such as speed, distance, acceleration, etc. to predict the behavior of a following vehicle using the current and past driving actions. These models typically use deterministic or stochastic methods to capture the dynamics of CF behavior [33, 69]. In addition, mathematical models are usually simple and computationally efficient, and are widely used in microsimulation tools. However, they fail to capture sophisticated driving situations. Most of these models are developed to replicate the driving behavior of human-driven vehicles, however, they are also widely utilized for approximating the driving behavior of AVs. The parameters of a mathematical CF model are calibrated using a mass-field driving data, whereas for AVs these parameters are often assumed.

Generally mathematical CF models are categorized into physics-based and psychophysical models. Physics-based models primarily rely on physical laws (like Newtonian mechanics) and principles such as speed, acceleration, deceleration, distance, and relative speed. These models focus on the vehicle's dynamics and the mechanical response required to maintain safe and efficient traffic flow. According to [69], physics-based models could be technically categorized into stimulus-based, safety distance, desired measures, and optimal velocity models.

2.1.1 Physics-based Models

Stimulus-based models are some of the earliest types of CF models. They are grounded in the idea that a driver's acceleration or deceleration response (the "response") is a direct reaction to the behavior of the vehicle ahead (the "stimulus"). In these models, the stimulus is typically measured in terms of the relative speed or distance between the following vehicle and the leading vehicle. The core concept is that the follower vehicle's driver adjusts their speed based on the change in relative speed or the gap to the car in front. The relationship between stimulus and response can be modeled using either linear or nonlinear functions, depending on the complexity desired in representing driver behavior. Stimulus-based models emphasize the driver's sensitivity to changes in relative speed and distance, often assuming that the response is proportional to the stimulus. Stimulus-based models include the Chandler, Herman, and Montroll (CHM) Model, also known as the Gazis-Herman-Rothery (GHR) model [49]. This model assumes that the acceleration of the following vehicle is directly proportional to the relative speed and inversely proportional to the distance from the leading vehicle, introducing sensitivity factors to adjust the driver's responsiveness to different stimuli. Another example is the General Motors (GM) Model, which follows a similar concept where the acceleration is a function of the relative speed and distance between vehicles [70]. The GM model provides a simple linear form that relates driver reaction to changes in traffic conditions, making it a foundational model in early traffic flow theory [33, 69, 71, 72].

Safety distance models are centered on the concept of maintaining a safe distance between vehicles to prevent collisions. These models prioritize safety by ensuring that the following vehicle maintains a sufficient distance to allow for safe braking in response to the actions of the leading vehicle. The key idea is to maintain a buffer zone that accommodates sudden deceleration or stops by the leading vehicle, thereby reducing the risk of rear-end collisions. Safety distance models take into account various factors, such as relative speed, reaction time, and braking capabilities, and often include safety margins to compensate for human reaction times and braking delays. Examples of safety distance models include the Gipps Model [50], which calculates a safe distance based on the maximum acceleration, desired speed, and a safety margin that accounts for reaction time and deceleration capabilities of both vehicles. This model provides a realistic representation of safe CF behavior by incorporating the psychological comfort of drivers in maintaining a safe distance. Another example is the Krauss Model [73], which is designed for microscopic traffic simulation and uses a safety distance formula that considers both the speed of the following vehicle and the relative speed difference. The Krauss model is widely used in traffic simulators due to its simplicity and computational efficiency, allowing for practical application in various traffic analysis scenarios.

Desired measure models are based on the notion that drivers have specific preferences or "desired" values for certain traffic parameters, such as speed, headway (time gap), or acceleration. These models aim to adjust the behavior of the following vehicle to achieve or maintain these desired measures. The focus is on aligning the vehicle's acceleration or deceleration with the driver's preferred speed or desired time gap, reflecting individual driving styles and preferences. Desired measure models emphasize the idea that each driver has unique behavioral tendencies that influence their driving decisions, such as maintaining a certain speed or following distance. Desired measure models include the Helly Model [74], which integrates desired speed and desired time gap into the CF behavior. The Helly model adjusts the acceleration of the following vehicle based on the difference between the current and desired headway, as well as the difference between the current speed and the desired speed. Another example is the Intelligent Driver Model (IDM), which considers a driver's desired speed and a dynamically adjusted spacing that reflects traffic density [51]. The IDM model calculates the acceleration based on the difference between the current and desired speed, incorporating driver preferences and traffic conditions to simulate realistic CF behavior. Additionally, Adaptive Cruise Control (ACC) and Cooperative Adaptive Cruise Control (CACC) are advanced implementations of desired measure models, where ACC model estimates the speed of an ACC-equipped vehicle in next time steps focusing on maintaining a desired headway using onboard sensors, and CACC extends this by incorporating V2V communication for cooperative vehicle behavior, enabling smoother traffic flow and greater synchronization among vehicles.

Optimal velocity models are based on the principle that each driver has an "optimal" velocity depending on the distance to the vehicle ahead. These models assume that drivers adjust their acceleration to reach this optimal velocity, which varies according to the spacing to the preceding vehicle. The key idea is that the optimal velocity reflects the safest and most efficient speed a driver should maintain based on the current traffic conditions. Optimal velocity models are particularly useful for studying traffic flow instabilities, such as the formation of traffic jams and stop-and-go waves, as they provide insights into how drivers' speed adjustments can lead to different traffic flow phenomena. Optimal velocity models include the Bando Model [52], which posits that drivers adjust their speed to achieve an optimal velocity that depends on the distance to the leading vehicle. This model uses a nonlinear function to represent the optimal velocity, which changes with the headway, allowing the study of traffic phenomena like stop-and-go waves and shockwaves. Another example is Newell's CF Model [75], a simplified version of the optimal velocity concept, where drivers are assumed to maintain a constant headway and adjust their speed to follow the leader while maintaining this spacing. Newell's model is simple yet effective in capturing essential traffic behaviors, such as smooth acceleration and deceleration.

2.1.2 Psycho-physical Models

On the other hand, psycho-physical models incorporate psychological and perceptual thresholds to describe driver behavior [53, 76]. These models consider how drivers perceive their environment and react based on psychological factors such as comfort, stress, and safety. Psycho-physical models often involve multiple regimes of behavior, depending on the distance and speed differences between vehicles. The idea is to capture the variability in human behavior by considering different thresholds for driver reactions, such as reaction time and perception limits. Psycho-physical models reflect a more nuanced approach to CF behavior by considering how different psychological and perceptual processes influence driving decisions. Wiedemann Model is a well known example of psycho-physical models, which is widely used model in microscopic traffic simulation [53]. The Wiedemann model divides CF behavior into several regimes, such as free driving, approaching, following, and emergency braking. It incorporates driver perception thresholds and stochastic elements to reflect the variability in driver response, making it suitable for simulating real-world traffic conditions.

2.2 Data-driven Models

Data-driven models leverage the availability of open-access trajectory data and the success of machine learning-based techniques to capture the complex, often non-linear interactions between vehicles. Unlike traditional mathematical models that are based on predefined equations and physical laws, data-driven models use machine learning methods, such as neural networks, support vector machines, reinforcement learning or deep learning, to learn from large datasets of real-world driving behavior. These models could be categorized into two main types: CF-based models and trajectory-based models.

2.2.1 CF-based Models

CF-based models focus on capturing the behavior of a vehicle when following a leading vehicle. These models rely on data that describes the interactions between a lead vehicle and a following vehicle, including how the following vehicle adjusts its speed, acceleration, and braking in response to the actions of the leading vehicle. Machine learning techniques are employed to learn these behaviors from large datasets (i.e., HighD [77], NGSIM [78], pNEUMA [79], Waymo [80], and nuScenes [81]), enabling the model to predict how drivers would react in various traffic scenarios. Studies relevant to data-driven CF models can be categorized into five main types: nonparametric models, artificial neural networks (ANNs), reinforcement learning (RL), deep reinforcement learning (DRL), and combined mathematical and data-driven models. Each of these approaches offers unique strengths in modeling and predicting complex driver behaviors and vehicle interactions in a traffic scene.

Nonparametric models are capable of fitting a large number of functional forms with no or weak assumptions. These models, such as k-nearest neighbors (KNN) and locally weighted regression, do not assume a fixed form for the relationship between variables. They rely on the data itself to determine the model's structure, making them flexible and adaptable to complex, nonlinear relationships. In CF models, nonparametric methods can effectively capture diverse driving behaviors by focusing on local patterns rather than global trends [54–56, 82].

ANNs on the other hand are a class of machine learning models inspired by the human brain's architecture, consisting of interconnected layers of nodes or neurons [83]. In

CF models, ANNs can learn to predict vehicle behavior such as acceleration or braking based on various inputs like current speed, distance to the leading vehicle, and road conditions [84,85]. Feedforward Neural Networks (FNNs) might be used for straightforward predictions, while Recurrent Neural Networks (RNNs) are suitable for modeling temporal dynamics by remembering past behaviors and predicting future states [61,86–88]. ANNs are powerful in capturing complex, non-linear relationships and can adapt to diverse driving conditions. However, they require careful tuning and may lack interpretability, making it challenging to understand the basis of their predictions.

Furthermore, RL is a method where an agent learns to make decisions by receiving rewards or penalties based on its actions. In CF scenarios, RL algorithms such as Q-learning train the agent to optimize driving strategies, like how to adjust speed or maintain safe distances, to maximize overall rewards [89, 90]. The agent learns from interactions with the environment and refines its policy based on feedback. Policy gradients, another RL approach, optimize the strategy directly to improve performance. While RL can adapt to various driving situations and continuously learn from experience, it often requires extensive training and computational resources, and designing effective reward functions can be challenging.

DRL combines deep learning with RL, utilizing deep neural networks to handle complex, high-dimensional input data. This approach is particularly useful in CF models where inputs may include raw sensor data or images from cameras. For example, Deep Q-Networks (DQN) use deep neural networks to approximate the Q-function, enabling the model to learn effective driving policies even in complex environments. Additionally, Actor-Critic methods, integrate both value-based and policy-based approaches for improved efficiency. DRL can manage intricate and high-dimensional data, but it requires significant computational power and careful tuning of network architectures and hyperparameters to achieve stable and effective learning [62, 63].

Finally, combined mathematical and data-driven models integrate traditional mathematical approaches with empirical data-driven techniques to create a more robust and interpretable model. In CF scenarios, these models might start with a mathematical framework based on CF theories or physical laws and then use data-driven methods to refine or adapt these models based on real-world observations [91–93]. This approach leverages the strengths of both theoretical and empirical methods, potentially leading to more accurate and generalizable models. However, it requires expertise in both domains to effectively develop and balance the mathematical and data-driven components.

2.2.2 Trajectory-based Models

Trajectory-based models analyze the complete path or trajectory of a vehicle over time, taking into account not just the interactions with a leading vehicle but also lateral movements, lane changes, and interactions with multiple vehicles. These models utilize detailed trajectory data to learn complex driving patterns and maneuvers, often incorporating spatial and temporal dependencies. They are widely used in the development of autonomous driving systems, where understanding the full vehicle trajectory is critical for navigating complex environments, executing safe lane changes, and merging in traffic. These methods often employ techniques such as RNN [94], Convolutional Neural Network (CNN) [95, 96], Long Short-Term Memory (LSTM) [64, 97–100] methods, Transformer models [101–103], and graph-based deep learning methods [66, 104, 105], to capture the complex dependencies in vehicle's trajectory in a wide driving scenarios.

RNNs are particularly suited for sequential data and time-series predictions due to their ability to maintain temporal context. In trajectory-based models, RNNs can learn patterns and dependencies in vehicle trajectories over time. They are capable of processing sequences of data, making them useful for predicting future positions based on past movements. However, RNNs can struggle with long-term dependencies due to issues like vanishing gradients. In contrast, LSTM networks which are a special type of RNN designed to address the limitations of standard RNNs. LSTMs have mechanisms like gates to control the flow of information and maintain long-term dependencies, which is crucial for accurately predicting vehicle trajectories over extended periods. They are effective in capturing complex temporal relationships and handling longer sequences of data, making them suitable for modeling vehicle movements in diverse driving scenarios.

CNNs which are traditionally used for image and spatial data, have been adapted for trajectory-based models, especially when dealing with spatial-temporal data. CNNs can extract features from data representations like trajectory maps or grids, capturing spatial patterns that might be important for understanding vehicle movement. For example, CNNs can process data from traffic cameras or maps to infer patterns and predict vehicle trajectories.

Transformer models, known for their effectiveness in natural language processing, have also been applied to trajectory prediction [106]. Transformers use self-attention mechanisms to weigh the importance of different parts of the input data, allowing them to capture complex dependencies across time and space. In the context of vehicle trajectories, transformers can model intricate patterns and relationships in the trajectory data, providing robust predictions across varied driving scenarios.

Meanwhile, Graph-based deep learning methods are used to model data that is structured as graphs, where nodes represent entities (e.g., vehicles) and edges represent relationships between them. In trajectory-based models, these methods can represent the dynamic interactions between multiple vehicles and their surroundings. Graph Convolutional Networks (GCNs), for instance, can capture the dependencies and interactions in traffic networks, making them useful for understanding and predicting complex vehicle movements in scenarios involving multiple agents and interactions [107]. GCNs can well mimic the spatial dependencies among vehicles in traffic scenes; however, to capture the temporal dependencies and predict the future trajectories, temporal extractors such as Gated Recurrent Unit (GRU), LSTM, or Temporal Convolution Network (TCN) are combined with the GCN model, which is called the Spatio-temporal GCN (STGCN) model.

2.3 Summary

Mathematical models are foundational tools in vehicle simulation, characterized by their simplicity and computational efficiency. These models are built upon deterministic or stochastic equations to represent CF behavior based on predefined physical laws and relationships between parameters like speed, distance, and acceleration. While traditional mathematical models are well-established and commonly used in impact assessment studies, they often lack the flexibility to accurately capture the complex, real-world dynamics of driving behavior, especially for AVs where no specific models are yet established. Researchers frequently adapt conventional mathematical models to approximate AV CF behavior by assuming the values of their parameters. However, this approach may not fully account for all driving intricacies.

In contrast, data-driven models leverage machine learning techniques to learn from extensive real-world driving data, offering a more nuanced and flexible alternative for modeling CF behavior. These models excel at capturing complex, non-linear interactions and adapting to various driving conditions. However, their application is constrained by the limited availability of trajectory data for AVs, which is often restricted to specific locations and does not cover the full spectrum of potential driving scenarios. This limitation hinders the ability to develop comprehensive data-driven models and remains an open area of research. Additionally, data-driven models face challenges in integration with existing simulation tools and are less prevalent in impact assessment studies. Their reliance on large datasets and advanced computational resources makes them less accessible for certain applications but provides a more detailed and accurate representation of driving dynamics. Figure 2.1 illustrates the categorization of mathematical and data-driven car-following (CF) models, providing an overview of their respective types and methodologies.

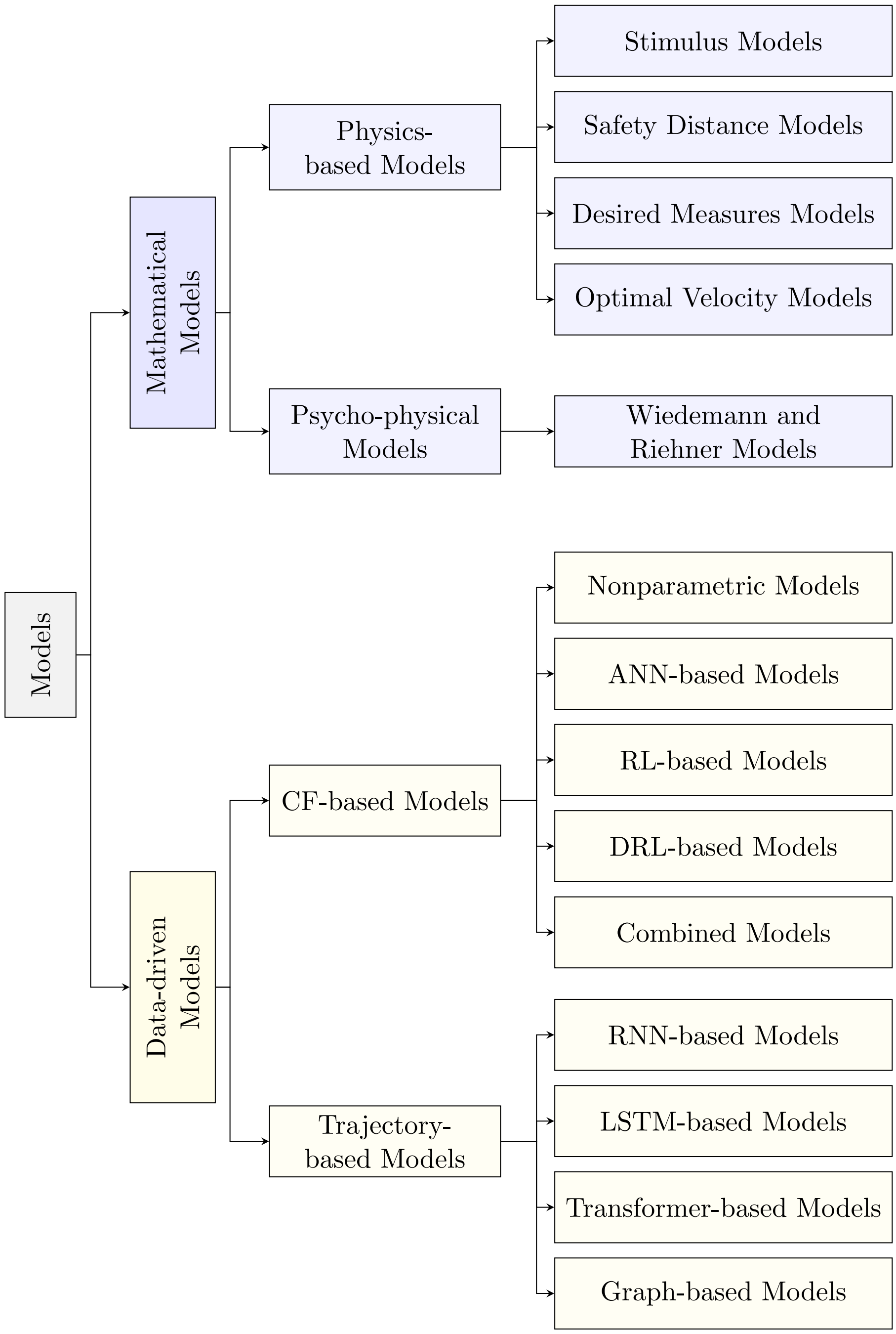

Figure 2.1: Classification of Mathematical and Data-driven CF models.

3 Methodology

The methodology of this dissertation is designed to address the main goal and sub-objectives of this research. A comprehensive simulation-based impact assessment of AVs deployment scenarios in an urban network requires the exploration of two primary aspects, namely: (i) the modeling of their driving behavior and (ii) development of a simulation platform to systematically simulate and assess their impacts on urban networks under varying PRs and traffic conditions. This research is structured to provide a comprehensive analysis through detailed simulations and scenario evaluations. However, both developing a model and simulation platform requires understanding the current state-of-the-art on different modelling techniques, identification of the KPIs and the potential impacts on efficiency and safety reported by other researchers. Thus, in line with the goals of this dissertation, we develop four main research questions. The methodological approach of this dissertation employs a research design to address these research questions.

3.1 Research Questions

The research questions outlined in this dissertation are crucial for advancing our understanding of AVs modelling, simulation, impact assessment, and integration within urban traffic systems. They aim to address the complex challenges associated with AV deployment and provide a foundation for developing effective modeling and simulation strategies. The specific research questions are as follows:

3.1.1 RQ1: Current Trends and Challenges in Autonomous Vehicle Modeling & Impact Assessment

What is the current state-of-the-art on modelling techniques and reported impacts of AVs?

Understanding the current state of AV modeling is essential for identifying effective techniques and methodologies that can improve traffic systems. This research question addresses the need to synthesize existing literature to reveal gaps and challenges, facilitating informed decisions in model development and integration strategies for AVs.

3.1.2 RQ2: Simulating Autonomous Vehicles Behavior with a Mathematical Model

How can a mathematical car-following model replicate the potential driving behavior of AVs in an urban traffic network?

Developing accurate mathematical models to replicate AV driving behavior is crucial for predicting their interactions within urban traffic networks. This research question highlights the necessity of creating robust models that can effectively simulate AV dynamics, ultimately to inform traffic management systems and enhance overall road safety.

3.1.3 RQ3: Deep Learning Approach for Predicting Autonomous Vehicles Motion

In what ways can a data-driven model leveraging deep learning techniques effectively capture the potential motion of an AV across various driving conditions?

As AVs rely on complex decision-making processes influenced by various environmental factors, leveraging deep learning techniques is vital for capturing this complexity. This research question addresses the need for advanced predictive models that can adapt to diverse driving conditions, thereby improving the reliability and safety of AV navigation.

3.1.4 RQ4: Impacts of Autonomous Vehicles Deployment Scenarios on Urban Traffic

What are the potential impacts of AV deployment scenarios on overall traffic efficiency, congestion, and traffic safety in urban networks?

Assessing the impacts of AV deployment scenarios is essential for understanding their potential effects on traffic efficiency, congestion, and safety. This research question underscores the importance of scenario-based simulations to provide policymakers and stakeholders with insights on how AV integration can reshape urban transportation systems, guiding future infrastructure investments and regulations.

3.2 Research Design and Methodology

The research design and methodology of this dissertation follows a three-phase approach as illustrated in Figure 3.1. First, we conduct a comprehensive literature review on modelling the longitudinal driving behavior of AVs to identify the research gaps both in mathematical and data-driven models. Additionally, we explore the potential impacts of AVs reported by other researchers including the used KPIs for impact assessment. The second phase includes the development of modelling methods for replicating the driving behavior of AVs. The findings of phase II are utilized in phase III to develop the impact assessment simulation platform for AVs and conduct network-wide evaluation of the AVs deployment scenarios. The description of each step is described as follows:

3.2.1 A Comprehensive Review of the Current State-of-the-art on Modelling and Simulation of Longitudinal Driving Behavior of AVs

Developing an accurate CF model to replicate the driving behavior of AVs and to conduct a network-wide impact assessment, a thorough understanding the state-of-the-art

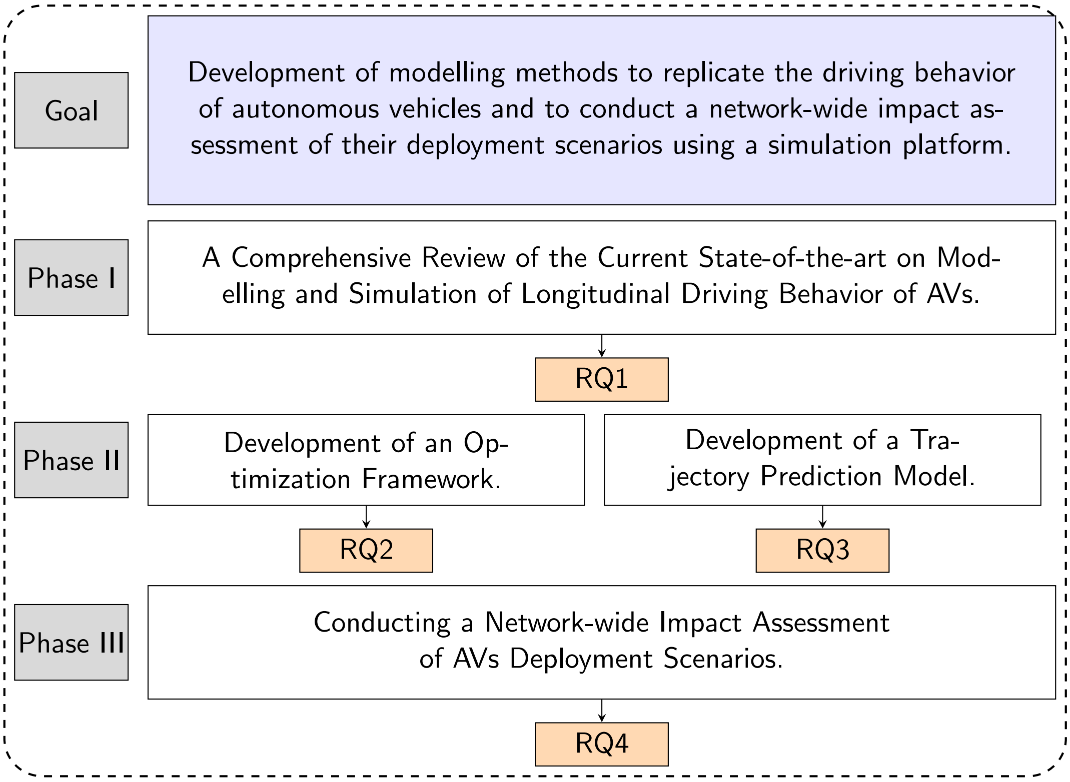

Figure 3.1: Overview of the Research Design: Main Goal, Key Phases, and Alignment with the Research Questions.

on AVs modelling and simulation is an essential step. This phase involves a comprehensive meta-analysis focusing on three critical aspects of AV-related studies. First, we investigate various mathematical modeling techniques used to capture AV CF behavior and explore how researchers differentiate the driving characteristics of AVs from human-driven vehicles within microsimulation environments. Second, we evaluate the potential of data-driven methods in modeling AV driving behavior by analyzing state-of-the-art techniques and identifying key research gaps, such as scalability, interpretability and adaptability to diverse driving scenarios. Third, to prepare a robust simulation platform for AV deployment scenarios, we examine recent studies on impact assessment criteria, including the definition of study scopes, impact areas, and KPIs. This analysis not only identifies limitations in existing approaches but also helps in addressing research gaps to enhance the impact assessment platform. The findings of this phase culminate in a review article, as detailed in Section 4 of this dissertation.

3.2.2 Development of an Optimization Framework to Replicate the Car-following Behavior of AVs

The second phase of this research focuses on developing an optimization framework integrated into a simulation platform to extract the optimized driving behavior of AVs. AVs are expected to exhibit an optimized driving behavior throughout their trips. However, this optimized behavior is defined based on a certain policy target (e.g. reaching efficiently to destination, or safe or both). The proposed optimization framework aims to determine the parameter values of a widely used mathematical CF model (e.g. IDM, Krauss, ACC) to generate optimal driving behavior. Given the unavailability of mass-field data for AVs and the limitations of existing trajectory data confined to specific locations and driving conditions, it is not possible to calibrate (behavioral) the parameters of a CF model to mimic AVs. As a result, the generated optimized parameters could be potentially used as representative of their driving behavior in an impact assessment study.

Methodologically, the framework integrates an optimization module with a simulation platform to iteratively search for the optimal solutions that minimizes specific policy targets within the simulation environment. To achieve this, we utilize Differential Evolution (DE), a stochastic, population-based, and gradient-free optimization technique well-suited for global optimization problems. DE is particularly advantageous for this application due to its robustness in handling complex, multi-dimensional search spaces and its efficiency in converging to optimal solutions.

The policy targets for optimization may include minimizing the average network travel time, reducing the total number of conflicts in the network, or achieving a weighted combination of both KPIs. Within the optimization module, scenario variables such as PRs, demand levels, and the boundary and initial values of decision variables (parameters of CF models) are predefined. The primary objective of the framework is to identify parameter values that minimize the objective function, which reflects the selected policy targets.

The objective function is formulated to account for diverse combinations of KPIs by assigning varying weights to each, expressed as follows:

$$w \cdot T + (1 - w) \cdot C,$$

where $0 \leq w \leq 1$ represents the weight of the KPI, T is the normalized mean network travel time, and C denotes the normalized total number of conflicts. This flexible formulation allows for prioritizing different policy objectives by adjusting the weight w to reflect specific priorities, such as emphasizing safety or efficiency. The overall methodology of this task is illustrated in Figure 3.2, providing a visual representation of the framework's structure and workflow. A detailed description of the framework, including its implementation and performance, is further elaborated in Section 5.

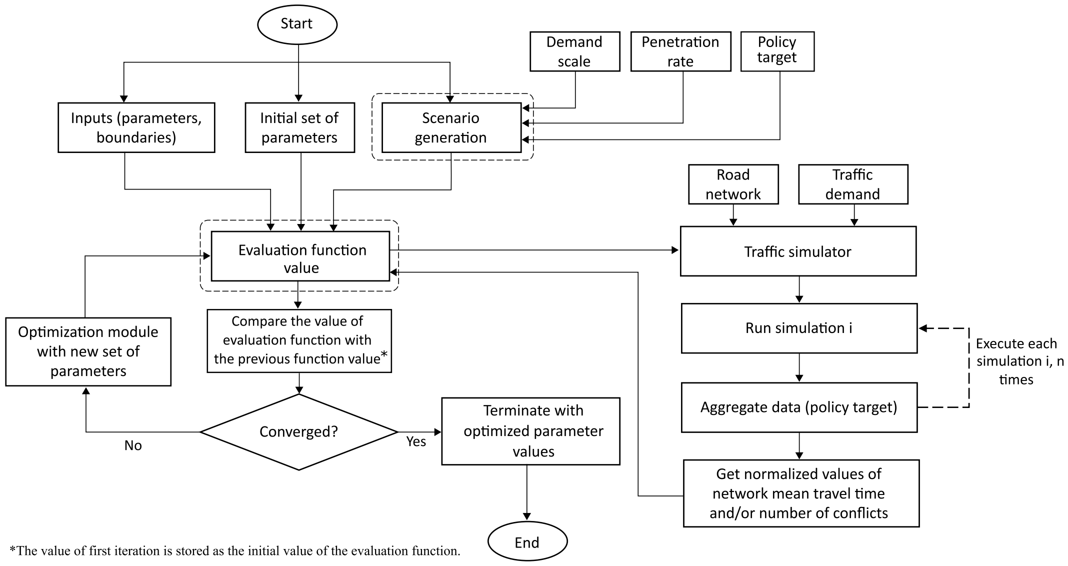

Figure 3.2: The methodological framework in this research. (Source: [68])

3.2.3 Development of a Trajectory Prediction Model

In phase II, we also develop a graph-based deep learning model to predict the trajectory of AVs in mixed traffic scenarios. Data-driven models are particularly effective at capturing the complexities of driving behaviors and often outperform traditional mathematical models. The proposed model utilizes a graph structure to represent the traffic scene and the interactions among vehicles. The interaction among vehicles vary in each traffic scene, depending on the motion features of each vehicle. As illustrated in Figure 3.3, the relationship between the target vehicle (the black-colored vehicle) and nearby vehicles, in terms of their strategic positions and distances, changes over time. The strategic position identifies the true influence of surrounding vehicles on the target vehicle based on their driving positions (e.g., leading, following, right-lane, left-lane, etc.). This dynamic interaction renders the trajectory prediction problem inherently variable across both temporal and spatial dimensions.

To formalize the trajectory prediction problem, we consider a traffic scene with N observed vehicles over t_{obs} discrete time steps. The state of a single vehicle i, where $i \in \{1, \ldots, N\}$, at a specific time step t, where $t \in \{1, \ldots, t_{\text{obs}}\}$, is characterized by a set of attributes denoted as:

$$X_i^t = \left[(x_i^t, y_i^t), (v_{xi}^t, v_{yi}^t), (a_{xi}^t, a_{yi}^t), \ldots\right],$$

where (x_i^t, y_i^t) are the vehicle's spatial coordinates, (v_{xi}^t, v_{yi}^t) are its velocity components, and (a_{xi}^t, a_{yi}^t) are its acceleration components, with additional attributes as needed to capture the driving state comprehensively.

Given the observed attributes of vehicle i over the observation horizon t_{obs}, represented as:

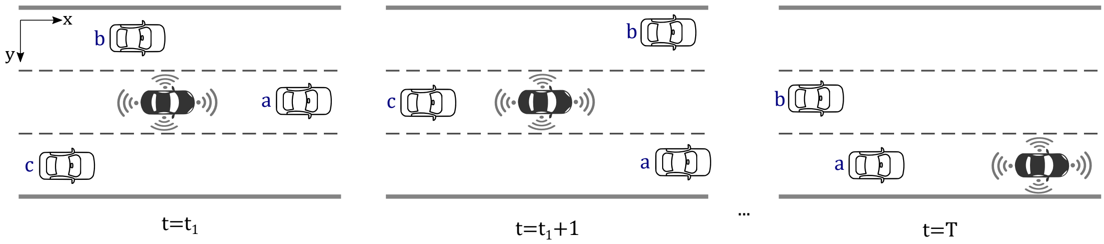

Figure 3.3: The illustration of the interaction among vehicles over time; both the strategic position and distance of vehicles in respect to the target vehicle changes over time.

$$X_i^{1:t_{\text{obs}}} = [X_i^1, X_i^2, \ldots, X_i^{t_{\text{obs}}}],$$

the objective is to predict the future attributes of all vehicles in the scene. The predicted attributes for vehicle i over the prediction horizon t_{pred} are denoted as:

$$Y_i^t = [Y_i^{t_{\text{obs}+1}}, Y_i^{t_{\text{obs}+2}}, \ldots, Y_i^{t_{\text{pred}}}],$$

where $t \in \{t_{\text{obs}+1}, \ldots, t_{\text{pred}}\}$.

The model maps the observed states $X_i^{1:t_{\text{obs}}}$ to the predicted future states Y_i^t by considering both the dynamics of individual vehicles and their interactions within the traffic scene, represented through a graph structure.

Considering a traffic scene as a graph structure $G = (V, E)$, where vehicles represent the nodes V of the graph and the interactions among vehicles are the edges E. The construction of the interaction matrix is a core aspect of this research, where distance-based interactions are combined with strategic-based interactions among vehicles to generate the adjacency matrix. For a connection between node i and node j at time t, the adjacency matrix is defined as:

$$A_{ij}^t = \begin{cases} d(p_i^t, p_j^t) + \cos(\theta_{ij}^t), & \text{if edge } e_{ij}^t = 1, \\ 0, & \text{otherwise,} \end{cases} \tag{3.1}$$

where:

$$d(p_i^t, p_j^t) = \frac{1}{\sqrt{(p_{ix}^t - p_{jx}^t)^2 + (p_{iy}^t - p_{jy}^t)^2}}$$

and

$$\theta_{ij}^t = \arctan\left(\frac{p_{iy}^t - p_{jy}^t}{p_{ix}^t - p_{jx}^t}\right).$$

here, $p_i^t = (p_{ix}^t, p_{iy}^t)$ and $p_j^t = (p_{jx}^t, p_{jy}^t)$ represent the position of node i and j at time t respectively, and e_{ij}^t indicates whether there is an edge (interaction) between nodes i

and j at time t. The adjacency matrix A_{ij}^t effectively captures both spatial proximity and directional alignment of the interactions between vehicles.

This graph-based representation enables the model to incorporate both individual vehicle dynamics and relational information, facilitating more accurate trajectory predictions in complex mixed traffic scenarios. The outcome of this task is a peer-reviewed journal paper. A detailed description of this research paper is presented in Section 6.

3.2.4 Conducting a Network-wide Impact Assessment on Traffic Efficiency and Safety

In the phase III of this dissertation, we focus on integrating the optimized CF behavior of AVs into a simulation platform to systematically evaluate the impacts of AVs deployment scenarios in urban networks. The platform comprises three main modules, namely: (i) a scenario generation module, (ii) a simulation module, and (iii) output module. The scenario generation module takes a specific PR of AVs together with the related optimized CF behaviors (generated in Section 5) and demand scale and sends it into the SUMO-based simulation environment module. Within the simulation environment, several simulation runs are conducted and the outputted data are sent into the output module. The output module processes, analyzes, and visualizes the data.

To prepare the base model for impact assessment scenarios, behavioral calibration based on real-field travel time data is conducted using the Particle Swarm Optimization (PSO) algorithm. Inspired by the collective behavior of bird flocks, PSO efficiently explores the solution space to optimize parameters such as desired time headway, acceleration, and deceleration limits for the CF model of human-driven vehicles.

Each particle in the algorithm represents a candidate set of parameters, iteratively updated based on its personal best-known position (pbest) and the global best-known position (gbest). The objective is to minimize the root mean square normalized error (RMSN) between simulated and observed travel times. The diagram 3.4 illustrates the integration of PSO with the SUMO traffic simulator, where PSO iteratively refines parameters, simulates traffic flow, and evaluates the objective function. This calibration process ensures a realistic replication of traffic behavior, creating a robust base model for analyzing mixed traffic scenarios with varying AV PRs.

Furthermore, in this research, we select traffic efficiency and safety as evaluation areas to estimate the impacts of AVs deployment scenarios on transport network performance. To evaluate traffic efficiency, KPIs such as travel time, density, and average speed are analyzed across various AV PRs. The study utilizes Generalized Estimating Equations (GEE), a statistical method well-suited for clustered or longitudinal data, to model the relationship between traffic characteristics and AV deployment scenarios. For instance, edge-level travel times are treated as repeated measures within each road segment cluster, capturing temporal and spatial dependencies. Meanwhile, for safety evaluation, the study uses the total number of conflicts in the network as a KPI, with conflicts identified using the Time-to-Collision (TTC) metric. Each vehicle is equipped with a surrogate

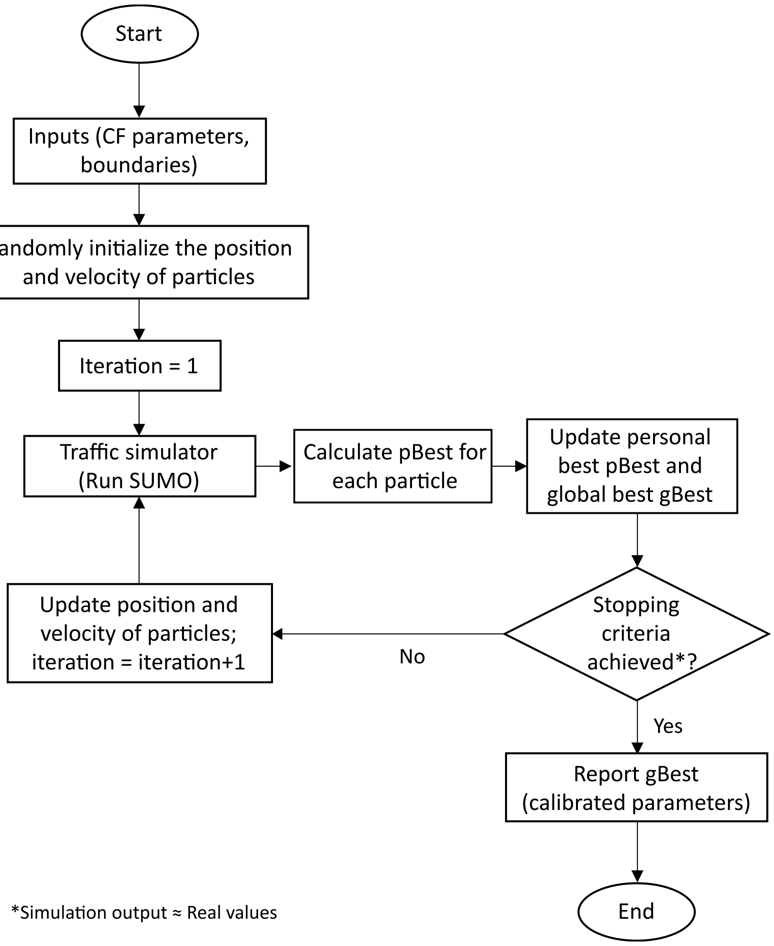

Figure 3.4: Illustration of PSO calibration method

safety measure (SSM) device to log conflicts, which are analyzed to estimate unsafe interactions. To further investigate the relationships between traffic characteristics, PRs, and conflict counts, a zero-truncated Poisson (ZTP) regression model is employed. This statistical approach is particularly suited for count data without zero values, enabling a detailed understanding of how increasing AV PRs, alongside other factors, influences network safety. The outcome of this task is also published in a scientific journal, with details provided in Section 7.

4 Modelling and Simulation of Autonomous Vehicles

Sadid, H., Antoniou, C.: Modelling and simulation of (connected) autonomous vehicles longitudinal driving behavior: A state-of-the-art. IET Intell. Transp. Syst. 17, 1051–1071 (2023). https://doi.org/10.1049/itr2.12337

4.1 Summary

In this research, we present a comprehensive review on different CF models including their adopted parameters for mimicking the driving behavior of AVs and CAVs. Additionally, we reviewed the recent research on data-driven CF models. We also report the findings of several simulation-based impact assessment studies on potential impacts of AVs, together with the employed KPIs and assessment areas.

In the context of AVs behavioral modelling, there is not an established CF model to replicate the longitudinal driving behavior of AVs. Most researchers utilize the existing mathematical CF models and modify their parameters to investigate the driving behavior of AVs. However, the values of the parameters of these models are based on assumptions made by the authors. In most studies, IDM, MIXIC (MICroscopic Model for Simulation of Intelligent Cruise Control) and their modified versions are frequently used for modelling of AVs. The Wiedemann 99 and Krauss models are also used for AVs impact assessments. Depending on the different CF model, researchers differentiate the driving behavior of AVs from human-driven vehicles for time gap, reaction time, headway, and driving imperfection factor. Among these parameters, time gap is the most sensitive and crucial parameter which distinguishes AVs from human-driven vehicles. Although, many studies make similar assumptions for potential driving behavior of AVs, still there is still no concrete practical basis for the exact values of the assumed parameters. Thus, AVs might behave differently than what are expected.

Additionally, data-driven models could accurately replicate the CF behavior of AVs. There are various methods proposed in the literature. We found that the recent deep-learning based models such as DDPG, RNN, GRU, LSTM, DDPG equipped with a LSTM, and GAIL with GRU outperform mathematical CF models, nonparametric models, and conventional neural network-based models and could be potentially used for modelling CF behavior of AVs. However, most of these proposed models are not integrated into a simulation tool and hence they are not used in impact assessment studies.

Meanwhile, used KPIs for impact assessment in MTMs differ depending on the assessment criteria and study area (i.e. intersection, link, freeway, city network). First, in mobility analysis, we noticed that most studies select flow, density, string stability, lane capacity and throughput when conducting capacity and flow analysis in freeways, highways and ring roads. Travel time and speed are frequently selected for traffic efficiency analysis both on link level and city-wide. Second, for safety analysis, the number of conflicts is the most commonly used KPI in all type of study areas, where, in freeway analysis, some studies also used TTC, TET and TIT. Finally, the studies related to emission analysis depict that CO_2 and NO_X emissions per kilometers (g/km) are widely used KPIs for impact assessment.

4.2 Research Directions

Based on the findings of this review article, we identified the importance of developing a CF model to replicate the driving behavior of AVs. Since there is no established CF model for AVs, their driving behavior is often based on assumed parameters. Thus, a potential work would be to develop a framework to find reasonable parameters' values rather than relying on weak assumptions. Second, deep learning models could present promising opportunities to enhance our understanding of AVs driving behavior. The development of a model that utilizes deep learning to replicate AVs driving actions could provide valuable insight into how these vehicles respond to dynamic traffic environments.

In the following chapters, we introduce our proposed approaches: first, a mathematical CF model aimed at simulating AV driving behavior, and second, a deep learning-based model designed for AVs trajectory prediction. These contributions are intended to address the gaps identified in the existing literature and offer potential pathways for improving the modeling and prediction of AV behavior.

5 Optimized Driving Behavior of Autonomous Vehicles

H. Sadid and C. Antoniou, "Policy-aware Optimization-based Modeling of Autonomous Vehicles' Longitudinal Driving Behavior". Submitted to: IEEE Open Journal of Intelligent Transportation Systems

5.1 Introduction and Research Objectives

The driving behavior of AVs differs significantly from that of human-driven vehicles, and this disparity is captured in MTMs through their CF and LC configurations. A CF model outlines the sequence of decisions a driver makes to follow a leading vehicle efficiently and safely. Depending on the model, researchers differentiate AV driving behavior from human-driven vehicles based on factors such as time gap, reaction time, headway, and driving imperfection [68]. However, since mass-field data for AVs are limited, accurately quantifying AV behavior and calibrating CF parameters is challenging, leading researchers to rely on assumptions about AV driving behavior. This practice results in inconsistent conclusions about AVs' potential effects. Unlike human-driven vehicles, where their behavior is inherently stochastic and uncontrollable, AVs are controllable agents, and their behavior can be optimized. AVs could be trained to drive in most efficient manner possible, such as traveling safely from point A to point B while optimizing travel time. This training can be conducted in a simulated environment, where we regulate AVs to generate optimal trajectories for their trips. The resulting CF driving behavior could approximate the desired optimal behavior of AVs and can be used in simulation-based impact studies. Hence, in this research, we develop a framework to identify a set of optimized driving parameters for AVs, with the goal of achieving specific optimization objectives via a carefully defined simulation-based objective function. These objectives could target improvements in traffic efficiency (e.g., reduced travel time), enhanced safety (e.g., fewer number of conflicts), and more.

5.2 Methodology

We introduce an optimization framework designed to identify the optimal driving behavior parameters for AVs to meet predefined policy targets. The framework consists of two key components: an optimization module and a simulation environment. In the optimization module, predefined scenario variables and initial parameters of the AVs' CF model are provided as inputs for optimization. The module evaluates the objective function using potential solution sets, along with the scenario settings, into the simulation environment. The simulation environment then performs multiple runs under these conditions, evaluating the performance of the AVs with respect to the policy targets. The output from the simulation runs is a set of policy targets, which are normalized and fed back into the objective function in the optimization module. The module iteratively tests different combinations of AVs' CF model parameters by sending them back into the simulation environment, updating the policy target values after each run. This process continues until convergence is reached, meaning no further improvements can be made to the policy targets.

5.3 Experiment and Results

In this research, we employ a SUMO-based simulation platform to systematically simulate and analyze mixed traffic with varying levels of AVs deployment scenarios. The platform is built on three main components: (i) Scenario execution, (ii) SUMO environment, and (iii) Output module. For each scenario, inputs such as demand scale, AV PRs, and origin-destination (OD) matrices are fed into the scenario execution tool, which assigns trips across the network and runs the SUMO microscopic model. The CF behaviors of both AVs and human-driven vehicles are provided to guide the interactions between vehicles in the network. Given the inherent stochasticity of microscopic simulations, results are aggregated over multiple simulation runs to account for variability and ensure reliability. We integrate the optimization framework into the simulation platform to extract the optimized driving behavior. The study focuses on the traffic network of Maxvorstadt, a central district in Munich, during morning peak-hour traffic. A trip-based stochastic user route choice assignment is used for allocating OD pairs in this urban network (see Figure 5.1).

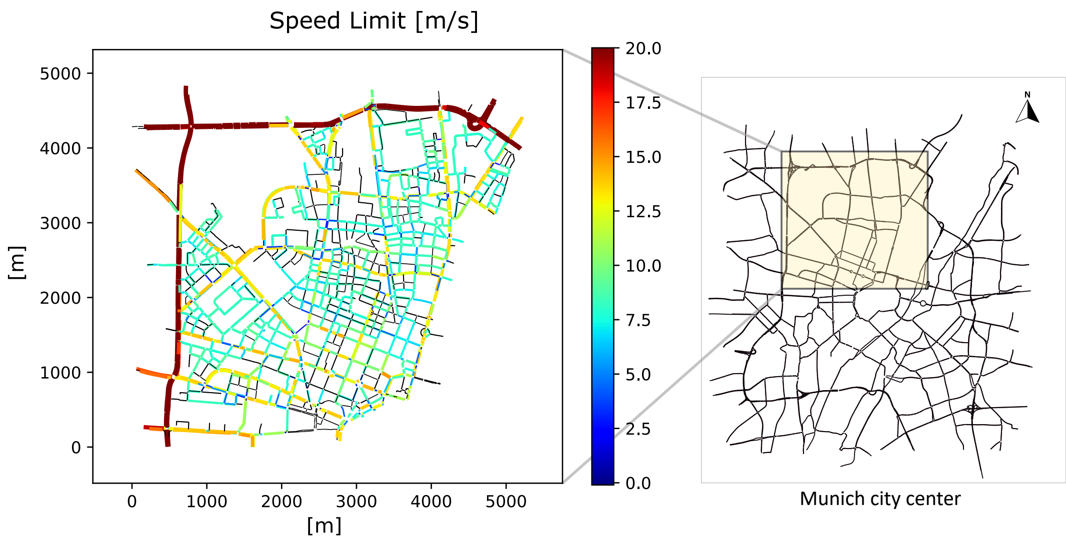

Figure 5.1: Road network of Maxvorstadt district in Munich city center. (Source: [68])

The convergence analysis demonstrates that optimizing the total number of conflicts as a policy target initially leads to substantial fluctuations in the objective function before achieving the optimal solution. This indicates that optimizing the CF parameters can significantly enhance network safety. However, the speed of convergence and the degree of fluctuation depend on the specific CF model. For instance, the IDM and Krauss models are highly sensitive to the number of conflicts in the network, causing more dramatic changes, whereas the ACC model shows more stability and less fluctuation. Furthermore, fluctuations in the objective function are more pronounced at higher AV PRs, likely due to the larger search space or greater impact of optimization on the KPIs. When the mean network travel time is chosen as the policy target, the variations in the objective function are smoother. However, optimizing for travel time leads to a significant increase in the number of conflicts, particularly in the IDM and Krauss models, whereas the ACC model sees only minimal changes. Interestingly, when conflicts are targeted as the policy, travel time does not worsen across all CF models as the optimization converges.

The optimized values of the objective function show that choosing the total number of conflicts as the policy target significantly reduces conflicts as AV PRs increase. Conversely, selecting average network travel time as the policy target does not lead to substantial improvements compared to a fully human-driven vehicle scenario. Additionally, the analysis of parameter values reveals that using conflicts as the policy target generates generalized CF parameters that are applicable across different demand scales and PRs for all CF models.

The sensitivity analysis further indicates that the minimum gap (mingap) and time headway (tau) are the most sensitive parameters affecting the total number of conflicts in the IDM and Krauss models. Other parameters have a less significant influence on the policy targets.

5.4 Discussion and Conclusion

The proposed optimization framework identifies the optimal set of CF model parameters for AVs, which can be utilized in impact assessment studies instead of relying on assumed values. However, one limitation of this study is that the framework was tested in a single study area. To generalize the findings, future research will need to apply the framework in different locations with varying demand patterns to extract optimized CF parameters accordingly. Additionally, this research employed the Wiedemann model to simulate human-driven vehicles, but it would be beneficial to model both human-driven vehicles and AVs using the same CF model and then optimize the AV parameters. This approach would provide a more accurate assessment of the effects of varying AV PRs on the network. Future work could involve a comprehensive network-level impact assessment of AV PRs using the optimized CF parameters identified in this study. Moreover, this study focused on extracting CF parameters for AVs where the following vehicle communicates only with the leading vehicle via sensors. A future study could apply the methodological framework to generate optimal CF parameters for CAVs, possibly using a modified IDM model that accounts for interactions with multiple surrounding vehicles, as proposed in [46]. Finally, expanding the optimization framework to generate optimal driving parameters that consider both CF and LC models is also an essential research work. This will provide a more holistic view of AV driving behavior optimization across different traffic scenarios.

6 Deep Learning-based Trajectory Prediction of Autonomous Vehicles

H. Sadid and C. Antoniou, "Dynamic Spatio-temporal Graph Neural Network for Surrounding-aware Trajectory Prediction of Autonomous Vehicles," in IEEE Transactions on Intelligent Vehicles, doi: 10.1109/TIV.2024.3406507

6.1 Introduction and Research Objective

Trajectory prediction is a crucial component of AVs to navigate safely and efficiently in complex traffic environments [108–110]. An AV should predict the motion and trajectory of surrounding road users to make informed and safe decisions regarding its own future driving actions. A key challenge in trajectory prediction is accurately modeling the interactions between vehicles, which are inherently dynamic and non-linear. Traditional approaches often struggle to accurately represent these interactions effectively, especially in non-Euclidean spaces where vehicle relationships do not follow simple grid patterns. To address this, the current research focuses on enhancing trajectory prediction accuracy by developing a dynamic STGCN that operates on directed graphs, capturing the nuanced spatial and temporal dependencies among vehicles.

In this research, we introduce a novel approach for the construction of a weighted adjacency matrix that serves as the foundation for the STGCN. Unlike conventional methods that rely solely on distance-based metrics, this research presents a novel approach that combines angular encoding with reciprocal distance to better represent the strategic positioning of vehicles—whether leading, following, or adjacent—relative to a target vehicle. This weighted adjacency matrix is crucial for accurately capturing the directional influences that vehicles exert on each other in a traffic scene. The STGCN leverages this matrix to perform graph convolution operations on directed graphs, allowing it to dynamically adjust to changes in vehicle positions and interactions over time. The research aims to significantly improve prediction accuracy, demonstrate the model's robustness across different datasets, and ultimately contribute to the safety and reliability of autonomous driving technologies.

6.2 Problem Formulation and Methodology

In the context of autonomous driving, the problem of trajectory prediction is defined as the task of predicting the future motion of all vehicles surrounding a target AV in order to enable the AV to make decisions regarding its future actions. This is essential in dynamic traffic scenarios where vehicle positions, speeds, and interactions are changing. The proposed methodology of this research involves combining a STGCN with a TCN to capture both the spatial dependencies among vehicles and the temporal evolution of these dependencies over time.

The first step in the methodology is to represent the traffic scene as a dynamic spatio-temporal graph. In this graph, vehicles are represented as nodes, and the interactions between them are represented as directed edges. To model these interactions more accurately, a novel weighted adjacency matrix is constructed. The adjacency matrix incorporates two important factors:

- **Reciprocal Distance:** This captures the influence of proximity between vehicles. Vehicles closer to each other are more likely to influence each other's movement stronger.

- **Angular Encoding:** This factor accounts for the strategic positioning of vehicles. For instance, leading vehicles exert more influence on a following vehicle's trajectory compared to vehicles behind. The angular encoding allows the model to distinguish between vehicles based on whether they are leading, following, or alongside the target vehicle.

These two factors are combined in the weighted adjacency matrix, which ensures that the spatial dependencies are accurately represented. The adjacency matrix evolves over time as the positions and interactions between vehicles change.

Second, the STGCN performs convolution operations on the directed graph. Each node (vehicle) aggregates information from its neighboring nodes based on the weights assigned by the adjacency matrix. This operation allows the STGCN to capture spatial dependencies between vehicles at each time step. However, since vehicle interactions are dynamic and change over time, the model also needs to capture how these spatial dependencies evolve. For this, the TCN is applied. The TCN processes the sequence of spatial embeddings generated by the STGCN to learn the temporal evolution of vehicle interactions. By combining the spatial and temporal features, the model can predict the future trajectory of each vehicle based on its historical interactions and movements. The schematic diagram in Figure 6.1 depicts the overall methodology of this research.

6.3 Experiment and Results

The proposed dynamic STGCN was evaluated using the HighD dataset, with 80% of the data allocated for training, 10% for validation, and 10% for testing. The model was tested over a 5-second prediction horizon with a 3-second observation window. We use the root mean square error (RMSE) to evaluate the performance of the proposed model. The RMSE is calculated based on two key metrics: Average displacement error (ADE) and final displacement error (FDE).

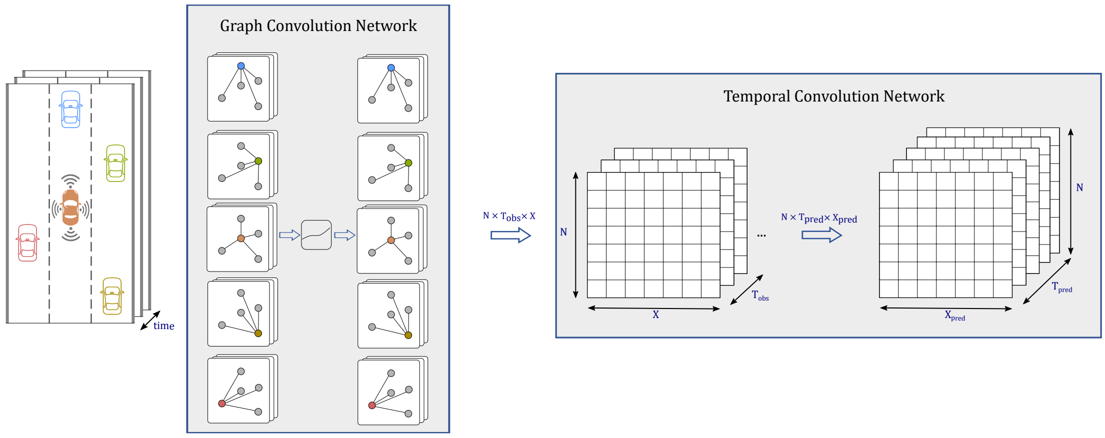

Figure 6.1: The overall architecture of the proposed dynamic STGCN architecture. In each traffic scene, GCN takes the trajectories of vehicles as input and learns the spatial dependencies among them. This is done for all traffic scenes, and the results are mapped on the features maps. The TCN module then operates on the features maps to extract the temporal dependencies and predict the future trajectories. (Source: [65])

An ablation study was conducted to understand the contributions of key components. The weighted adjacency matrix, which combines angular encoding with reciprocal distance, was crucial in improving model accuracy. Without angular encoding, the model's performance decreased by approximately 30%. The best performance was achieved with a single STGCN layer and five TCN layers, demonstrating that additional layers beyond this configuration led to diminishing returns. Compared to state-of-the-art models, the STGCN achieved a 34% reduction in FDE-based RMSE over the 5-second horizon, significantly improving the accuracy of trajectory predictions across different traffic conditions.

The model's generalizability was tested using the NGSIM dataset through transfer learning, where the pre-trained model from HighD was fine-tuned on a small portion of NGSIM data. The transfer model outperforms the state-of-the-art methods, showing strong adaptability to new environments with limited additional data. In terms of computational efficiency, the model demonstrated an inference time of 0.037 milliseconds per vehicle, making it suitable for real-time AV systems. The results affirm the STGCN's superior accuracy, generalizability, and efficiency compared to existing models, making it a promising solution for trajectory prediction in autonomous driving.

6.4 Conclusion

In this research, we presented a dynamic STGCN model to predict the motion and trajectories of vehicles in a traffic scene. The model successfully integrates GCN to capture spatial dependencies among vehicles on a directed graph and a TCN to capture temporal dependencies in vehicle trajectory sequences. A key contribution of this work is the construction of a weighted adjacency matrix that accounts for the strategic positions and distances of surrounding vehicles relative to the target vehicle. The experimental evaluation using the HighD dataset demonstrated that our model outperforms existing state-of-the-art models, with a 34% reduction in error over a 5-second prediction horizon. Additionally, transfer learning on the NGSIM (US-101) dataset further validated the generalizability of the model, showing strong performance even with limited data availability.

7 Impact Assessment of Autonomous Vehicles Deployment Scenarios

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7.1 Introduction and Research Objectives

AVs have the potential to significantly enhance traffic safety, reduce congestion, and lower emissions, largely due to their advanced sensing and decision-making capabilities. Unlike human-driven vehicles (HDVs), AVs can accurately detect their surroundings and communicate with other vehicles and infrastructure through Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) technologies. These capabilities allow AVs to respond more efficiently and safely to dynamic traffic conditions. However, the actual impact of AVs on transportation networks remains uncertain due to the variability in assumptions made about their driving behavior in existing studies. These assumptions often lead to conflicting conclusions about the potential impacts of AVs [35, 37, 41, 44, 45, 48, 111, 112]. This paper uses optimized AV driving behaviors rather than weak assumption within a simulation framework to assess their impact on an urban network. The focus is on evaluating the effects of different AV PRs on traffic efficiency and safety in a city-wide network of Munich city center. Additionally, the research incorporates advanced statistical methods, including Generalized Estimating Equations (GEE) and Zero-truncated Poisson (ZTP) regression, to provide a robust analysis of the factors influencing AV performance in urban settings.

7.2 Methodology

This research utilizes a simulation-based platform with the microscopic traffic simulator SUMO to evaluate the impact of AVs on urban traffic networks. For AVs, the study uses optimized driving parameters derived from our previous research in [113]. These optimized parameters reflect the expected performance of AVs, including their ability to maintain safe distances and react quickly to traffic situations. In contrast, the CF behavior of HDVs is modeled using the Krauss CF model, which is calibrated using the Particle Swarm Optimization (PSO) algorithm. PSO is employed to fine-tune the CF model parameters based on real-world traffic data from Munich, ensuring that the HDV behavior in the simulation environment accurately reflects observed driving patterns .

The simulation platform is structured into three main components. First, different scenarios are generated, varying the PRs of AVs from 0% to 100% and considering different traffic demand levels, such as peak hour and 30% below peak demand. Next, the simulations are conducted within a detailed model of Munich's city center, where the calibrated CF model direct HDVs' interactions. Multiple replications are performed for each scenario to ensure robustness. Finally, the simulation data is analyzed to evaluate traffic efficiency (including KPIs like travel time, speed, and density) and safety (measured by the number of conflicts using Time-to-Collision (TTC) as a KPI). The methodology also includes statistical analyses, such as one-way ANOVA and regression models (GEE and ZTP), to assess the significance and relationships between different variables, allowing for a comprehensive evaluation of AV impacts under various urban traffic conditions. The schematic diagram in Figure 7.1 demonstrates the research methodology, outlining scenario generation, simulation execution, and output analysis.

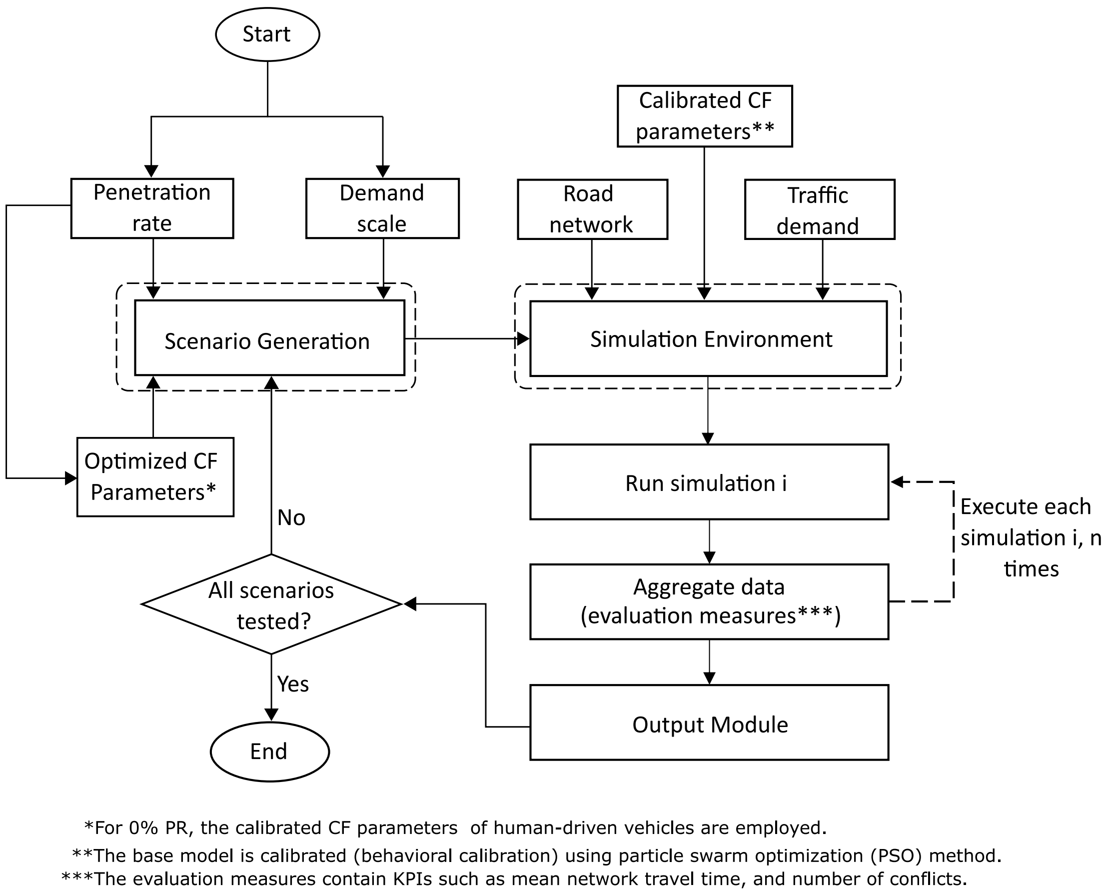

Figure 7.1: Schematic of the research methodology, showing scenario generation, simulation environment, and output analysis. (Source: [34])

7.3 Results

The findings of this research reveal that the impact of AVs on urban traffic networks varies depending on their PRs. For traffic efficiency, the study found that at low to moderate AV PRs (20% to 40%), there was a slight increase in average network travel time compared to a fully HDV environment. However, as AV PRs increased beyond 40%, travel times began to decrease, approaching those observed in a fully HDV scenario. Despite these variations, the overall impact of AVs on network performance was minimal, suggesting that existing infrastructure, speed limits, and traffic signal controls may limit the efficiency benefits of AVs. At intersections, no significant changes were observed in average time loss per vehicle or passing speed, indicating that the distinct driving behaviors of AVs did not substantially enhance efficiency under current traffic controls.

In terms of safety, the research found that increasing AV PR up to 40% initially led to a higher number of traffic conflicts, likely due to the interaction between AVs and HDVs. However, as AV PRs continued to rise, the total number of conflicts significantly decreased. In a fully AV environment, the number of conflicts was reduced by approximately 25% compared to a fully HDV scenario, highlighting the potential for AVs to improve traffic safety at higher PRs. A sensitivity analysis further showed that AVs' advanced sensing capabilities could enhance safety, as they allow quicker responses in potential conflict situations.

Additionally, the results of the GEE regression analysis indicated that there is a significant relationship between AV PR and travel time, with the GEE model successfully accounting for the correlated nature of traffic data across the network. The ZTP regression model further supported these findings by showing that higher AV PR were associated with a reduction in the total number of traffic conflicts, particularly as AVs become more prevalent in the network. Overall, the findings suggest that while AVs may offer limited improvements in traffic efficiency, their potential to enhance safety is significant, particularly at higher PRs. This underscores the need for further optimization of AV behaviors and infrastructure adjustments to maximize the benefits of AV deployment in urban networks.

7.4 Conclusion

This research demonstrates that AV deployment can lead to substantial safety improvements, particularly at higher PRs. However, the effect of AVs on traffic efficiency is more complex. At lower AV PRs, the mixed environment of AVs and HDVs creates inefficiencies due to differing driving behaviors, which results in increased travel times and delays. As AV PRs exceed 60%, these inefficiencies diminish, and the optimized driving behavior of AVs begins to positively influence network efficiency. The results suggest that while AVs contribute to significant safety benefits, their efficiency advantages are most pronounced when their penetration is sufficiently high. Additionally, factors such as infrastructure and intersection control mechanisms play crucial roles in the overall impact of AVs on urban networks.

Future research should focus on addressing several limitations of the current study. First, incorporating more real-world AV trajectory data for calibrating AV models would lead to more accurate simulations. Second, expanding the study to include different urban environments and a wider range of traffic conditions, including multi-modal transport systems, would provide a more comprehensive view of AVs' potential impact. Third, integrating advanced adaptive traffic control systems into simulations would reveal how AVs can interact with smart infrastructure to further improve traffic efficiency and safety. Fourth, future studies should explore mixed traffic environments with varying levels of vehicle automation, such as semi-autonomous and CAVs, to assess their collective impact on traffic dynamics. Finally, while this study focused on traffic efficiency and safety, future work should evaluate the environmental impacts of AV deployment, including emissions and energy consumption, under different scenarios. Addressing these research directions will offer deeper insights into the long-term implications of AV deployment and guide better strategies for integrating AVs into the transportation system.

8 Discussion, Limitations, and Directions for Future Research

The potential impacts of AVs on efficiency and safety in our transportation system are associated to their behavioral differences compared to human-driven vehicles. Replication of the potential driving behavior of AVs is therefore an important step for impact assessment of their deployment scenarios. Meanwhile, to design an experimental setup and conduct impact assessment, selection of set of assessment objectives, KPIs and the study scope are essential. In line with goal and sub-objectives of this dissertation, we investigated the current state-of-the-art on the modelling of AV longitudinal driving behavior, including the mathematical and data-driven methods. This dissertation also contains the adopted parameters for AVs modelling, which leads to understand how and with what magnitude the driving behavior of AVs might differ from the human-driven vehicles. It addition, it identifies the assigned assessment areas, set of KPIs, and the revealed impacts (Chapter 4). An optimization framework is proposed to extract the optimized CF parameters related to assigned policy targets (Chapter 5). Meanwhile, a data-driven model using dynamic STGCN is proposed to predict the trajectory of an AV in a traffic scene aiming to improve accuracy, and strengthen the model reliability under various traffic conditions. The proposed model not only predicts the CF configurations of AVs in next time steps but also the LC decision of the vehicles (Chapter 6). Finally, an experimental setup is designed to conduct impact assessment of AVs using the optimized CF behavior of AVs in an urban network on efficiency and safety (Chapter 7). This chapter will provide a general discussion of the results and limitations of the researchers performed, and recommendations for future researched will be provided.

8.1 Discussion

8.1.1 Driving Behavior of AVs

The advanced sensing and communication capabilities of AVs enable them to demonstrate driving behavior distinct from that of human-driven vehicles. These distinctions might include faster decision making, smoother driving patterns, elimination of driving errors, and the ability to follow leading vehicles more closely. However, the extend of these changes largely depends on assumptions made by the researchers, given the current scarcity of extensive real-world AV data. As discussed in our comprehensive review in Chapter 4, most studies suggest that AVs might tend to maintain shorter following distances and could react relatively faster. Conversely, some researchers assume that

AVs may have more cautious behavior and strictly follow the traffic rules, especially the speed limits, compared to human-driven vehicles.

The results of our review paper in Chapter 4 show that in most studies related to AVs and CAVs, the IDM, MIXIC and their modified versions are commonly used for modelling the CF behavior. The Wiedemann 99 and Krauss models are also frequently applied in impact assessments. Researchers distinguish the driving behavior of AVs from human-driven vehicles by parameters such as time gap, reaction time, headway, and a driving imperfection factor. Among these, time gap is the most critical parameter that sets AVs apart from human-driven vehicles. In the IDM, it is typically assumed that AVs can follow the leading vehicle with a time gap roughly 50% shorter than that of human-driven vehicles, where the headway for AVs is often set at 0.6 seconds, compared to over 1 second for human-driven vehicles. Other parameters in the IDM, such as maximum acceleration and comfort deceleration, are generally kept identical for both AVs and human-driven vehicles. Similarly, the MIXIC model assumes that CAVs can maintain lower time gaps. For instance, when a CAV follows another CAV, the time gap may be up to three times shorter than when it follows a human-driven vehicle. In ACC-CACC models, AVs and CAVs are primarily distinguished by their time gap settings. Due to their communication capabilities and faster environmental analysis, CAVs are expected to follow the leading vehicle at half the distance of AVs.

In our research in Chapter 5, we propose a different approach for modeling AVs. Instead of relying on fixed assumptions, we suggest that AVs might optimize their driving behavior based on specific targets. These targets could vary, ranging from reaching a destination faster to ensuring the safest possible trip, or achieving a balance between the two. To achieve this, we introduce an optimization framework designed to fine-tune the parameters of existing CF models (e.g., IDM, Krauss, ACC) to generate optimal AV driving behavior in relation to a defined policy target. This approach allows for more accurate replication of AV behavior. By doing so, we can move away from the weak assumptions often used in AV studies and instead provide more robust findings on the potential impacts of AVs on traffic systems.

According to the findings of this research, the potential driving behavior of AVs in regards to a policy target could be categorized into three regimes, namely: safe, neutral and aggressive behaviors. A safe driving behavior exhibits higher gaps to the leading vehicle, whereas the reaction time is relatively faster. In contrast, the aggressive driving behavior shows that AVs might drive closer to the leading vehicle to reach the destination faster. Meanwhile, the results reveal that a safe driving behavior of AVs improve the driving safety (fewer conflicts in a traffic network) without deteriorating the efficiency. Whereas, aggressive driving behavior does not significantly improve the efficiency of a network (in terms of average network travel time), but instead increases the number of traffic conflicts in the network and thus detriotes the traffic safety. Given that the expectation from AVs in the future would be to have safe and compfortable driving behavior, our recommendation for a possible driving behavior of AVs is a safe driving profile. Thus, the findings of our research on safe driving behavior of AVs could be potentially used in impact assessment studies.

8.1.2 Data-driven Models Synergies

There are two pillars supporting the researches working on developing data-driven models, namely: the availability of open-source trajectory datasets such as HighD [77], NGSIM [78], pNEUMA [79], Waymo [80], and nuScenes [81], and the success of deep learning methods. The findings of our review article in Chapter 4, and the research article in Chapter 6 reveal that attempts have been made to replicate the driving behavior of AVs and predict their possible movements in the next time steps. The proposed methods are distinguished whether they predict the CF decision of a vehicle or trajectory of a vehicle which includes both longitudinal and lateral configurations. In our review article, we found that the recent deep learning-based models such as DDPG, RNN, GRU, LSTM, DDPG equipped with a LSTM, and GAIL with GRU are proposed in the literature to predict the CF decision of a target vehicle. These models outperform mathematical CF models, nonparametric models, and conventional neural network-based models and could be potentially used for modelling CF behavior of AVs.

On the other hand, the findings in [65] indicate that RNN, LSTM, Transformer, and Graph-based methods are the core approaches for trajectory prediction of automated driving in the literature. Among others, graph-based approaches have the better interpretability, making it easy to understand the rationale behind the decision they make. However, we found that in proposed graph-based methods in the literature, the building of adjacency matrix and the graph structure do not match with real-world driving pattern and interaction among vehicles. In our research in Chapter 6, we proposed a novel graph-based model to better capture the interactions between vehicles, including AVs. This model builds an interaction matrix using a graph structure, which represents the relationships between vehicles in a traffic scene. By incorporating angular encoding into a weighted adjacency matrix, our model can effectively replicate the decision-making process for each vehicle's driving actions in the subsequent time steps. Compared to other state-of-the-art methods, such as LSTM-based models, and other graph-based approaches, our model offers better performance and high interpretability.

To summarize, data-driven models have the potential to more accurately capture the driving behavior of AVs under various driving conditions including the availability of other road users (i.e., pedestrians, bicycles). However, they come with their own set of challenges. They require significant computational effort and large amounts of training data, which are currently not available for AVs. additionally, due to the complexity of a traffic model, data-driven models are not integrated into simulation tools and hence they are not used in impact assessment studies.

8.1.3 Impact Evaluation of AVs Deployment Scenarios

Simulation-based impact assessment of AVs is indeed a challenging and complex task due to the wide range of factors that influence the results. The potential impacts reported from simulation studies can vary significantly based on numerous aspects, and understanding these aspects is key to interpreting simulation outcomes. These aspects include the calibration of the base model, the selection of an appropriate CF model for replicating the driving behavior of AVs, defining the study scope (i.e., motorway, urban links, urban network), setting the assessment areas and related KPIs to quantify the impacts, and the choice of a powerful traffic simulation tool. The findings of our review in Chapter 4, reveal that most studies selected mathematical models to estimate the CF behavior of AVs. The reason is that most simulation tools are build based on conventional mathematical models and they are computationally efficient to run large-scale simulations. In addition, vast majority of researches conduct impacts assessment of AVs and CAVs for safety and efficiency, where some also conduct investigation on environmental effects. For each assessment area, various KPIs are chosen depending on the scope of the study. For efficiency assessment, most researchers employed KPIs such as traffic flow (e.g. traffic flow, density), average travel time, string stability, average velocity, and more [36, 38–40]. For safety analysis, the number of conflicts is the most used KPI in all type of study areas, where in freeway analysis, some studies also used TTC, TET and TIT [35, 37, 39, 114].

Given that in most studies the CF behavior of AVs is set based on assumptions, the resulting impacts also differ among researchers. Regarding the mobility impacts, researchers reported that higher PRs of AVs and CAVs reduce travel time and increase capacity and throughput [37, 39, 41, 44, 112]. However, other studies claimed that in a mixed driving environment where AVs interact with HDVs, the capacity degrades [40, 45], and travel time increases [115]. In addition, it is reported that in higher speed limits, the impact of AVs on Freeway capacity is significant. In contrast, in lower speed limits, the change is not considerable [116]. Meanwhile, most studies reported that CAVs outperform AVs in many aspects due to their communication capabilities. Second, regarding safety impacts, most studies suggested that by increasing the PR of AVs, the total number of conflicts in the network reduces significantly. Some also highlighted the negative impacts of AVs on roundabout safety [117].

Meanwhile, in our research detailed in Chapter 7, we utilized an optimized CF behavior of AVs for conducting the impact assessment. The findings of our study reveal that a mixed environment of AVs and HDVs increases the network travel time, vehicle time loss, and average flow. Regarding the safety, our research revealed that a comparable mix of AVs and HDVs might result in an increased number of conflicts. Since different driving behaviors of AVs and CAVs may lead to the frequent adjustment of driving actions, the number of conflicts increases. However, with higher PRs of AVs (e.g. more than 80%), the total number of conflicts significantly reduces in comparison to a fully HDV environment. With 100% AV PR, the total number of conflicts decreases by around 25%.

The inconsistent conclusion on the impacts of AV PRs could be associated with two main influencing factors: the assumption on the potential CF parameters of AVs driving behavior and the scope of the study.

First, a cautious driving behavior assumed for AVs results in more smoother and safer behavior in the network which results in improved safety. Whereas, an aggressive behavior (driving closer to the leading vehicle and reacting faster) results in improved traffic efficiency reported in literature. In contrast, our optimized view on the driving behavior of AVs, result in improved safety in the network without deteriorating the traffic efficiency. Another important aspect is the scope of the study, most studies conduct the impact assessment on freeways and highways, where the fluctuation of traffic flow elements is not huge. Thus, AV driving behavior brings a significant change in efficiency and safety. In contrast, in an urban network, many other influencing factors such as the type of roads, number of lanes, type and number of intersections, curvatures, control devices, speed limits, and more could have direct impacts on the driving performance and impress the potential effects of driving behavior itself. In other words, these influential factors could diminish the effects of AV driving behavior on traffic efficiency. Therefore, in this research, the findings differ for efficiency evaluation. A similar result is also reported by [115], where the investigation is conducted at the network level. On the other hand, regarding safety, driving behavior significantly affects the number of conflicts. Since a conflict occurs between two vehicles (following and leading) in a short period and is unrelated to the entire vehicle's trip, the driving behavior is responsible for any possible conflict.

8.2 Limitations and Directions for Future Research

The proposed methodological models and experimental setup for conducting the impact assessment of AVs in urban network have successfully addressed the goals and sub-objectives of this dissertation. However, like all research, this dissertation is not without limitations that could potentially raise new lines of work for further studies. This section is divided into two parts: (i) limitations related to AV behavioral modeling and impact assessment, and (ii) recommendations and directions for future research.

8.2.1 Limitations

This dissertation focuses on two key aspects of AVs in mixed traffic: the modeling of AV driving behavior and the impact assessment of AV deployment scenarios. Within each of these areas, several limitations exist that should be acknowledged.

In this dissertation, we developed two modelling approaches (mathematical and data-driven) to replicate the driving behavior of AVs. Regarding the mathematical model, the proposed optimization framework finds the optimal CF model parameters for AVs. However, the key limitation was that this framework was tested in one study area. The experimental findings of this research are limited to similar study area, and demand patterns, and therefore could not be generalized in all traffic situations. Second, the extracted optimized CF model parameters are limited to AVs, where an AV only communicates with the leading vehicle through its sensor. However, in real application, it is expected that all AVs might have communication capabilities with other AVs (CAVs). Third, the generated optimal parameters are only related to CF configurations, whereas, considering both CF and LC models would bring new insight into the optimal driving behavior of AVs.

Regarding the data-driven models, the major limitation of our proposed model is that it is not integrated into a simulation tool and thus it can not be used in impact assessment study. Second, the model is trained with HighD dataset, given that HighD dataset is gathered from highways and includes only human-driven cars and trucks. Third, the proposed model only considered the past trajectories involving the coordinates of AVs, however, other important data sources, such as LiDAR and Radar with more features are not considered.

Similarly, in conducting the impact assessment, we faced several challenges that limited our investigations. First, while conducting the impact assessment of AVs PRs, we only consider the changes associated to driving behavior, whereas infrastructure related factors are ignored. By deployment of AVs in our transportation system, we might also witness substantial changes in infrastructure and traffic regulations. These changes may include smart traffic control devices, speed limit and lane-free traffic regulation, and more. Second, we considered a fixed driving behavior for human-driven vehicles resulted from the calibration process. However, the behavior of human-driven vehicles might also change with different PRs of AVs. Third, the findings of our impact assessment is related to a specific CF model, where it might give different results when a different modelling technique is used.

8.2.2 Recommendations and Directions for Future Work

Based on the limitations mentioned in Section 8.2.1, this dissertation highlights several areas for further research that are crucial to improving the modelling techniques for AVs driving behavior and impact assessment. This section offers recommendations for follow-up studies that address these challenges, alongside suggestions to overcome the aforementioned limitations.

Optimization Framework:

Future research should focus on the advanced calibration and validation of AV behavioral models, using real-world data from AVs to enhance model accuracy. While the optimization framework developed in this study is robust, its potential will be fully realized when more extensive AV-specific datasets are available. Collaborations with AV manufacturers or pilot projects could facilitate data collection across diverse traffic conditions, significantly improving the calibration of CF models. In addition, the current framework optimizes AV behaviors based on policy targets such as safety and efficiency. Expanding the framework to incorporate new policy goals, like environmental sustainability and equitable mobility, could offer more comprehensive insights into AV impacts. Research in this area could integrate emissions reduction and access equity into the optimization process, providing a broader perspective on AV deployment.

There is also a need to extend simulation scenarios to different network types. While this study focused on urban networks, the effects of AVs in highways, rural roads, and suburban areas remain underexplored. Future research should incorporate these varied settings to better understand how AVs perform across diverse infrastructures and traffic patterns. Another important direction is the study of mixed traffic dynamics, particularly how human drivers adapt to AVs over time. Long-term simulations could reveal how driving behaviors evolve as AV penetration increases, influencing safety and deployment strategies. Further development of Surrogate Safety Measures (SSMs) is also recommended. While this study took an important step forward in safety analysis, more nuanced and diverse SSMs could better capture the safety impacts, especially in complex urban environments with significant pedestrian and cyclist activity.

As vehicle-to-everything (V2X) communication systems are increasingly integrated into AV operations, models should account for these technologies. Future research should incorporate V2X capabilities into simulation environments to better predict how AVs communicate with infrastructure and other vehicles, improving traffic flow and safety. Additionally, testing the robustness of the optimization framework under a variety of traffic conditions, including unpredictable events such as accidents or road closures, will be crucial to adapting AVs for real-world scenarios. Finally, further sensitivity analysis exploring AV behavior in response to diverse policy objectives, such as minimizing environmental impacts or promoting public transport integration, will offer deeper insights into how AVs can align with broader societal goals.

Deep Learning-Based Trajectory Prediction Model:

In the domain of trajectory prediction, future research should investigate the integration of multi-modal sensing data, such as lidar, radar, and camera inputs, to improve prediction accuracy in complex urban environments. While this study relied on highway datasets (e.g., HighD and NGSIM), urban traffic scenarios with intersections, pedestrians, and mixed road users present additional challenges. Future studies should apply the model to these urban networks and incorporate data from a broader range of road users, such as cyclists and buses, to better capture the dynamics of urban traffic.

There is also an opportunity to enhance the generalization of the model across diverse datasets. While transfer learning was successfully applied, testing the model in a wider variety of environments—including rural roads and high-density urban areas—will improve its robustness and applicability. Furthermore, the current models do not explicitly incorporate traffic rules such as speed limits, traffic lights, or lane restrictions. Future research should integrate these regulatory constraints into the trajectory prediction models to ensure compliance with legal and road regulations, thus improving the real-world applicability of the predictions.

Optimizing the computational efficiency of trajectory prediction models is another promising direction. While the current model performs well, further optimizations, such as using more efficient graph convolution methods or hardware acceleration (e.g., GPUs or TPUs), could enhance real-time processing, particularly for large-scale implementations. Moreover, future research should consider human-in-the-loop simulations to reflect mixed traffic scenarios, where AVs interact with human-driven vehicles. This approach could provide valuable insights into how human drivers respond to AV behavior, contributing to a better understanding of safety and acceptance in real-world deployments.

Additionally, as traffic systems evolve, there is a need to adapt models for lane-free environments, such as autonomous-only lanes or shared spaces with no clear road markings. These environments will offer greater flexibility in vehicle movement and trajectory planning. Finally, future studies should explore how improved trajectory prediction can impact broader traffic efficiency, congestion, and safety in mixed AV-human traffic environments. Integrating trajectory prediction models into traffic simulation tools could help assess the effects of AV deployment on traffic throughput, traffic conflicts, and fuel consumption.

Impact Assessment:

For more accurate impact assessments, future research should prioritize refining AV behavioral models to capture the complex decision-making processes of AVs, particularly in challenging situations such as lane-merging, pedestrian interactions, or responding to unexpected events. Real-world AV trajectory data and advanced data-driven models could significantly enhance the behavioral accuracy of these simulations. Machine learning techniques could also be leveraged to improve AV control algorithms, further enhancing the realism of AV behaviors in traffic simulations.

Improving models of interactions between AVs and human-driven vehicles in mixed traffic is also crucial. Human drivers' responses to AVs are not yet fully understood, and future studies should explore the long-term adaptation of human drivers to AV presence. Conducting human-in-the-loop simulations or real-world trials could offer valuable insights into these evolving dynamics. Expanding the scope of deployment scenarios beyond urban networks is another key area for future research. Rural areas, highways, and suburban settings offer different challenges, and understanding how AVs perform in these environments will help generalize their potential impacts on traffic efficiency, safety, and environmental outcomes.

As AV adoption increases, there will be shifts in travel demand, trip frequency, and modal choice. Future studies should incorporate dynamic traffic demand models to reflect these changing mobility patterns. Such models could also capture induced demand or shifts to AV-based public transport systems. Additionally, as AV technology continues to evolve, future research should develop flexible models that can adapt to advancements in AV capabilities, such as improved V2V communication or enhanced sensors.

Beyond traffic flow and safety, future impact assessments should include broader metrics related to environmental and social outcomes, such as emissions, energy consumption, and equity in AV access. Finally, addressing regulatory uncertainties is essential. Future studies should simulate the effects of different regulatory approaches—such as AV-only lanes, AV speed limits, or taxation incentives—on AV behavior and traffic network performance. A better understanding of how these policies influence AV deployment and interactions with human-driven vehicles will be invaluable for shaping effective AV regulations.

9 Conclusion

This doctoral dissertation consolidates the research conducted by Sadid and Antoniou [1, 34, 65, 68], focusing on the microscopic behavioral modeling and simulation-based evaluation of AV deployment scenarios. The research addresses several critical research questions and fulfills the primary objective and sub-objectives related to AV modeling and impact assessment in urban traffic systems.

Within the scope of this dissertation, various modeling approaches, including both mathematical and data-driven models, were investigated to assess the state-of-the-art, identify research gaps, and explore the potential for developing more accurate CF models for AVs. In addition to modeling, several key aspects of impact assessment studies—such as impact areas, KPIs, and reported effects of AV deployment—were identified and discussed.

A core contribution of this dissertation is the development of an optimization framework designed to extract optimized parameter values for widely used CF models, enabling a more realistic replication of AV driving behavior in urban traffic contexts. This framework allows for more accurate simulations of AV impacts by fine-tuning driving behaviors to meet specific traffic objectives, such as reducing travel time or enhancing safety. The findings from this framework were then used in an impact assessment study, presented in Chapter 7, to evaluate how different AV deployment scenarios influence traffic performance.

Furthermore, a novel deep learning-based trajectory prediction model was introduced to capture AV driving behavior. This model utilizes a dynamic STGCN model to predict the trajectories of AVs, considering both CF and LC configurations. By leveraging historical driving data, the model can accurately forecast future driving actions, significantly enhancing the ability to model complex AV interactions in real-world scenarios.

The final impact assessment study examined how varying PRs of AVs affect traffic efficiency and safety in urban networks. In this research, the optimized driving behavior of AVs was used to mimic the potential AV driving patterns. The results revealed that while AVs have the potential to enhance road safety, especially at higher PRs, their influence on traffic efficiency is more limited, particularly under current infrastructure and traffic management systems. These findings underscore the importance of further optimizing AV driving behaviors and adjusting traffic infrastructure to maximize the benefits of AV deployment in urban environments.

In conclusion, this dissertation advances the state-of-the-art in AV modeling and impact assessment by providing novel methodologies for simulating AV behavior, developing data-driven prediction models, and conducting comprehensive impact assessments.

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REVIEW

Modelling and simulation of (connected) autonomous vehicles longitudinal driving behavior: A state-of-the-art

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Abstract
Microscopic traffic models (MTMs) are widely used for assessing the impacts of (connected) autonomous vehicles ((C)AVs). These models utilize car-following (CF) and lane-changing models to replicate the (C)AVs driving behaviors. Numerous studies are being lately published regarding the approximation of the driving behaviors of (C)AVs (especially CF behavior) with many state-of-the-art modelling methods. Still, there is no established CF model to mimic the accurate behavior of (C)AVs. Researchers often utilize existing mathematical CF models as well as limited data-driven models for (C)AVs modelling. Meanwhile, several studies conduct simulation-based impact assessments with various key performance indicators (KPIs). Identification of these KPIs is a crucial step for future studies. Hence, this paper presents a comprehensive outlook on different CF models with their adopted parameters for (C)AVs modelling and investigates how and in which aspects might the CF behaviors of (C)AVs are different from human-driven vehicles. In addition, the recent publications in data-driven CF models including their methodologies are explicitly discussed. This work also reviews simulation-based studies with the reported impacts and used KPIs. Finally, in light of the findings of this paper, several future research needs are highlighted.

1 | INTRODUCTION

With the development of advanced driving assistance systems (ADAS), such as adaptive cruise control, cooperative adaptive driving control, lane keeping assistance, or emergency brake assistance, our future transportation system is not far away from the revolution of autonomous vehicles [1]. We will soon witness a different traffic situation, where vehicles with a high degree of automation interact with low-level automated vehicles [2]. According to the Society of Automotive Engineers (SAE), vehicles are classified based on the degree of automation from non-automated (level 0) to full automation (level 5) [3]. Full automation level is commonly known as full self-driving, autonomous or driverless vehicles, where the vehicle itself is responsible for all safety functions and navigation of the road [1, 4].

The recent advanced sensing technologies (e.g. radar, lidar) and pattern recognition together with processing capabilities of artificial intelligence enable autonomous vehicles (AVs) to detect the precise image of the surrounding environment and react accordingly with the help of complex machine learning algorithms. Meanwhile, pervasive communication technologies allow AVs to exchange their driving status (i.e. speed, acceleration, position, and more) with other connected vehicles (V2V), as well as infrastructure (V2I), which is labeled as connected autonomous vehicles (CAVs) [5, 6]. In the remainder of this article, where applicable, we use the term (Connected) autonomous vehicles-(C)AVs to summarily describe AVs+CAVs.

(C)AVs have the potential to largely change traffic safety, mobility pattern, and transport network. It is expected that (C)AVs could improve traffic safety as a large number of accidents are associated with the drivers' errors and unfitness to drive (e.g. fatigue, alcohol, or drugs) [7–9]. (C)AVs open more mobility freedom by removing driving barriers, such as disability, driving license and old age [10, 11]. Meanwhile, (C)AVs could potentially change travel behavior, reduce traffic congestion [12], fuel consumption [13–15], and vehicle emissions [14], however, their certain effects are quantitatively not confirmed yet [4, 16]. Several corridor-wide trials of AVs have been conducted to estimate the impacts, however, due to large costs of AV fleets, as well as legal restrictions, large-scale tests are currently impractical. Researchers conduct simulation-based assessments to extrapolate the potential impacts of (C)AVs on a large-scale using traffic models. Especially several studies utilized microscopic traffic models (MTMs) to analyze and predict the impacts of (C)AVs on safety and traffic efficiency [6, 17–19].

The driving behavior of (C)AVs might significantly differ from human-driven vehicles. In MTMs, these behaviors are modelled with their longitudinal and lateral configurations. Longitudinal and lateral dynamics of a vehicle are also called car-following (CF) and lane-changing behaviors, respectively. A CF model is comprised of a set of actions that a driver decides on to follow the leading vehicle efficiently and safely. Several mathematical CF models have been developed to estimate driving behavior under various traffic conditions. However, many studies criticized the limitations of these models in capturing the diversity of driving behavior, as these models are simplified and only contain a small number of parameters [5, 20, 21]. Hence, data-driven models have attracted attention to replicate the complex driving behavior more accurately.

While most of the mathematical, as well as data-driven models, are used for modeling human-driven vehicles, there is no established CF model of the behavior of (C)AVs. Most of the researchers adopt and modify the parameters of the existing CF models to study the driving maneuvers of (C)AVs. Meanwhile, machine learning-based models are also developed based on human-driven vehicles' trajectories [due to limited (C)AVs traffic data], and thus can not guarantee to fully approximate the behavior of (C)AVs. However, the proposed methodologies in these studies could be potentially used for (C)AVs modelling, when field data of (C)AVs are available.

Numerous review articles have been published relevant to (C)AVs modelling in MTMs (e.g. [5, 20, 22]). For instance, [5] reviewed the summary of studies relevant to (C)AVs CF models and their impact assessments, where [20] recently reviewed the traditional CF models utilized for modelling (C)AVs including simulation tools. However, in both studies, they do not discuss how largely the CF behavior of (C)AVs differs from the human-driven vehicles. Mathematical CF models are comprised of relations and parameters to capture the driving behavior of vehicles. It is expected that the CF behavior through acceleration distributions, safety gaps, reaction time, and other CF model-related parameters of the (C)AV under specific traffic situation are different from human-driven vehicles. Researchers assume that (C)AVs could drive very close to the leading vehicle, and react very fast. However, the magnitude of these differences is subjective among researchers and have not addressed in the above-mentioned review articles . In addition, existing review papers cover the general impacts of (C)AVs on safety, mobility and the environment in various scenarios. However, key performance indicators (KPIs) used in simulation-based studies involving (C)AVs are not specifically reported. Hence, to fill these research gaps, a review reporting specific values of the mathematical CF model parameters for capturing the behavior of (C)AVs, as well as the identification of the KPIs for (C)AVs related studies under different situations is a necessity. It fosters a wide understanding of the potential driving behavior of (C)AVs from a scientific perspective and also helps future simulation-based impact assessments to select proper KPIs and CF model parameters. In addition, the output of this review will reveal interesting research gaps on (C)AVs modelling and impact assessment.

On the other hand, [22] studied research works related to the microscopic modelling of CAVs including traditional and newly developed models. However, there have been many recent studies utilizing machine learning techniques to model CF behavior. Several studies have proposed new methods to develop data-driven CF models. Since in existing review papers these data-driven models are not reported, a more recent review to cover the studies which have been recently published is required. Therefore, considering the above limitations, research gaps and the importance of the (C)AVs modelling and simulation-based impact assessment, this paper aims to provide a comprehensive review of relevant studies in the field of (C)AVs modelling, and impact assessments.

The collection of these articles follows a semi-structured approach. The reviewed articles in this paper include journal papers, conference papers, and technical reports. First, we gathered studies from the Scopus search engine using 8 keywords (*autonomous vehicles, connected autonomous vehicles, self(-)driving cars, car following models, simulation of autonomous vehicles, autonomous vehicles modelling, data-driven car following models, autonomous vehicles impact assessments*) for the publication year range 1990 - June 2022. The obtained papers were further screened according to their relevance and topics. Additionally, we collected related articles from the references of the screened papers. To have a general idea about different CF models, some studies related to CF models have been included.

The main contributions of this research work are as follows: (i) Overview of different CF models with their adopted parameters for (C)AVs modelling. This leads to understand how potentially the CF behavior of (CAVs) is different from human-driven vehicles and which CF model parameters are more crucial and sensitive in differentiating (C)AVs from human-driven vehicles. (ii) Summary of the lately published data-driven models for (C)AVs CF behavior, and (iii) Identification of set of KPIs used for impact assessments and the revealed impacts. This section reports the importance of KPIs in impact assessment studies, and reveals an outlook for future studies on usage of a certain KPI for a specific study area and under different conditions.

The remainder of this paper is structured as follows: In the following section, we review the recent literature on mathematical CF models for (C)AVs and adopted parameters. In Section 3, we introduce a summary of data-driven models mimicking (C)AVs CF behavior. Identification of KPIs utilized in impact assessments and the revealed reports are presented in Section 4. Finally, a conclusion in Section 5 explains the overall contribution of this article alongside further research directions.

2 | MATHEMATICAL CAR FOLLOWING MODELS

Driving behavior is the key element in microscopic traffic modelling and simulation. (C)AVs have significantly different driving behaviors in comparison to human-driven vehicles. These differences are due to sensing and communication technologies integrated in (C)AVs. AVs for instance have the ability to sense necessary information from the leading vehicles, whereas for CAVs, a stream of data (such as position, speed, acceleration etc.) are exchanged among CAVs as well as between CAVs and infrastructure (thanks to V2V and V2I communications). In case of human-driven vehicles, it is the driver who is responsible to capture the environment and act accordingly. Therefore, the driving behavior parameters, especially parameters for CF behavior such as acceleration, deceleration, desired speed, minimum gap etc. for human-driven vehicles, AVs and CAVs are different.

For human-driven vehicles, there are many established mathematical models to mimic their CF behavior. Most of these models focus on a driver's physical actions such as desired speed, acceleration, deceleration (i.e. Gazis-Herman-Rothery (GHR) model [23], Gipps model [24], intelligent driver model (IDM) [25], optimal velocity model (OVM) [26]), however, some also consider the psychological inputs of the drivers (i.e. Wiedemann model [27]). For (C)AVs simulation, however, there are no established models. A recent review of literature shows that a considerable amount of studies utilizing conventional mathematical models (i.e. IDM [25] and modified versions, MIXIC [28], Wiedemann [27], Krauss [29] etc.) to approximate the CF behavior of (C)AVs in a microsimulation framework [18, 30–33]. In many studies, the modelling of Adaptive Cruise Control (ACC) and Cooperative Adaptive Cruise Control (CACC) are refereed to AVs and CAVs modelling, respectively [18, 34–36].

2.1 | Intelligent driving model (IDM)

IDM and its modified versions are broadly used CF models for (C)AVs microsimulation studies [19, 37–44]. IDM first developed by [25] is one of the simplest and accident-free model which uses both the desired speed and space headway to generate realistic acceleration profile. The model ignores the reaction time, therefore, it and its modified versions can replicate the characteristics of AVs and CAVs, respectively. The basic form of IDM acceleration function is expressed as:

$$a_n(t) = a_{\max}^{(n)}\left[1-\left(\frac{V_n(t)}{V_0^{(n)}(t)}\right)^{\delta}-\left(\frac{S_n{}^*(t)}{S_n}\right)^2\right], \tag{1}$$

where $a_{\max}$ is the maximum acceleration/deceleration of the vehicle n, V_n is the speed of the following vehicle, $V_0^{(n)}$ is the desired speed of the following vehicle, S_n is the gap distance between two vehicles, $S_n{}^*$ is the desired spacing between two vehicles (see Figure 1), and δ is the model parameter.

The model is comprised of three terms. When the distance between the leading and following vehicles is relatively high, the third term becomes negligible, and thus the model acts as a free-flow model, where the desired speed of the driver controls the acceleration of the vehicle. On the other hand, for closer space headway between vehicles, the following vehicle will apply the CF strategy and reduce the free-flow acceleration by the magnitude of third term in Equation (1). Thus, one single equation can mimic both free-flow and CF regimes depending on different situations. Meanwhile, the desired space headway between two vehicles $S_n{}^*$ is a function of the following vehicle speed V_n, and the speed difference between the leading and following vehicles ΔV_n, which can be calculated using Equation (2):

$$S_n{}^*(t) = S_0{}^{(n)} + V_n(t)T_n(t) + \frac{V_n(t)\Delta V_n(t)}{2\sqrt{a_{\max}^{(n)}b^{(n)}}}, \tag{2}$$

where $S_0{}^{(n)}$ is the minimum spacing at standstill situation, T_n is the desired (safe) time headway, and $b^{(n)}$ is the desired (comfortable) deceleration. The maximum acceleration and a comfortable deceleration rate ensure that the model does not produce unrealistic high acceleration/deceleration.

IDM was later extended by [45] to replicate the driving style adaptation effect to the surrounding traffic using a memory function. The IDM with memory (called IDMM) assumes that after experiencing congested traffic for while, most drivers adapt their driving behavior, for instance by increasing their desired time gap to the leading vehicle. According to [45], a single internal dynamic impacts the desired time gap decision. Thus, the new desired time gap $T_n(t)$ in Equation (2) is replaced by $T_n(\lambda)$, which is approximated as follows:

$$T_n(\lambda) = T_n\left[\beta_T + \lambda_n(1-\beta_T)\right], \tag{3}$$

where $\beta_T = T_{jam}/T_n$ is an adaptation factor, λ_n is the subjective level of service which takes values between 0 (standstill traffic) and 1 (free-flow traffic).

There exist many revised versions of IDM, each with different objectives [17, 19, 37, 38, 46–48]. For instance, [46] introduced some multiplication factors to ensure smooth driving behavior in different traffic situations (i.e. free-flow, upstream front, congested traffic, bottleneck, downstream front). It is assumed that the maximum acceleration of a vehicle is increased when leaving congestion, and the comfortable deceleration is decreased when an upstream-front is detected. Depending on

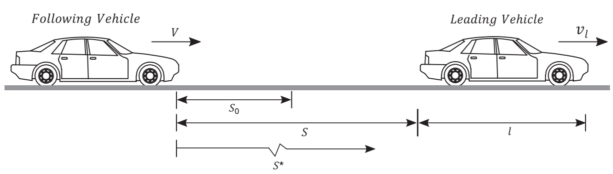

FIGURE 1 Illustration of IDM CF model parameters.

TABLE 1 Multiplication factors of IDM Model [46].

Traffic situation	λ_a	λ_b	λ_c	Driving style
Free flow	1	1	1	Comfort driving
Upstream front	1	1	0.7	Safe driving
Congestion	1	1	1	Comfort driving
Bottleneck	0.7	1.5	1	Breakdown prevention
Downstream front	0.5	2	1	High dynamic capacity

TABLE 2 IDM parameters for AVs modelling [18, 19].

Model parameters	Values
Desired speed (V_0)	120 km/h
Model parameter (δ)	4
Maximum acceleration ($a_{\max}$)	1.4 m/s^2
Desired deceleration (b)	2 m/s^2
Minimum gap distance at standstill (S_0)	2 m
Desired headway (T)	0.6 s
Maximum deceleration	2.8 m/s^2

the which state is noticeable in next time step, the following factors are multiplied by the main IDM model parameters:

$$a^{(s)} = \lambda_a{}^{(s)} \cdot a, \quad b^{(s)} = \lambda_b{}^{(s)} \cdot b, \quad T^{(s)} = \lambda_T{}^{(s)} \cdot T,$$

where the superscript (s) indicates the traffic situation, a, b and T are maximum acceleration, comfort deceleration, and time gap, respectively. The values of the multipliers are listed in Table 1.

IDM model generates unrealistic deceleration rates when the gap is significantly lower than the desired gap. To avoid this, [19] combined the IDM with the Constant Acceleration Heuristics (CAH). The CAH is developed based on three main assumptions: (i) the acceleration of the following and leading vehicles will not change in the near future (in a few seconds), (ii) safe time headway or minimum distance is not required at any moment, and (iii) reaction time is neglected (drivers react without delay). To calculate the maximum acceleration of a vehicle while keeping the situation crash-free, two possible conditions (zero or nonzero velocity of the leading vehicle) at the time where the minimum gap is reached are distinguished. Hence, the maximum acceleration a_{CAH} given actual values of the gap s, velocity of the following vehicle v_f, velocity and acceleration of the leading vehicle v_l, a_l is expressed as:

$$a_{CAH} = \begin{cases} \frac{v_f{}^2 \cdot \bar{a}_l}{v_l{}^2 - 2s \cdot \bar{a}_l} & \text{if } v_l\left(v_f - v_l\right) \leq -2s \cdot \bar{a}_l \\ \bar{a}_l - \frac{\left(v_f - v_l\right)^2 \Theta\left(v_f - v_l\right)}{2s} & \text{otherwise} \end{cases}, \tag{4}$$

where $\bar{a}_l = min(a_l, a_f)$ is the effective acceleration, which avoids the artifacts that may cause by a leading vehicle with higher acceleration capabilities. The Heaviside step function Θ is used to eliminate negative approaching rates. [19] proposed an ACC model by combining the acceleration from the IDM and CAH. Depending on the CF situation, the decisive acceleration of the ACC vehicle is controlled by a comparison of the IDM and CAH acceleration profiles as follows:

$$a_{ACC} = \begin{cases} a_{IDM} & \text{if } a_{IDM} \geq a_{CAH} \\ (1-c) \cdot a_{IDM} + c \cdot [a_{CAH} & \\ +b \cdot tanh(\frac{a_{IDM} - a_{CAH}}{b})] & \text{otherwise} \end{cases}, \tag{5}$$

where the coolness factor c is an additional parameter compared to the original IDM model, which is assumed 0.99 in [19].

In addition, [47] attempted to improve the safety of IDM model by modifying the desired gap equation (Equation 2) by adding a new term ($c_n \frac{v_n^2}{b_n}$). The new term indicates that with higher velocities, the desired minimum gap increases, and consequently the driver safety is improved. In addition, [37] added a reaction time variable in the original IDM acceleration equation. This study assumes that the reaction time variable can reasonably distinguish AVs from human-driven vehicles. The model parameters are adopted from literature with few adjustments. For instance, the time headway and reaction time for AVs are assumed 1 s and 0 s respectively. On the other hand, [38] proposed an improved IDM model to consider multi-front and rear vehicles. The model generates the acceleration profile of the following vehicle by employing information of multiple front and rear vehicles. Weight factors are added to each vehicle's information depending on their locations. The model parameters are based on assumptions by the authors.

The basic IDM model has been widely used to approximate the driving behavior of AVs in several studies. However, the main difficulty of the model is the observation of desired measures such as desired spacing, desired time headway, and desired speed for AVs. Thus, several studies used the IDM parameters from the literature which are either based on assumptions or limited field experiments. The parameters of AVs behavior utilized in many simulation studies are presented in Table 2.

Recent studies such as [17, 33], and [41] utilized IDM and its modified versions to conduct (C)AVs impact assessments. [17] studied the safety and mobility effects of AVs, CAVs, and connected vehicles (CVs) in a major freeway in Orlando, Florida. This study utilized the basic IDM to model the driving behavior of AVs, and a modified IDM based on [48] for CAVs modelling. In this study, a set of parameters of the IDM is adopted from [18, 19] both for AVs and CAVs modelling (see Table 2).

Similarly, [33] investigated the impacts of commercially available ACC vehicles on traffic stability and throughput. In this study, IDM is used to capture the CF behavior of human-driven, theoretical ACC and commercially available ACC vehicles. The parameters for both human-driven and theoretical ACC vehicles are take from [44, 46], where for commercially available ACC, set of calibrated parameters from the field experiment are deployed in the simulation platform. [41] utilized a revised version of IDM to study the effect of CAVs on freeway capacity. The revised IDM is based on [18] and [47] to ensure realistic behavior, and to improve the driving safety of CAVs. This study also uses the values of IDM parameters from the previous studies as depicted in Table 2. Similarly, [42] used IDM to model the behavior of ACC vehicles. In this study, several parameter settings of the IDM model are implied. In the base scenario, the parameters of the model are taken from [18, 19, 44], where other parameter settings are considered based on the commercially available ACC vehicles behavior and are taken from [18, 36].

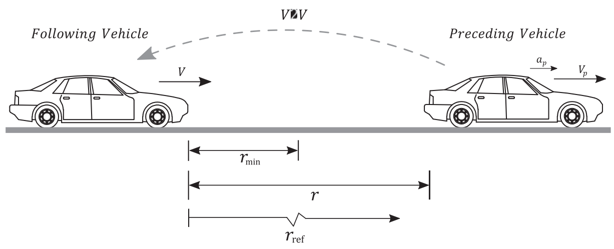

FIGURE 2 MIXIC CF model.

2.2 | MIXIC model

MICroscopic Model for Simulation of Intelligent Cruise Control (MIXIC) first developed by [28] to model ACC and later revised by the author in 2006 to incorporate CACC characteristics [49]. The model assumes that the following vehicle attempts to keep the relative speed to the leading vehicle at zero and the space gap at the desired speed. Thanks to the V2V communication, where certain driving information such as position, speed, acceleration etc. of both following and leading vehicles are exchanged. MIXIC model approximates the acceleration profile with two distinct components: (i) the controlling component, which delivers reference values, (ii) the vehicle model component, which converts the reference values into realized values. The reference acceleration can be calculated based on the speed difference of the following vehicle (intended speed and current speed) denoted as $(a_{ref,\Delta v})$ or the gap and speed differences between the following and leading vehicles symbolized as $(a_{ref,d})$. Minimum of both acceleration references $(a_{ref} = \min(a_{ref,\Delta v}, a_{ref,d}))$ is the final acceleration reference value which is the input for the vehicle control. Meanwhile, the model considers the comfort driving behavior, and thus a_{ref} is limited to maximum acceleration of 2 m/s^2 and comfort deceleration of -3 m/s^2. The estimation of the reference acceleration based on speed difference is as follows:

$$a_{ref,\Delta v} = k \cdot (v_{\mathrm{int}} - v), \tag{6}$$

where v_{int}, and v are intended and current speed, respectively, and k is the speed error factor constant.

The reference acceleration based on the speed and gap differences between the following and leading vehicles is calculated as:

$$a_{ref,d} = k_a \cdot a_p + k_v \cdot \left(v_p - v\right) + k_d \cdot \left(r - r_{ref}\right), \tag{7}$$

where a_p and v_p are the leading vehicle's acceleration and speed, respectively, r and r_{ref} are the current and reference gap to the leading vehicle as depicted in Figure 2, k_a, k_v, and k_d are the constant factors. The reference gap (r_{ref}) is defined as: $r_{ref} = \max(r_{safe}, r_{system}, r_{\min})$, where r_{safe}, r_{system}, r_{min} are the safe following distance, following distance based on the system time setting, and minimum following distance (set to 2 m), respectively. The safe following distance is a function of the deceleration capabilities of the following vehicle (d) and the leading vehicle (d_p) and is expressed as:

$$r_{safe} = \frac{v^2}{2} \cdot \left(\frac{1}{d_p} - \frac{1}{d}\right). \tag{8}$$

Similarly, the following distance according to the system time setting (time gap) is computed as: $(r_{system} = t_{system} \cdot v)$. If the leading vehicle is equipped with CACC, t_{system} is set to 0.5 s, and 1.4 s otherwise.

[6] further developed a CAV model based on the MIXIC model. The proposed model also considers the sensor detection ranges of CAVs; however, the model parameters remain the same as the MIXIC model. According to [49], the model parameters are chosen as: $k = 1.0$, $k_a = 1.0$, $k_v = 0.58$, and $k_d = 0.1$.

Several studies utilized MIXIC and developed models based on MIXIC to conduct impact assessments of CAVs [6, 49–54]. For instance, [49] used MIXIC model to evaluate the influence of CACC on traffic flow characteristics. [39, 53] utilized the enhanced MIXIC model based on [6] to mimic the driving behavior of CAVs. This study approximates the driving behaviors of CAVs using CACC vehicles while cruising. Similarly, [51] recently used MIXIC model with default parameters values to replicate the driving behavior of (C)AVs and conduct impact assessments.

2.3 | ACC and CACC models

[54] developed a control algorithm similar to MIXIC to estimate the speed of an ACC-equipped vehicle in the next time steps. The proposed control method consists of two modes: (i) speed control mode, and (ii) gap control mode. The speed control mode aims to keep the speed of the following vehicle close to the speed limit, whereas in the gap control mode the goal is to maintain the desired gap between the two vehicles. According to this approach, the acceleration of a vehicle under the following conditions is controlled both by speed and gap and calculated as:

$$a = k_g(s - s_d) + k_s(v_d - v), \tag{9}$$

where k_g and k_s are the gap and speed control constants, s is the current space gap, $(s_d = t_d \cdot v)$ is the desired distance between

TABLE 3 ACC-CACC model parameters.

Model parameters	Values
Desired time gap (t_d)	1.5 s (ACC), 0.7 s (CACC)*
Max. acceleration (a)	2 m/s^2
Max. deceleration (b)	-2 m/s^2
Constants (k_g, k_s)	-0.4, 0.25

*The average time gap of field test vehicles.

two vehicles, t_d is the desired time headway, and v_d is the desired speed. On the other hand, the acceleration of a vehicle under free-flow situations is only controlled by the speed and it is described as:

$$a_f = \max\left(\min\left(k_s(v_d - v), a\right), b\right), \tag{10}$$

where a and b are the maximum acceleration and deceleration, respectively. The minimum of the CF acceleration and free-flow acceleration is the decisive acceleration which is the input for estimation of the vehicle's speed in the next time step.

$$v_{t+\Delta t} = v_t + \min\{a, a_f\} \cdot \Delta t. \tag{11}$$

Utilizing the above model, [54] investigated the effects of CACC system on freeway traffic flow with different market penetration rates. In this study, certain parameters of the control algorithm are based on set of assumptions, where the desired time gap for ACC and CACC were extracted from the field test (see Table 3). The ACC-CACC model by [54] was used in [39, 53] to model the driving behavior of AVs and to study the impact of (C)AVs on traffic flow and CO_2 emissions. In [39], the parameters of the model are adjusted as follows: $t_d = 1.6$ s, $a = 2$ m/s^2, and $b = -3$ m/s^2.

[18] further improved the ACC model based on experimental results. In this study, the maximum acceleration and deceleration were limited to 1 and 2.8 m/s^2, respectively. On the other hand, [36] developed the ACC and CACC models utilizing experimental data from a field test of production vehicles. The model consists of a gap regulation and gap closing controllers. The simplified version of this model is applied in [18]. The gap error and its derivative are used to estimate the vehicle speed on each control cycle. The gap error of the n-th consecutive vehicle (e_n) is expressed as:

$$e_n = x_{n-1} - x_n - t_w \cdot v_n, \tag{12}$$

where x_{n-1} is the current position of the leading vehicle, x_n and v_n are the current position and speed of the following vehicle, respectively, and t_w is the time gap. The goal of the gap regulation controller is to minimize the gap error by a constant time-gap following policy. The speed of the following vehicle is therefore estimated as:

$$v_n = v_{nprev} + k_p \cdot e_n + k_d \cdot \dot{e}_n, \tag{13}$$

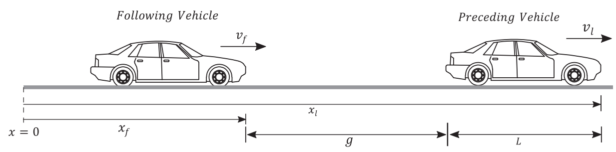

FIGURE 3 Description of the Krauss CF model parameters.

where v_{nprev} is the speed of the following vehicle in the previous iteration, k_p and k_d are the coefficients adjusting the time-gap error and its derivative ($k_p = 0.45$, and $k_d = 0.25$).

Several simulation-based impact assessment studies used the ACC and CACC models to approximate the behavior of (C)AVs. For instance, [55] used the ACC-CACC model of [54] to represent the ACC vehicle longitudinal behavior and to investigate the effects of AVs on traffic safety and efficiency . In this study, the maximum acceleration and deceleration were selected 2 and -3 m/s^2, respectively.

2.4 | Krauss model

The Krauss CF model developed by Stephan Krauss in 1997 is a space-continuous model [29]. Krauss model estimates the speed of the vehicle without deriving it from the acceleration profile of the vehicle. In Krauss model, the safe velocity of the following vehicle is calculated as follows:

$$v_{safe}(t) = v_l(t) + \frac{g(t) - v_l \cdot t_r}{\frac{v_l(t)+v_f(t)}{2b} + t_r}, \tag{14}$$

where v_l, v_f are the speed of leading and following vehicles at time t, respectively (see Figure 3), t_r is the reaction time of the driver, b is the maximum comfort deceleration of the vehicle, and $g(t)$ is the gap between the following and leading vehicles, which is computed as: $g(t) = x_l(t) - x_f(t) - L$, (x_l, x_f are the position of the leading and following vehicles, and L is average length of a vehicle). Meanwhile, to estimate the desired speed which is a decisive variable for determining the speed of the vehicle in next time step, the model takes the minimum of safe velocity, the road speed limit, and the vehicle's maximum capable speed to generate the desired speed of the vehicles, expressed as:

$$v_{des}(t) = \min[v_{\max}, v(t) + a \cdot \Delta t, v_{safe}(t)]. \tag{15}$$

Finally, the velocity and location of the vehicle at the next time step are computed as follows:

$$\begin{aligned} v(t+\Delta t) &= \max[0, v_{des}(t) - \eta], \\ x_f(t+\Delta t) &= x_f(t) + v(t+\Delta t) \cdot \Delta t' \end{aligned} \tag{16}$$

where η is the random perturbation (to capture the driving imperfection) and Δt is the simulation time step. According to [56], the η value is assumed to be 0.5 for human-driven vehicles and 0 for CAVs. In addition, several studies assumed

TABLE 4 Krauss model's parameters for different levels of automation [57].

Automation level	Mingap (m)	Accel (m/s^2)	Decel (m/s^2)	Sigma	Tau (s)
Level 0	2.5	2.6	4.5	0.5	1
Level 1	2	3.05	4.5	0.4	0.95
Level 2	1.5	3.5	4.5	0.3	0.9
Level 3	1.25	3.6	4.5	0.2	0.8
Level 4	0.75	3.7	4.5	0	0.7
Level 5	0.5	3.8	4.5	0	0.6

sigma = driving imperfection factor, Tau = reaction time.

Krauss model's parameters for (C)AVs [57]. These assumptions are often done based on the level of automation as presented in Table 4.

The findings of literature review depict that attempts have been made to study the impacts of (C)AVs using Krauss model [57–59]. [59] studied the effects of CAVs on traffic flow using the Krauss model. This research distinguishes the human-driven vehicles and CAVs by the reaction time and driving imperfection factor (sigma). The reaction time and sigma for human-driven vehicles are set to 1 s and 0.5, where for CAVs, 0.5 s and 0, respectively. Similarly, [58] investigated the impact of CAVs on signalized and unsignalized intersections safety. In this study, Krauss model is used to replicate the driving behavior of CAVs, assuming that CAVs have perfect driving behavior (sigma = 0) and can drive very close to the leading vehicle (mingap = 0.5 m), where sigma and mingap for human-driven vehicles are set to 0.5 and 1.5 m, respectively.

2.5 | Wiedemann model

The Wiedemann CF model originally formulated by Reiner Wiedemann in 1974 (also called Wiedemann 74 model) is one of the most widely used CF models. The model is the default CF model in PTV Vissim microsimulation tool. In this model, the term "perceptual threshold" is used to define threshold values for actions, that a driver perceives and responds to it. The perceptual threshold is a function of space headway and speed difference between the leading and following vehicles. The threshold values differentiate the driving regime into four parts: (i) free-flow, (ii) approaching slower vehicle, (iii) car following, and (iv) emergency braking regimes. The distribution of these thresholds is shown in Figure 4, and they are defined as:

- AX: The desired spacing between the front sides of two vehicles in standstill.
- BX: The desired minimum following distance, which is a function of AX, the safety distance, and the speed of the vehicle.
- SDV: It is the action point, where a driver consciously notices that he/she is approaching a slower leading vehicle; SDV increases with increasing speed difference between the leading and following vehicles.

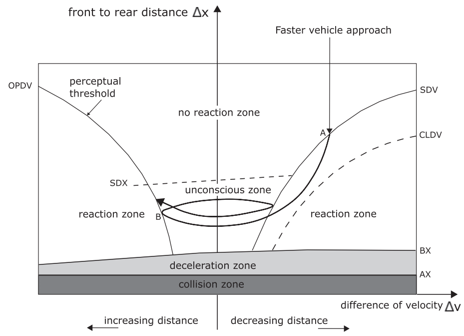

FIGURE 4 Wiedemann CF model [27].

- CLDV: It stands for closing delta velocity. Its an additional threshold that considers additional deceleration by applying the brakes.
- OPDV: The action point where a driver observes that the leading vehicle is driving fast, and thus he/she starts acceleration.
- SDX: The maximum distance when following a vehicle, which is approximately 1.5–2.5 times BX.

The model assumes that the driver acts differently in each regime, and therefore, the acceleration is estimated in each regime separately. According to the Figure 4, when a faster vehicle approaches relatively a slower vehicle, the relative distance between vehicles reduces until the deceleration perceptual threshold (SDV) is passed (point A in Figure 4). The driver will start deceleration to match the leading vehicle's speed. However, the driver also attempts to increase the space until the acceleration perceptual threshold (OPDV) is reached at point B. Then, the driver begins again the acceleration to reach the leading vehicle's speed. This process continuous in the unconscious reaction zone until it crosses the SDX line and reaches back to no reaction zone.

Besides Wiedemann 74 model, Rainer Wiedemann proposed the Wiedemann 99 CF model. Wiedemann 99 model was initially developed for replicating driving behavior on freeways, however, its application is not limited and several recent studies utilized it for urban traffic. Wiedemann 99 model is often used to represent the driving behavior of (C)AVs. In Wiedemann 99 model, besides the physical signs of driving, psychological reactions (such as observed width of the leading vehicle, visual angle change etc.) are also considered. The parameters of this model have been already extracted within the CoEXist project to capture the driving behavior of (C)AVs, however, the calibration of these parameters is based on a few AVs trajectories. The Wiedemann 99 model comprises 10 parameters, which are defined in Table 5.

[60] utilized trajectories of three test AVs (collected within CoEXist project), where two of them were driven autonomously on public roads and under normal traffic conditions to calibrate the parameters of the Wiedemann 99 model (see Table 6). Two longitudinal control communications such as CACC (which communicates with the leading vehicle) and degraded CACC referred as dCACC (without communication

TABLE 5 Wiedemann 99 CF model parameters.

Parameters	Description	Default value
CC0	Standstill distance: desired minimum distance between leading and following vehicles [m].	1.50
CC1	Time gap: desired headway time between leading and following vehicles [s].	0.90
CC2	Following distance variation: additional distance over the desired safety distance, where at this point following vehicle recognizes a slower leading vehicle [m]	4.00
CC3	Threshold for entering the deceleration zone: The time before a vehicle begins decelerating to the safety distance [s].	−8.00
CC4	Negative following threshold: negative speed variation between following and leading vehicles (the lower the value, the more sensitive the following vehicle's driver)	−0.35
CC5	Positive following threshold: a positive speed variation between the following and leading vehicles (the positive value of CC4).	0.35
CC6	Speed dependency of oscillation: influence of distance of speed variation (the larger the value, the higher the speed oscillation with increasing distance).	11.44
CC7	Oscillation acceleration: minimum variation of acceleration or deceleration while following.	0.25
CC8	Standstill acceleration: desired acceleration when starting from standstill [m/s^2].	3.50
CC9	Acceleration at 80 km/h [m/s^2]	1.50

TABLE 6 Wiedemann 99 CF model parameters for AVs modelling [60–62].

Model parameters	AV with CACC	AV with dCACC	AV cautious	AV normal	AV aggressive
CC0	4	6	1.5	1.5	1
CC1	0.3, 0.6, 1.0	1.0	1.5	0.9	0.6
CC2	0	0	0	0	0
CC3	−40	−40	−10	−8	−6
CC4	0	0	−0.1	−0.1	−0.1
CC5	0	0	0.1	0.1	0.1
CC6	0	0	0	0	0
CC7	0.25	0.25	0.1	0.1	0.1
CC8	3.5	3.5	3	3.5	4
CC9	1.5	1.5	1.2	1.5	2

with the leading vehicle) were installed on AVs in this pilot project. Meanwhile, the CoEXist project proposed modified parameters of AVs in the Wiedemann 99 model to capture different potential driving styles of AVs namely: AV cautious, AV normal, and AV aggressive as presented in Table 6.

Many articles utilized the Wiedemann 99 model with the proposed parameters by PTV Vissim to study the impacts of (C)AVs [1, 31, 32, 63–65]. Worth-mentioning that two extra driving behavior parameters are introduced within PTV Vissim simulation tool namely: the maximum look-ahead distance, and number of interaction vehicles. First, maximum look-ahead distance is the maximum area around the vehicle that can be detected by the radar and ultrasonic sensors of the AV. This parameter is usually assumed to be between 200 and 300 m. Second, the number of interaction vehicles refers to the number of preceding vehicles that the vehicle perceives downstream or adjacent to it on the same link to interact with them.

CF models for (C)AVs are not limited to established models such as IDM, MIXIC etc., several attempts have been made to propose new models, especially for ACC and CACC equipped vehicles. These proposed CF models are designed in such a way as to achieve certain objectives. Depending on various objectives, these models generate the velocity or acceleration profile of a vehicle to optimize specific policy targets including efficiency, safety, string stability, energy consumption, comfort and more [52, 66–75]. For instance, in a recent study, [66] developed a novel ACC algorithm based on model predictive control (MPC) and active disturbance rejection control (ADRC). This study considered driving safety, tracking capability, fuel economy, and comfort as the main policy targets for the optimization module. Similarly, [52] proposed a predictive cruise control approach to improve driving safety and comfort. In this study, the proposed model generates the acceleration profile of the following vehicle using the finite horizon constrained optimal control problem. In addition, [69] developed an ACC algorithm based on MPC and constraints softening. The aims is to optimize the CF requirements, safety, comfort, and economy. A detailed review of these microscopic models for CAVs is conducted by [22]. Since these methods are not integrated in microscopic simulation tools and require high computational resources, they are not widely used for impact assessment studies. Hence, a revisit is not the scope of this paper. In Table 7, the summary of reviewed simulation-based studies is presented, which describes specific information on the used CF model, vehicle type, and description of the model parameters. The table is sorted based on the publication date of the citations, which are displayed in reverse chronological order (newest to oldest).

To summarize, in most (C)AVs related studies, IDM, MIXIC and their modified versions are frequently used for modelling of (C)AVs. The Wiedemann 99 and Krauss models are also used for (C)AVs impact assessments. Depending on different CF model, researchers differentiate the driving behavior of (C)AVs from human-driven vehicles for time gap, reaction time, headway, and driving imperfection factor. Among these parameters, time gap is the most sensitive and crucial parameter which distinguishes (C)AVs from human-driven vehicles. When using IDM, it is assumed that (C)AVs could drive closer to the leading vehicle by around 50% less than the human-driven vehicles. The time headway is set 0.6 s in majority of studies for (C)AVs where this value is more than 1 s for human-driven vehicles. Considering other parameters of IDM model, researchers expected the same driving capabilities as in human-driven vehicles. Hence, maximum acceleration and comfort deceleration

TABLE 7 Summary of reviewed simulation-based studies: CF model, vehicle types, and description of the adapted parameters.

References	Year	CF model	Vehicle type	Description
[58]	2022	Krauss, IDM and CACC	CAV	Minimum headway, minimum gap, and acceleration values for all models are taken from [61], where deceleration value for CAVs is taken from [76].
[17]	2021	IDM	CAV	The parameters of the model are taken from literature as in Table 2.
[33]	2021	IDM	ACC vehicles	The parameters for both human-driven and theoretical ACC are take from [44, 46], where for commercially available ACC, set of calibrated parameters from the field experiment are deployed in the simulation platform.
[50]	2021	CACC	AV & CAV	The parameters of the model are adopted from [49].
[37]	2021	Modified IDM	AV	A reaction time variable is added in the original IDM model to distinguish AVs from human-driven vehicles. The parameters are adopted from literature where the time headway is assumed 1s for AVs.
[59, 77]	2021	Krauss	AV	Adjustments of the reaction time ($\tau = 0.5$) to mimic AVs.
[51]	2021	MIXIC	AV & CAV	The default model parameters based on [49] are used.
[78]	2021	Krauss, IDM and ACC	AV	Trajectories of human-driven vehicles were used to estimate the parameters of the models and use it for AVs.
[38]	2021	Improved IDM	CAV	The model considers multiple front and rear vehicles information to generate the following vehicle's acceleration. The model parameters are set based on assumptions.
[41]	2020	Modified IDM	AV	The parameters of the model are set as in Table 2, where the time headway between a CAV and human-driven vehicles is assumed 0.9s.
[30]	2020	IDM	CAV	The parameters' values of the model are selected from Table 2.
[76]	2020	Krauss	CAV	The emergency deceleration value was set based on a study by [79], where the values of minimum gap, maximum acceleration, and time headway are taken from [61].
[39, 53]	2020, 2018	ACC-CACC and enhanced MIXIC	AV & CAV	The parameters of ACC-CACC model are adopted from [54], where for enhanced MIXIC model the parameters are taken from [6].
[64]	2019	Wiedemann 99	CAV	The parameters of the Wiedemann 99 model are set as in Table 6, where the time headway is assumed 0.6s.
[60]	2019	Wiedemann 99	AV	The parameters of the Wiedemann 99 model are derived from empirical data (see Table 5, AV with CACC and AV with dCACC).
[32]	2018	Wiedemann 99	AV	The parameters are adopted from [1], where some modifications to the values of the parameters are set based on the assumptions.
[55]	2018	ACC-CACC and MIXIC	AV & CAV	ACC-CACC model based on [54] with default parameters, and enhanced MIXIC model of [6] are utilized.
[31]	2018	Wiedemann 99	AV	Modifications of the parameters of the model based on [61] to capture cautious and aggressive behaviors of AVs.
[57]	2018	Krauss	AV	The values of the model parameters are set based on assumptions.
[80]	2018	CACC	CACC	The parameters of CACC model are adopted from [18, 36].
[48]	2018	IDM	CAV	The default parameter values are modified from [19].
[42]	2017	IDM	ACC	The parameters the model are taken from [18, 19, 44, see Table 2].
[43]	2017	Modified IDM	AV	The enhanced IDM model includes multiplication factors for different traffic situations. The parameters are modified from [46, 81].
[6]	2016	IDM and enhanced MIXIC	AV & CAV	The model parameters are chosen based on recommendations of [49].
[1]	2016	Wiedemann 99	AV	The parameters of the model are adopted from [61], where the time headway ($cc1$) of the model is assumed (0.3s) for AVs.
[54]	2012	ACC-CACC	ACC & CACC	Parameters of the model are used from Table 3
[19]	2010	IDM with constant acceleration heuristic (CAH)	ACC	The coolness factor of the CAH is set to 0.99, where the parameters of IDM are taken from Table 2.
[46]	2007	Modified IDM	ACC	The modified IDM considers different driving situations using some multiplication factors (see Table 1), the other parameters remain as in Table 2.
[49]	2006	MIXIC	CACC	The model parameters are set as $k = 1.0$, $k_a = 1.0$, $k_v = 0.58$, and $k_d = 0.1$.

are identical for both (C)AVs and human-driven vehicles. Similarly, for MIXIC model, it is assumed that CAVs could drive with lower time gaps than human-driven vehicles. When a CAV follows another CAV, the time gap could be around three times lower than the condition when a CAV follows a human-driven vehicle. In ACC-CACC models, AVs are differentiated from CAVs by the time gap parameter. It is expected that due to the communication capabilities of CAVs and faster analysis of the surrounding environment, they could drive twice closer to the leading vehicle than the AVs.

Regarding the Krauss model, (C)AVs are differentiated from human-driven vehicles by two main parameters namely: reaction time and driving imperfection factor (sigma). Considering the reaction time, it is assumed that in comparison to human-driven vehicles where there is delay between the perception and reaction to a driving task, (C)AVs do not require extra time to react. The reaction time of (C)AVs is set to zero, where for human-driven vehicles it is more than 1 s. Meanwhile, it is expected that (C)AVs have perfect driving behavior (sigma = 0) and never make mistakes, whereas for human-driven vehicles this parameter is set to 0.5. Finally, Wiedemann model, the driving behavior of AVs is expected to be diverse, and three different driving styles are proposed (cautious, normal and aggressive). Different driving styles are categorized mainly based on the standstill distance and time gap. It is assumed that AV with aggressive driving style might have smaller distance to the leading vehicle and lower time gap. Although, many studies have the similar assumptions for potential driving behavior of (C)AVs, still there is not a concrete practical basis for the exact values of the assumed parameters. Thus, (C)AVs might behave differently than what are expected.

3 | DATA-DRIVEN MODELS

With the recent advancement in collecting high-fidelity traffic data, more accurate characteristics of driving could be achieved. Data-driven models provide the opportunity to approximate the CF behavior of human-driven vehicles as well as (C)AVs from field data. In contrast to mathematical models which are simplified and contain a small number of parameters, data-driven models have the flexibility to incorporate additional parameters that impact the driving behavior. Data-driven models require mass field data for verification and to ensure accuracy. Previous studies utilized human-driven vehicles' field data to verify data-driven models. Since the field data for (C)AVs are limited, there are explicitly few studies related to data-driven models for (C)AVs. Therefore, in this section, the aim is to review the proposed methodologies. Of course, these proposed methods could also be used for (C)AVs, when field data for (C)AVs are available. Studies relevant to the data-driven CF models can be divided into four main types: nonparametric models, artificial neural network, reinforcement learning, and deep reinforcement learning. However, many approaches have been proposed to combine mathematical models with data-driven models.

Nonparametric regression models are capable of fitting a large number of functional forms with no or weak assumptions. Attempts have been made to approximate the CF behavior using nonparametric methods [82, 83]. [82] developed a simple nonparametric CF model using the k-nearest neighbor approach. The k-nearest neighbor (kNN) is one of the simplest nonparametric method, which assumes the similarity between historical data/cases. In [82] the proposed model generates the average of the most similar driving cases. Similarly, [83] introduced a nonparametric CF model utilizing the locally weighted regression method, the Loess (locally estimated scatterplot smoothing) model. Similarly, [84] developed a nonparametric CF model to generate acceleration sequence in the next time step using a combination of the hidden Markov model (HMM) and Gaussian mixture regression (GMR). HMM is a stochastic model which is used to represent randomly changing systems. Since CF behavior has stochastic characteristics, [84] used the HMM to estimate the dependencies between the driving situation and the vehicle's acceleration. GMR on the other hand is utilized to classify different driving situation and vehicle's acceleration based on the probability distribution. Meanwhile, [85] proposed a CF model based on support vector regression to investigate the acceleration and deceleration asymmetry of driving behavior in traffic congestion environments. The model was used to obtain the equilibrium state of the vehicle during the CF process.

Several articles proposed CF models using artificial neural networks (ANNs) [86–92]. For instance, [88] introduced a CF model based on an ANN with one hidden layer. The proposed ANN takes speed, speed difference, and gap distance as inputs and generates the acceleration profile in the output layer. [89] further improved the model by considering the instantaneous reaction time delay as an extra input. In contrast to these conventional neural network-based models, recent studies proposed models considering several other influential inputs as well as the temporal variation of the data to accurately approximate driving behavior.

[93] and [94] proposed CF models using deep deterministic policy gradient (DDPG) algorithm. DDPG is a model-free method for learning continuous actions. In DDPG, two separate actor and critic networks are used. In [93] both networks are comprised of three layers: an input layer, one hidden layer, and an output layer. In the actor network, the input layer takes a state containing the speed of the following vehicle, the spacing between the following and leading vehicles, and the speed difference as inputs, where the following vehicle's acceleration is the output as a continuous action. In the critic network, the input layer includes both the state (same as the actor network) and the action (acceleration of the following vehicle), where the output layer is a generated scalar value. Different loss functions were considered in this study to maximize the output of the critic network by changing the action space of the actor network.

Similarly, [95] used real-world driving data gathered in the Next Generation Simulation (NGSIM) project to evaluate the performance of DDPG based CF model. [96] developed an encoder-decoder architecture-based CF model with transformer block to predict a long-sequence CF trajectories. The encoder uses multi-head self-attention to generate a mixed representation of past driving context utilizing historical speed and spacing data as inputs. The decoder takes the future leading vehicle speed as input and outputs the predicted future following vehicle speed profile in a generative way.

Since CF behavior of a vehicle follows a sequential pattern, several studies developed CF models based on Recurrent neural network (RNN) architecture [97–103]. [97] proposed a RNN model with the input layer containing the gap, speed difference, and the following vehicle's speed in different time steps (as a sequence), where the output is the predicted acceleration of the following vehicle in the next time step. [98] on the other hand, applied Gated Recurrent Unit (GRU) neutral networks. GRU is a temporal block that captures the temporal variation of data and predicts the output using inputs of several past time intervals. In the proposed model of [98], the input layer contains speed, the speed difference, and position differences in few last time intervals, where the output is the estimated speed in the next time interval. [99] proposed a CF model considering asymmetric driving behavior using Long Short-term Memory (LSTM) neural network. In comparison to GRU, LSTM considers longer sequential data and has more parameters than GRU, however, both methods are used to mimic the temporal variation of data. In [99], the input layer in different time intervals contains information such as the speed of the following vehicle, the speed difference to the leading vehicle, and the gap between vehicles in the current time step, whereas the output layer predicts the speed of the following vehicle in the next time step. On the other hand, [103] further enhanced the LSTM-based CF model by considering traffic oscillation in a platoon level. According to [103] the direct application of IDM/LSTM based models to predict the driving behavior in next time step in a platoon will induce an accuracy problem so-called error propagation. The prediction error propagates and accumulates both in temporal and spatial dimensions. Hence, in this study, an interconnected LSTM-based CF model is proposed.

[101] proposed a velocity control framework to address the phantom traffic jam using a DDPG equipped with a LSTM temporal block and attention mechanisms. In this framework, the spatial-temporal graph extracts information such as velocity and gap of multiple vehicles ahead in several time intervals, where the attention mechanism characterizes the interaction of the vehicle, and finally, the LSTM structure captures the driving behavior through time. This framework is specifically designed for CAVs, where a CAV can obtain driving information of multiple vehicles ahead through V2V communication. In addition, [102] further utilized LSTM architecture with a quantile-regression method. In this proposed framework, the output of the LSTM is not only a single output but a series of outputs as the different quantile of actions. For a given traffic state, the model predict set of actions, where kernal density estimation (KDE) is used to to estimate the continuous action distribution. The main advantage of this model is that it can obtain the driving behavior stochasticity.

[104] used generative adversarial imitation learning (GAIL) together with a temporal block-GRU to capture the CF behavior. The model consists of generator and discriminator parts. The generator scheme includes an actor critic structure (similar to DDPG) and extracts set of state-action pairs considering the temporal variation of the input states. The discriminator part compares the real state-action pairs with the generated one and updates the reward of the CF environment in an iterative way until the maximum reward is achieved. A similar method is used by [105] to develop a CF model which also considers the influence of driving time on driving behavior.

The findings of literature review show that several studies developed models by combining the mathematical models with the data-driven approaches. For instance, [106] proposed a novel CF model by combining a mathematical-based model (Gipps model) with a machine learning-based model (Back-propagation NN). This study assumes that the proposed model addresses both the lower accuracy of mathematical model and the shortcomings of machine learning-based models for the control of AVs. In the proposed method, the prediction values of machine learning-based and mathematical-based models are combined by weight values and the aim is to find the optimal combination weight value increasing the accuracy of the model. Moreover, [107] developed a family of CF models by integrating the parameters of mathematical CF models into a neural network. The aim is to take the advantage of mathematical models (data-efficient) and the data-driven model (generalizable). The loss function of the NN was designed in such a way to contain both the deviation from the data and the mathematical model [i.e. IDM, OVM (optimal velocity model)]. Similarly, [108] proposed a fusion modelling method, which combines the data-driven LSTM model with IDM. The adaptive Kalman filter algorithm is adopted to achieve an optimal estimation of the state of the system (CF behavior) based on both LSTM and IDM. The findings of this study proved that the combined LSTM-IDM model outperforms the accuracy of the IDM and LSTM models.

In summary, data-driven models could accurately replicate the CF behavior of (C)AVs. There are different methods proposed in the literature. However, we found that the recent deep-learning based models such as DDPG, RNN, GRU, LSTM, DDPG equipped with a LSTM, and GAIL with GRU outperform mathematical CF models, nonparametric models, and conventional neural network-based models and could be potentially used for modelling CF behavior of (C)AVs. However, most of these proposed models are not integrated into a simulation tool and hence they are not used in impact assessment studies. Table 8 presents the summary of reviewed data-driven models, which describes specific information on the developed CF model, model input and output, utilized dataset, and description of the model.

4 | SIMULATION-BASED IMPACT ASSESSMENT AND KPIs

A large spectrum of simulation-based studies focus on the identification of potential impacts of (C)AVs on the transportation system. Review of previous studies shows that an enormous amount of researches conduct impact assessments of AVs and CAVs for safety, mobility, and environmental effects (e.g. energy consumption and emissions). Key performance

TABLE 8 Summary of reviewed data-driven models: CF model, input, output, dataset, and description of the model*.

References	Year	Model	Input	Output	Dataset	Description
[82]	2015	kNN	$s, \triangle v, v$	v	NGSIM	In this study, k-nearest neighbor (KNN) generates the average of the most similar driving cases. The speed prediction in the next time step is based on the similar historical cases.
[83]	2015	Loess	s, v	v	Naples	The proposed method captures the releshionship between the speed of the following and leading vehicles, distance between them with the speed of the following vehicle in next time step (reaction time). Depending on the value of reaction time, the speed of the following vehicle is predicted.
[84]	2016	HMM + GMR	s, v	a	Driving trajectories	A combination of the hidden Markov model (HMM) and Gaussian mixture regression (GMR) to generate a sequence of acceleration in the next time step. HMM mimic the pattern between the driving situation and the vehicle's acceleration, where GMR generates the probability distribution of the acceleration to capture the stochasticity of driving behavior.
[85]	2013	SVR	$s, v, \triangle v$	v	NGSIM	The support vector regression (SVR) performs a linear regression by applying structural risk minimization (SRM) principle, to minimize the empirical risk and model complexity.
[86]	2003	ANN	$s, \triangle v, v_d, v$	a	Driving trajectories	This study utilized a simple ANN model with two hidden layers. The model inputs contains the following vehicle's desired and current speeds, the distance between leading and following vehicles, as well as their speed difference, where the output is the following vehicle's acceleration.
[87]	2007	ANN	s, v	v	Driving trajectories	The proposed one hidden-layer ANN model in this study predicts the speed of a vehicle and classifies the driving conditions into five categories namely: free driving, approaching, following I, following II, and danger. The results are compared with the Gipps CF model.
[88]	2011	ANN	$v, s, \triangle v$	a	NTDS	Similar to [87], this study proposed an ANN-based model to predict the acceleration of the vehicle in the next time step. The results are compared with the Gazis-Herman-Rothery (GHR) CF model.
[89]	2012	ANN	$v, \triangle v, s, \tau$	a	NGSIM	The proposed model considers the instantaneous reaction delay of the driver as an extra input to predict the acceleration of the following vehicle.
[90]	2013	ANN	$s, v, \triangle v$	v	NGSIM	The model is similar to [89], but predicts the speed of the following vehicle in next time step. The next time step depends on the reaction delay which is estimated by another neural network model.
[91]	2014	ANN	s, v	v	NGSIM	This study used a local neuro-fuzzy model to predict the speed of a following vehicle at time t based on the input information at time $(t - \tau)$, where τ indicates the reaction time of a vehicle. In this study, the CF behavior of heavy vehicles is considered.
[92]	2014	ANN	$s, \triangle v$	a	Trajectory data	This study utilized a feed-forward ANN similar to [89], with one hidden layer. However, the input information contains the speed difference, and distance to the leading vehicle for the last three time intervals. The output of the model is the acceleration of the following vehicle in the next time step.
[93]	2018	DDPG	$s, v, \triangle v$	Q	Trajectory data	In DDPG, two separate actor and critic networks are used. Both networks contain an input, one hidden, and an output layer. The actor-network generates the action (acceleration of the following vehicle), whereas the critic network exports a scalar reward value. The aim is to adjust the action in such a way as to maximize the reward.
[94]	2019	DDPG	v, P	v	Simulation data	In this study, DDPG same as in [93] is utilized to generate the time-optimal velocity of a vehicle.
[95]	2020	DDPG	$s, v, \triangle v$	Q	NGSIM	In this research, the reward function of the DDPG contains various features including safety, efficiency, and comfort. The model adjusts the output of the actor network (acceleration) aiming to maximize the reward function.
[96]	2022	Encoder-decoder	s, v	v	SH-NDS	In this framework, the encoder uses multi-head self-attention to generate a mixed representation of past driving context, where the decoder takes the future leading vehicle speed as input and predicts the future following vehicle's speed.
[97]	2017	RNN	$s, \triangle v, v$	a	NGSIM	The RNN model utilized in this study takes the sequence of the input information in different time steps and predicts the acceleration in the next time step.

(Continues)

TABLE 8 (Continued)

References	Year	Model	Input	Output	Dataset	Description
[98]	2018	GRU	s, $\triangle v$, v	v	NGSIM	The GRU temporal block is used to include the temporal variation of the input information in predicting the future speed profile.
[99]	2018	LSTM	s, $\triangle v$, v	v	NGSIM	This study utilized LSTM to capture the temporal variation of the input information. In comparison to GRU, LSTM considers longer sequential data.
[100]	2020	LSTM	s, $\triangle v$, a	a	Waymo	The model contains an encoder-decoder structure to learn the information hidden in the input features. This study uses the AV trajectories for training and validation of the model.
[101]	2021	LADDPG	s, $\triangle v$	a	NGSIM	In this study, a DDPG equiped with LSTM and attention mechanisms is proposed. In this framework, the spatial-temporal graph extracts information such as velocity and gap of multiple vehicles ahead in several time intervals, where the attention mechanism characterizes the interaction of the vehicle, and finally, the LSTM structure captures the driving behavior through time.
[102]	2021	QRLSTM	s, $\triangle v$, v	a	NDD	This study utilized LSTM architecture with a quantile-regression method. The output of the model is not only a single output but a series of values as the different quantiles.
[103]	2020	Int-LSTM	x, v, a	a	NGSIM	The interconnected-LSTM is used to solve the error propagation problem of a basic LSTM model.
[104]	2020	GAIL	s, $\triangle v$, v	a	NGSIM	The proposed model consists of generator and discriminator parts. The generator scheme includes an actor-critic structure (similar to DDPG) and extracts a set of state-action pairs considering the temporal variation of the input states. The discriminator part compares the real state-action pairs with the generated one and updates the reward of the CF environment in an iterative way until the maximum reward is achieved.
[105]	2020	GAN	s, $\triangle v$, v, a	x, v, a	Didi	The proposed model is similar to [104], however, it also includes the influence of driving time on driving behavior. The model contains the driver's reaction time model and the CF algorithm.
[106]	2019	Gipps + ANN	s, $\triangle v$, v, a	x, , v, a	NGSIM	In this research, a novel CF model by combining a mathematical-based model (Gipps model) with a machine learning-based model (Backpropagation ANN) is proposed. This study assumes that the proposed model addresses both the lower accuracy of mathematical model and the shortcomings of machine learning-based models for the control of AVs.
[107]	2021	IDM, OVM +ANN	s, $\triangle v$, v	a	NGSIM	This study developed a family of CF models by integrating the parameters of mathematical CF models into a neural network. The aim is to take the advantage of mathematical models (data-efficient) and the data-driven model (generalizable). The loss function of the NN was designed in such a way to contain both the deviation from the data and the mathematical model [i.e. IDM, OVM (Optimal velocity model)].
[108]	2019	IDM + LSTM	s, $\triangle v$, v	a	Trajectory data	This study proposed a fusion modelling method, which combines the data-driven LSTM model with IDM. The adaptive Kalman filter algorithm is adopted to achieve an optimal estimation of the state of the system (CF behavior) based on both LSTM and IDM.

x, s, v, a are the position, spacing, velocity, and acceleration of a vehicle, respectively. $\triangle v$ is the velocity difference between the following and leading vehicles, and τ is the reaction time.
*The studies are presented based on their categories from nonparametric models, artificial neural network, reinforcement learning, deep reinforcement learning and combined mathematical and deep learning models.

indicators (KPIs) used in these studies vary depending on the scope of the study. However, the identification of the most used KPIs and impact areas are very important for future studies in this field. Table 9 presents a brief description of all studies reviewed in this section, which explains specific information on the impact area, assessment criteria, KPIs, and findings. The table is sorted based on the publication date of the citations, which are displayed in reverse chronological order (newest to oldest). In the following paragraphs, we present a detailed explanation of selected articles, considering various impact areas together with the utilized KPIs in simulation-based studies.

4.1 | Mobility

Mobility impact assessments in the context of microsimulation-based studies refers to the traffic flow efficiency. The scope

TABLE 9 Summary of reviewed simulation-based studies including their assessment criteria, KPIs, network type and results.

References	Year	Assessment criteria	KPIs	Network	Results
[58]	2022	Traffic safety	Number of conflicts	Intersection	The higher the PRs of CAV, the safer the intersections. A 100% PR of CAV could totally ignore the number of crossing conflicts in both signalized and unsignalized intersections.
[50]	2021	Traffic efficiency	Capacity, queue length, total travel time	Urban road	A network with 100% PRs of CACC vehicle, increases the capacity, reduces the queue length in congested sections, and decreases the total travel time.
[37]	2021	Efficiency, throughput	Travel time, flow	Link	Higher PRs of AVs, reduce the travel time and increase the throughput. With 100% PR, the travel time reduces by 50%.
[17]	2021	Traffic safety and efficiency	TTC, number of conflicts, travel time	Freeway	AVs and CAVs improves travel time, however, CAVs outperform AVs, and at least 20% PR of CAVs and 40% PRs of AVs are required to reduce travel time. A system with both AVs and CAVs could also significantly improve safety. With high PRs of AVs and CAVs, number of conflicts reduced.
[33]	2021	Throughput and stability	Traffic flow, density	Freeway	The performance of commercially available ACC vehicles is different than theoretical ACC vehicles. Commercially ACC vehicles reduces the bottleneck capacity and string stability.
[78]	2021	Traffic efficiency	Mean speed, travel time	City center	With a 50% PR of AVs under different driving styles, mean speed of the network drops and travel time increases.
[51]	2021	Throughput	Speed, and traffic flow	Freeway	Under current traffic demand, a fully human-driven traffic shows better throughput, however, with a double demand, CAVs show the best performance.
[77]	2021	Flow analysis	Traffic flow, travel time	City	Traffic throughput improves by around 22% in a situation with automated vehicles in comparison to non-automated condition. Travel time reduces by 13.5% and 16.4% in partially and fully automated conditions, respectively.
[41]	2020	Capacity analysis	String stability, lane capacity	Freeway	Lower PRs of CAVs have negative impacts on the capacity, where 100% PR increases the capacity around 70–100% depending of the freeway speed limits.
[30]	2020	Traffic efficiency	Travel time	Freeway	With higher PRs of CAVs, average travel time decreases. This reduction is more obvious when PRs of CAVs increases under heavy traffic flows.
[76]	2020	Capacity analysis	Flow, density and speed	Urban road	Higher PRs of AVs increases the capacity. With a 100% PRs of AVs, the maximum capacity increases by 16–23%. Lower PRs of AVs does not show significant improvements, thus at least 40% PR is required.
[39]	2020	Traffic flow and emissions	Throughput and CO_2 per kilometer	Highway	A 100% PR of AVs reduce the average speed and flow, and generate the highest emission per kilometer. Whereas, CAVs improve the capacity of the network. However, in network wide, the total emission produced by AVs, and CAVs are not significantly different than human-driven vehicles.
[64]	2019	Safety analysis	Number of conflicts	Motorway	With a 100% PR of CAVs, more than 90% reduction in total number of conflicts is achieved.
[32]	2018	Safety	Number of conflicts	Roundabout	The higher the PRs of AVs results in increased number of conflicts. Negative safety impacts of AVs on roundabout does not change even with different design of roundabouts.
[80]	2018	Capacity analysis	Flow, string stability	Freeway	There is a quadratic relationship between the freeway capacity and PRs of CACC vehicles. At 100% PR, the freeway capacity is around 90% higher than a 0% PR.
[55]	2018	Throughput and emissions	Average harmonic speed, density, CO_2 and NO_x per kilometer	Ring road	With high PRs of AVs, the average speed of the network decreases and the density increases, where emissions also increases. In low PRs, CAVs have small negative impacts on average speed, density and emissions, where for high PRs, CAVs improves the situation. The best performance of CAVs is achieved with high demand scenarios.
[53]	2018	Throughput	Harmonic average speed	Ring road	In comparison to human-driven vehicles and with the constant demand, any PRs of AVs do not improve the traffic flow efficiency, however CAVs enhance the condition. In low traffic demands, human-driven vehicles always outperform CAVs.

(Continues)

TABLE 9 (Continued)

References	Year	Assessment criteria	KPIs	Network	Results
[31]	2018	Safety analysis	Number of conflicts	Signalized intersection and roundabout	Higher PRs of AVs with both driving styles (cautious and aggressive) could reduce the number of conflicts around 65% in signalized intersection and roundabout.
[42]	2017	Safety analysis	TET, TIT	Freeway	Driving behavior of ACC is a decisive factor for the safety impacts. Larger time headway and increased emergency deceleration capability results in improved safety.
[109]	2017	Traffic efficiency	Travel time, fuel consumption	On-ramp	With a 100% CAV PR, fuel consumption reduces by an average of 35% with different traffic flows. With high traffic flow, total travel time reduces drastically in comparison to 0% PR of CAVs. However, for low traffic volumes, no change in total travel time is achieved.
[43]	2017	Traffic efficiency, safety, string stability	Flow stability, travel time, speed dispersion	Freeway	With 0% AVs PR, irregular merging behavior of human-driven vehicles results in negative effect on string stability. However, only a 5% PR of AVs can improve string stability. Higher PRs of AVs leads to lower level of speed dispersion and results in enhanced safety. For average travel time, any PRs of AVs only slightly change is achieved. More reduction in travel time is achieved in congested sections of the freeway.
[6]	2016	Flow stability and throughput	Platoon size, flow and density	Ring road	AVs could prevent shockwave formation and propagation. Both AVs and CAVs can improve throughput and string stability, however AVs show better performance in terms of throughput than CAVs.
[1]	2016	Traffic efficiency	Average density, speed and travel time	Autobahn	A 100% PR of AVs improves the travel time by 9%, where average density enhances by around 8%.
[54]	2012	Capacity analysis	Lane capacity	Freeway	The higher the PRs of CACC vehicles, the better the freeway lane capacity could be achieved.
[49]	2006	Flow analysis, string stability	Traffic flow, number of shock waves, average speed	Freeway	Lower PRs of CACC (< 40%) does not improve the throughput. Higher PRs of CACC results in improved string stability and throughput. Also, higher PRs of CACC lead to higher average speed and high reduction in number of shock waves.

of the studies in this area varies from intersections to links, highways, and networks. Most researchers exploited KPIs, such as traffic flow (e.g. traffic volume, density), average travel time, string stability, average velocity, and more in their studies. For instance, [50] studied the impact of CACC-equipped vehicles on traffic efficiency in urban roads with congested sections. This study selects traffic capacity, waiting time, queue length, and total travel time as the main KPIs. The findings of this study indicate that in comparison to conventional vehicles, CACC-equipped vehicles with a penetration rate (PR) of 100% can increase the traffic capacity by more than 2.6 times. The study claims that by increasing the PR of CACC-equipped vehicles, the waiting time on congested roads decreases. In addition, with a 100% PR, the queue length and total travel time significantly decrease on congested roads. In [37] a research is conducted to investigate the utilization of road capacity in mixed traffic (AVs and human-driven vehicles). The study showed that in an idealized environment with a 100% PR of AVs, capacity utilization in terms of travel time and throughput is improved. However, in a mixed traffic situation, capacity utilization degrades fastly with the higher PR of human-driven vehicles. On the other hand, [17] investigated the traffic efficiency and safety impacts of (C)AVs in a major freeway in Orlando, Florida. The results of their study depict that travel time is significantly reduced with the penetration of (C)AVs. The study also implies that CAVs substantially outperform AVs with the same PR both in terms of travel time reduction, and number of conflicts. The findings also suggest that at least 20% PR of CAVs and 40% PR of AVs are required to achieve reduced travel time in the network.

Furthermore, [33] investigated the impacts of commercially available ACC vehicles on traffic stability and throughput. The simulation results show that in comparison to theoretical ACC vehicles, the commercially available ACC equipped vehicles decreases the bottleneck capacity at higher PRs. The study also claims that traffic flow is string unstable when simulating the commercially available ACC vehicles. On the network level, [78] studied the impact of AVs with different driving styles in Munich city network. The findings depict that with 50% PR of AVs under different driving styles, mean speed of the network drops and travel time increases. [41] conducted a simulation-based study on the effect of CAVs on freeway capacity. The study claims that there is a negative impact on freeway capacity with small PRs of CAVs, where with higher PRs, the capacity increases. Meanwhile, speed limit is also indicated as an important variable in freeway capacity, where higher speed limits leads to improvement of capacity. Another interesting finding based on demand fluctuation is reported in [51]. This study evaluated the impacts of (C)AVs on throughput in a Freeway segment. It is claimed that under current traffic demand scenario, a 100% human-driven vehicles show better throughput, where with a double traffic demand, CAVs show the best performance. Since CAVs strictly obey the speed limits, their performance is not significantly noticeable with the current demand. However, with increased demand a smooth flow of traffic is achieved and consequently leads to a better throughput and speed.

AVs will likely have more cautious behavior than human-driven vehicles, and thus findings of a study by [53] indicate that AV alone will not probably improve the traffic flow. This article studied the effects of (C)AVs on traffic flow in a freeway, and showed that with the constant demand, CAVs with the V2V communication will significantly enhance network capacity and reduce traffic congestion. This study also claims that AVs with any PRs will show negative performance than human-driven vehicles. In case of CAVs, low PRs will worsen the traffic flow (as they act like AVs), where higher PRs increases the traffic flow efficiency. On the demand side, human-driven vehicles outperform CAVs on low traffic demands with any PRs of CAVs. Unlike [6, 53] claimed that AVs are more effective in preventing shockwave formation and propagation. The findings of this study revealed that under the utilized model's assumptions, both AVs and CAVs can improve throughput and string stability. It is also shown that AVs result in higher throughput than CAVs with same PRs. Meanwhile, utilizing different CF models with various parameters lead to distinct conclusions. [1] studied a situation where all vehicles in the system are AVs. This study assumes that AVs can drive very close to the leading vehicle. The outcome of this study showed that AVs have positive effect in traffic flow efficiency in higher traffic demands. The study claims that in a fully AV driving environment, average density improves by around 8%, where travel time reduces by 9%. [54] investigated the impacts of CACC-equipped vehicles on freeway traffic flow. The results revealed that there is a linear relationship among PRs of CACC vehicles and the freeway lane capacity. The study also mentioned that capacity improvement could be enhanced if the leading non-CACC vehicles share information with CACC vehicles.

4.2 | Safety

Simulation-based studies utilize surrogate safety measure (SSM) to evaluate the impact of (C)AVs on traffic safety. Time-to-collision (TTC), Post-encroachment time (PET), number of conflicts (using certain TTC and PET thresholds) are the most used KPIs for safety assessment in the literature [17, 31, 32, 42, 47, 58, 63, 64]. [58] investigated the effects of CAVs on the safety of signalized and unsignalized intersections. The results of this study revealed that CAVs can significantly reduce the number of conflicts on both intersections. In addition, it is claimed that a 100% PR of CAVs could ignore any crossing conflicts between vehicles. [17] used the number of conflicts, time-to-collision (TTC), and time exposed time-to-collision (TET) to quantify the safety impacts of (C)AVs under mixed traffic scenarios. The results implied that any mixture of AVs and CAV PRs into the existing transport system could improve safety. Meanwhile, higher PRs of (C)AVs result in reduced number of conflicts. Considering the demand fluctuation, [64] studied the impact of CAV PRs on safety with different demands (peak and off-peak traffic) in a motorway segment. The results show that PRs of CAVs substantially reduce the number of conflicts. This effect is more noticeable in higher traffic demands even at low PRs of CAVs.

Similarly, [31] studied the safety effects of AVs with different driving styles (cautious and aggressive) on a signalized intersection and a roundabout. This study used the number of conflicts as a KPI to quantify the safety impacts. The results suggested that high PRs of AVs with both cautious and aggressive behaviors could significantly reduce the number of conflicts. With a 100% PR of AVs, the number of conflicts reduces by around 65% in both intersections and roundabouts. Unlike [31, 32] highlighted the negative impacts of AVs on roundabout safety. The findings of this study showed that with increased PRs of AVs, the potential number of conflicts at roundabout also increased. It is also mentioned that even redesign of the roundabouts can not neglect this negative safety effect of AVs. This study suggested that utilization of SSM might be not a suitable tool to quantify the safety in roundabouts and thus new models are needed. In addition, [42] investigated the safety impact of ACC vehicles in congested conditions on a freeway. In this study, several potential behaviors of ACC vehicles such as time headway, maximum deceleration and more were tested. The findings of this study showed that the safety impacts of ACC are largely affected by their driving behavior. The study implied that with larger time headway, and increased emergency deceleration capability, the safety has improved. In this research, time exposed time-to-collision (TET) and time-integrated time-to-collision (TIT) were used as KPIs. Both TET and TIT are aggregated indexes from TTC.

4.3 | Environment

Accurate approximation of environmental impacts of (C)AVs requires consideration of many decisive variables including vehicle technology, travel demand, new modes of transport etc. However, researchers attempted to quantify the effect of (C)AVs assuming the same energy consumption and emission factors as for existing human-driven vehicles. For instance, [39] investigated the impact of (C)AVs on traffic flow and emissions on a highway network. The study estimated emissions using both the average-speed EMEP/EEA fuel consumption factors and the generic version of the European Commission's CO_2 MPAS model. The results revealed that a transport network with 100% AVs has the highest CO_2 emissions (g/km), where CAVs also generate more emissions in peak hour traffic (due to high utilization of network capacity). The study implied that the overall effect on the network is statistically not significant. The study claims that usage of the various CF models and their limitations lead to distinct driving profiles and thus generate different emissions. Moreover, a 20% increase in demand does not significantly change the emissions. Similarly, [55] conducted a simulation-based study to investigate the impact of (C)AVs on throughput and emissions in a ring road. In this study, various demand scenarios and PRs of (C)AVs, and different desired time gaps for the model settings are considered. CO_2 and NO_x emissions per kilometer are selected for environmental impacts. The findings of this study showed that in free-flow traffic, where vehicles are not bounded to speed limits, human-driven vehicles have the highest emissions. On the other hand, any PRs of CAVs could result in low emissions. According to the study, AVs drive with low speeds and thus force the engine to work less efficient. Hence, in comparison to CAVs, AVs increase emissions.

To conclude, used KPIs for impact assessment in MTMs differ depending on the assessment criteria and study area (i.e. intersection, link, freeway, city network). First, in mobility analysis, we noticed that most studies select flow, density, string stability, lane capacity and throughput when conducting capacity and flow analysis in freeways, highways and ring roads. Travel time and speed are frequently selected for traffic efficiency analysis both on link level and city-wide. Second, for safety analysis, the number of conflicts is the most used KPI in all type of study areas, where in freeway analysis, some studies also used TTC, TET and TIT. Finally, the studies related to emission analysis depict that CO_2 and NO_X per kilometer are used KPIs for impact assessment.

Although, this section clearly reveals the relation between the used KPIs and the study area in different studies, a standardized guideline to indicate which KPIs to be used for a specific study area, demand scale, and other influencing factors is missing. A KPI (e.g. travel time) might be useful for traffic efficiency analysis under different PRs of (C)AVs in a city-wide network but for moderate and low demands, where for high demands (congested network), this KPI might not represent the impact of (C)AVs.

5 | CONCLUSION AND RESEARCH GAPS

Simulation-based studies are widely conducted to analyze and predict the impacts of on traffic efficiency and safety. In MTMs, accurate quantification of the potential impacts depends on the true configuration of AVs and CAVs driving behaviors. These behaviors are modelled with CF and lane-changing models. In this paper, we review and summarize the recent AVs and CAVs simulation-based studies including their utilized CF model, adopted parameters, the reported impacts and the used KPIs for impact assessments. Moreover, a review of recent data-driven CF models with their methodologies is presented. The present review is crucial both in understanding the CF models parameters used for AVs and CAVs modelling in simulation tools, as well as identification of the set of KPIs for impacts analysis.

Regarding the mathematical CF models for (C)AVs modelling, we found that the most frequently adopted CF models are IDM and MIXIC and their modified versions. Wiedemann 99 and Krauss models are also utilized in MTMs for impact assessments. For IDM, many studies adopt the parameters of the model based on research done by [19, 44, 46]. Similarly for MIXIC model, the parameters' values are taken from [6, 49]. ACC and CACC models developed similar to MIXIC model have been also utilized for ACC and CACC vehicles modelling. Certain parameters of these models are based on assumptions and some are gathered from test vehicles [18, 54]. For Wiedemann 99 model, the parameters' values are extracted using trajectories of test AVs within the CoEXist project. On the other hand, in the Krauss model researchers often differentiate the driving behaviors of human-driven vehicles, AVs, and CAVs by headway gap, reaction time, and driving imperfection factor. For instance, it is assumed that CAVs could drive very close to the leading vehicle and could have perfect driving behavior.

Furthermore, there were attempts to develop data-driven models using human-driven vehicles trajectories and assume it for (C)AVs CF behavior, but they cannot guarantee the true behavior of future (C)AVs. However, the methods proposed in these studies could be potentially used for (C)AVs CF models, when field data are available. The findings of the literature review show that reinforcement learning and deep reinforcement learning algorithms, such as DDPG, RNN, GRU, LSTM, DDPG equipped with a LSTM, and GAIL with GRU are the most recent methods used for replicating CF behavior.

The findings of literature review reveal that large amount of studies conduct the impact assessment of (C)AVs for safety, mobility, and environmental effects. Most authors exploited KPIs, such as traffic flow (e.g. traffic volume, density, throughput etc.), average travel time, string stability, average velocity and more to assess the mobility impacts of (C)AVs. For safety analysis, time-to-collision (TTC), post-encroachment time (PET), and number of conflicts are the most used KPIs in the literature. Finally, the amount of CO_2, and NO_X emissions per kilometers (g/km) are used for emissions' evaluation. One important note is that most studies assume the same energy consumption and emissions factors used for existing human-driven vehicles and for (C)AVs. However, future vehicles will likely have different consumption technology and thus quantification of emissions is not accurate. On the other hand, several studies use various CF models with their own assumption for models' parameters. This may lead to inconsistent conclusions to (C)AVs impacts. Despite their results inconsistency, most studies revealed that AVs and CAVs with sensing and connectivity could considerably increase the road capacity. More optimistic views are for CAVs in comparison to AVs due to communication capabilities of earlier. A general finding of most studies depicts that higher PRs of AVs and/or CAVs could highly change the existing transport network both in terms of efficiency and safety. In addition, it is reported that demand is a sensitive factor in impact assessments. Increased demand scenarios leads to significant changes in the network especially for CAVs. Some studies assume that AVs will have more cautious behavior with larger headway gaps, where in some other researches, an aggressive behavior of AVs is assumed. This has resulted in opposing findings especially in terms of number of conflicts and consequently safety.

Although numerous attempts have been made to model the CF behavior of (C)AVs, a considerable number of research gaps still exist. First, the true driving behaviors of (C)AVs are still under investigation, which leads to strong assumptions in most studies. A model to capture the driving behavior of (C)AVs with calibrated parameters using real data is needed. This model could consider the sensing and communication technologies of AVs and CAVs, respectively, to accurately mimic their driving behaviors under various situations. The parameter calibration could also be done for established CF models, such as IDM, MIXIC, and Krauss. These models are integrated within simulation tools and hence could widely be used for impact assessments. Second, data-driven models could accurately capture the driving behavior of (C)AVs, however, they still need a mass field (C)AVs data for training, testing and validation. A data-driven model based on deep reinforcement learning which could capture the spatial and temporal variation of the driving behavior with field test data of (C)AVs is a worth pursuing research. In this research, different potential driving styles of (C)AVs (cautious, normal, aggressive) under various traffic situations could be considered. Meanwhile, it is very crucial to integrate data-driven models into the existing widely used simulation tools in a computationally efficient method. This will help to conduct large-scale impact assessments with more accurate outputs. Third, in most studies, KPIs are assigned by the authors for impact assessments studies, however, there should be a differentiation by which KPIs to be used for different study areas, demand scales and more. Hence, a study to analyze the sensitivity of each KPI in varying scenarios both in terms of supply and demand is needed. This study could create a standardized guideline for impact assessments studies and could thus guide future researchers to use most reasonable KPIs for their specific studies. Finally, in this review paper we discussed the CF behaviors of C(AVs), however, a comprehensive review of lane-changing models of (C)AVs and studies relevant to impact assessment of (C)AVs lane-changing polices is a highly significant research need.

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CONFLICT OF INTEREST STATEMENT

There is no conflict of interest to be disclosed.

DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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Policy-aware Optimization-based Modeling of Autonomous Vehicles' Longitudinal Driving Behavior

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ABSTRACT Microscopic traffic models (MTMs) are widely used to evaluate the potential impacts of autonomous vehicles (AVs) deployment scenarios in our transportation network. Car-following (CF) and lane-changing (LC) models are the backbones of MTMs. Several studies attempt to accurately replicate these behaviors (especially CF behavior) using state-of-the-art modeling methods. A CF model consists of a set of relations and modifiable parameters that are calibrated by mass field driving data. Since mass field driving data of AVs are not available, researchers often assume these parameters and conduct impact assessments, leading to different conclusions on the potential effects of AVs. Meanwhile, AVs are agents and unlike human-driven vehicles, their behaviors are controllable and trainable. AVs might have safe and efficient driving behavior throughout a trip, therefore, we can train them to reach a destination optimally in a simulation environment. In this research, we develop an optimization framework that finds a set of optimized driving parameters for AVs under various scenarios, aiming to improve certain optimization targets (e.g., reducing travel time, number of conflicts) using a well-defined simulation-based objective function. The methodological framework consists of an optimization module and a simulation environment. The differential evolution (DE) method is employed within the optimization module to identify the optimized values of the CF parameters. The simulation environment is a SUMO-based platform where several simulation replications are conducted under certain scenario conditions. An experimental setup is designed to implement the proposed framework under different scenarios of mixed traffic and demand cases for the IDM (intelligent driving model), Krauss, and ACC (adaptive cruise control) models. The findings of this research reveal that safety could potentially be improved by optimized values of the CF model. For each policy where a higher weight is allocated to safety, generated optimized parameters significantly enhance safety as well as efficiency. In addition, the results show that minimum gap and desired time headway are the most sensitive parameters in regards to the policy targets, and their optimized values could replicate the potential CF behavior of AVs.

INDEX TERMS Autonomous vehicles (AVs); microscopic traffic modelling; simulation; optimization framework; policy analysis

I. Introduction

AUTONOMOUS vehicles (AVs) are one of the most disruptive innovations in the automotive industry. The current developments in advanced driving assistance systems (ADAS), such as adaptive cruise control, cooperative adaptive driving control, lane-keeping assistance, and emergency brake assistance, as well as existing autonomous driving features (e.g., autopilot, highway chauffeur) and trials of AV prototypes, will potentially pave the way for the mass deployment of AVs in our transportation system [1]. AVs might enhance traffic safety, given that a large number of accidents are linked with drivers' errors and unfitness to drive (e.g., fatigue, alcohol, or drugs) [2]–[4]. In addition, AVs offer additional mobility freedom by eliminating driving barriers, such as disabilities, driving licenses, and old age [5], [6]. Meanwhile, AVs could influence travel behavior, reduce traffic congestion [7], fuel consumption [8], [9], and vehicle emissions [10].

The recent advancement in sensing technologies (e.g., radar, lidar) and pattern recognition, with the processing capabilities of artificial intelligence, empower AVs to precisely detect the image of the surrounding environment and respond accordingly with the help of complicated algorithms in the decision processing unit (DPU) of the vehicle. Meanwhile, pervasive communication technologies facilitate the exchange of driving information (i.e., speed, acceleration, position, and more) of AVs with other connected vehicles (V2V), as well as infrastructure (V2I), which are labeled as connected autonomous vehicles (CAVs) [11].

Generally, any AV has four distinct design elements: sensing technology, the client system, the action system, and the human-machine interface (HMI) [12]. AVs create an internal map of the vehicle's surroundings using a wide range of sensor data in its client system. Initially, the raw sensor data is processed, and the relevant information is sent to the DPU of the vehicle for the decision-making task. The vehicle's DPU plots the vehicle's navigation path and delivers instructions to the vehicle's physical parts for necessary actions (i.e., acceleration, deceleration). Finally, the HMI is responsible for providing necessary driving information for the users. The DPU of AVs is comprised of pre-trained complex deep learning algorithms, which theoretically react to any sophisticated traffic conditions while maintaining safe and efficient driving maneuvers. The training of the DPU requires a significant amount of historical trajectory data of AVs to accurately capture driving conditions and safely respond to them. However, a question remains on whether the historical trajectories ensure that the optimal driving actions (safe and efficient) are taken not only in a specific situation but throughout the trip by the vehicle.

To train an AV to react optimally in all traffic conditions, we require a mass field trajectories of AVs. Several corridor-wide trials have been carried out to generate trajectories of AVs; however, the high cost of AV fleets and legal restrictions make large-scale tests currently impractical. Meanwhile, the available AV-related data are limited to specific locations and driving behaviors and, therefore, are not generalizable. Some researchers even assume that AVs might have similar driving behavior to human-driven vehicles and, therefore, utilize human-driven vehicle trajectories to approximate the driving actions of AVs [13], [14].

On the other hand, the impact assessment of AVs deployment on our transportation system is a crucial topic for researchers and policymakers. Although it is expected that AVs have the potential to significantly impact traffic safety, mobility patterns, and transport networks [15], their specific impacts are not confirmed yet. Therefore, researchers conduct simulation-based impact assessments to quantify the potential effects of AVs on a large scale using traffic models. Several studies used microscopic traffic models (MTMs) to analyze and predict the effects of AVs on safety and traffic efficiency [16]–[20]. However, the methods utilized in many studies to reflect AVs' driving behavior are deemed weak and thus always questionable.

The driving behavior of AVs might vary considerably from that of human-driven vehicles. In MTMs, these behaviors are modelled with their longitudinal (car-following) and lateral (lane-changing) configurations. A car-following (CF) model consists of a series of actions that a driver decides on to efficiently and safely follow the leading vehicle. Depending on different CF model, researchers distinguish the driving behavior of AVs from human-driven vehicles for time gap, reaction time, headway, and driving imperfection factor [15]. Since the mass field data of AVs are not available to quantify their potential driving behavior and hence calibrate the CF parameters, researchers often assume AVs' driving capabilities. This practice often results in varying conclusions regarding the potential effects of AVs.

Since AVs are agents and in contrast to human-driven vehicles, where their behaviors are naturally stochastic and uncontrollable, AVs are controllable, and their automated driving behavior could be trained in such a way to behave in the best possible manner [21]. For instance, we can train AVs to drive safely from point A to B, considering the travel time to be efficient. This could be conducted in a simulation environment, where we regulate the AVs to generate optimal trajectories throughout their trips. The extracted CF driving behavior for AVs in a calibrated simulation model could approximate the planned optimal CF behavior of AVs and, thus, could be utilized in simulation-based impact assessment studies. Hence, in this research, we develop a framework that finds a set of optimized driving parameters of AVs, aiming to enhance certain optimization targets through a well-defined simulation-based objective function. The policy targets could include e.g., enhancing traffic efficiency (i.e., travel time), improving safety (i.e., number of conflicts), etc.

The main contributions of this research work are as follows: (i) Development and integration of an optimization framework into a traffic simulation platform to find optimized driving behavior of AVs. This framework could be utilized in any network and demand pattern. (ii) Generation of the optimized set of parameters for widely used CF models to replicate the driving behavior of AVs. These parameters could be potentially utilized in simulation-based impact assessment studies of AVs. (iii) Sensitivity analysis of different CF model parameters to identify the most sensitive parameters in changing policy targets of AVs.

The rest of this paper is organized as follows. The subsequent section reviews the recent literature on AVs and CAVs' CF models and key performance indicators utilized for impact assessment. Section III introduces our proposed optimization framework, integrated with a microsimulation platform, along with a scenario generation tool for testing several demand scenarios and penetration rates of AVs. Section IV explains CF models employed in mimicking human-driven vehicles and AVs in our experimental setup. In Section V, we design an experimental setup to test the proposed framework in a city scale network with calibrated and validated features and with various scenarios. The results of this research and set of optimized driving parameters for different AV scenarios are presented and discussed in Section VI. Finally, Section VII concludes the article by explaining its overall contribution and suggesting further research directions.

II. Related Studies

CF behavior is the key element in MTMs and simulation tools. Replication of vehicular CF behavior has been always a research topic in the field of traffic modelling and simulation. There have been many attempts to develop models and methods to replicate the CF driving behavior of vehicles in literature. These models are categorized into mathematical and data-driven models. Mathematical models are comprised of set of modifiable parameters that mimic the driving behavior of vehicles under different traffic conditions. The modifiable parameters of these models are often calibrated with mass field driving data of vehicles. On the other hand, data-driven models employ different algorithms and trajectory datasets to create the relationship between the following vehicle's driving decisions and influencing inputs (e.g., leading vehicle's speed, gap, etc.). Although data-driven models outperform many mathematical models in replicating CF behavior of vehicles, they are not extensively utilized in impact assessment studies.

In simulation-based impact assessment studies, selecting a CF model depends first on whether a model can replicate the actual driving behavior and second on whether it is well-integrated in a widely used simulation tool. Considering the complexity of traffic flow elements, as well as high computational resources required for microsimulation tools, simpler and established mathematical models are integrated in microsimulation tools. These models, which are widely used in simulation-based impact assessment studies, comprise of models focusing on a driver's physical actions, such as desired speed, acceleration, deceleration, i.e. Gazis-Herman-Rothery (GHR) model [22], Gipps model [23], intelligent driver model (IDM) [24], optimal velocity model (OVM) [25]; however, some also consider the psychological inputs of the drivers, such as the Wiedemann model [26]. Worth-mentioning that these models are utilized to mimic the driving behavior of human-driven vehicles, for AVs there are no established mathematical models and researchers often employ widely used mathematical models to approximate the CF behavior of AVs by assuming the parameters of these models. In this section, we conduct a comprehensive literature review on AVs simulation-based studies to determine which mathematical models are widely used for approximating the CF behavior of AVs.

IDM and its modified versions are widely utilized CF models in microsimulation studies focused on AVs [20], [27]–[34]. Recent researches, such as [17], [35], and [31], employed IDM and its revised versions to evaluate the impacts of AVs. For instance, [17] investigated the safety and mobility impacts of AVs, CAVs and connected vehicles (CVs) on a freeway. In this research, the basic IDM is used to approximate the driving behavior of AVs, whereas a modified IDM according to [36] is utilized for CAVs simulation. This study adopts IDM parameters from [19], [20] for both AVs and CAVs modelling.

Additionally, [35] examined how commercially available ACC vehicles influence traffic stability and throughput. The study utilized IDM to model the CF behavior of human-driven, theoretical ACC, and commercially available ACC vehicles. The model parameters for human-driven and theoretical ACC vehicles were derived from [34], [37], while calibrated parameters from a field experiment were used for commercially available ACC vehicles. Meanwhile, [31] employed a modified version of IDM to examine the impacts of CAVs on freeway capacity. The revised IDM, based on [19] and [38], ensures realistic behavior and enhances the safety of CAVs. This research incorporated the values of IDM parameters from the previous studies [19], [20].

In addition to IDM, some studies employed MIXIC (MICroscopic model for Simulation of Intelligent Cruise control) model to simulate CAVs [18], [39]–[42]. The model was originally developed by [43] to replicate ACC and later modified by [42] to include the CACC characteristics. For a more comprehensive description, readers are referred to [15]. [44] investigated the impacts of ACC and CACC-equipped vehicles on traffic efficiency and energy consumption in an ideal expressway using MIXIC model. Meanwhile, [41] studied the effect of CAVs on traffic congestion and network capacity. This research approximated the driving behaviors of CAVs employing CACC vehicles while cruising. Additionally, [39] developed a control algorithm similar to MIXIC to estimate the speed of an ACC-equipped vehicle in upcoming time steps. Using this model, [39] explored the effects of varying CACC vehicles deployment scenarios on freeway traffic flow. This study developed control algorithms for ACC and CACC vehicles, where the performance of those control algorithms are based on set of assumptions. Furthermore, [30] and [41] both utilized the ACC model to mimic the driving behavior of AVs and to examine the effect of AVs on traffic flow and CO_2 emissions.

Meanwhile, various studies employed the Wiedemann CF model to approximate the driving behavior of AVs and CAVs [1], [45]–[49]. The Wiedemann model exists in two versions: Wiedemann 74 (2-parameters model) and Wiedemann 99 (10-parameters model), with the latter being more frequently utilized in the literature. Within the Wiedemann model, considerations of the driving actions extend beyond physical signs of driving to psychological reactions, such as the perceived width of the leading vehicle and changes in visual angle. The parameters of the model, previously derived within the CoEXist project, aim to mimic the driving behavior of AVs and CAVs. However, the calibration of these parameters relies on a limited number of AV trajectories.

In a related study, [45] evaluated the safety impacts of AVs using the Wiedemann 99 model, adapting the values of parameters from [50]. Moreover, efforts have been made to investigate the effects of AVs and CAVs using Krauss model [51]–[54]. Exploiting the communication capability of CAVs, several studies proposed novel methods for modelling the CF behavior of CACC, CAVs, and associated technologies [55]–[63]. However, these methods often require the development of extensive case-specific modeling facilities in MTMs and, therefore, are generally not integrated into microscopic simulation tools, limiting their widespread use in impact assessment studies.

In summary, IDM, MIXIC, and their revised versions are commonly utilized for modelling of AVs in most studies. The Wiedemann 99, and Krauss models are also prevalent in AVs impact assessment studies. In this paper, we use IDM, ACC, and Krauss models to replicate the CF behavior of AVs and further extract the optimized values of these models' parameters. Meanwhile, the Wiedemann 99 model is utilized to mimic the CF behavior of human-driven vehicles. In Section IV, we present these models in detail. In addition, a significant amount of literature conducts the impact evaluation of AVs and CAVs for safety, mobility, and environmental impacts (e.g., energy consumption and emissions). Key performance indicators (KPIs), including traffic flow (e.g., traffic volume, density, throughput), average travel time, string stability, average velocity, and more, are commonly exploited to evaluate the mobility impacts of AVs. For safety analysis, time-to-collision (TTC), post-encroachment time (PET), and number of conflicts are frequently utilized KPIs. Finally, the amount of CO_2 and NO_X emissions per kilometer (g/km) are employed for emissions' assessment [15]. Table 1 provides a summary of reviewed papers related to simulation-based impact assessment of AVs, offering specific details on the employed CF model, assessment criteria, and used KPIs. The table is organized in reverse chronological order, presenting the studies based on their publication dates from newest to oldest.

III. Methodological Framework

A. Overall Approach

The proposed methodology of this paper is an extended version of our previous work in [21]. This research involves conducting experiments on various CF models under different scenarios to extract the optimized CF behavior of AVs. We introduce an optimization framework designed to find optimal sets of AVs driving behavior against assigned policy targets. The framework in this research consists of an optimization module and a simulation environment. The optimization module takes in predefined scenario variables and a set the initial parameters of the AVs CF model for optimization. Within this module, the objective function is assessed by inputting the possible solution sets, along with the scenario settings, into the simulation environment to evaluate the resulting policy targets. The simulation environment conducts multiple simulation runs under the specified conditions and outputs the selected policy targets. These policy targets are normalized and serve as the primary inputs for the objective function within the optimization module. The optimization module iteratively sends various combinations of AVs CF model parameter into the simulation environment, obtaining updated values of the policy target until convergence is achieved and no further improvement is feasible. A schematic diagram illustrating the main methodology of this research is shown in Figure 1.

B. Optimization Module

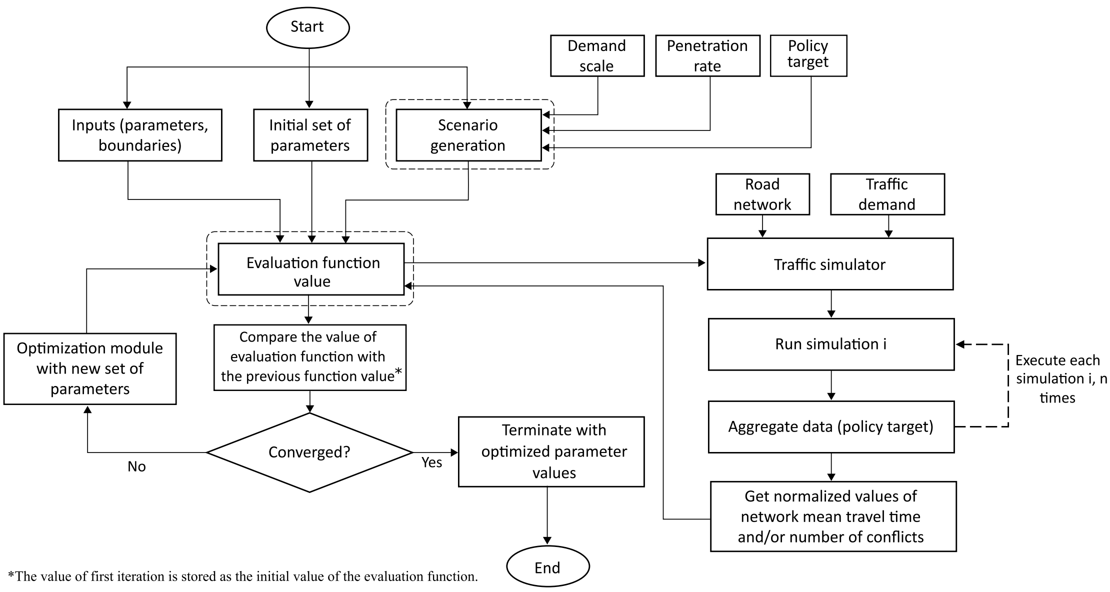
Simulation-based optimization is an established field that integrates optimization algorithms with simulation models [70]–[73]. The primary goal of simulation-based optimization is to identify a set of input variables that result in an optimal or near-optimal simulated output. Given the intricate and non-linear relationships among input variables and simulated results, iterative methods are employed to determine the model's optimum. One such method is Differential Evolution (DE), a stochastic population-based optimization technique designed for global optimization problems. DE is used in scenarios where gradient information is not available, making it particularly effective for simulation-based non-linear optimization problems [74]. The DE algorithm systematically explores the design space, refining a candidate solution based on predefined policy targets. The candidate solution moves around the design space to assess whether improvements to the objective function are achievable. If a new candidate solution surpasses its parent, it replaces the parent; otherwise, it is discarded. This research evaluates the objective function, primarily the simulated results (such as travel time and number of conflicts), with the input variables representing the CF model parameters. DE attempts to adjust the parameters of the CF model within boundary conditions (i.e., realistic driving behavior, acceleration and deceleration capability, comfort driving, etc.), aiming to identify the optimal solution for the policy targets.

C. Policy Targets

In this research, our main focus is on enhancing traffic efficiency and safety; therefore, they are used as policy targets. We evaluate efficiency by analyzing travel data, particularly the average network travel time. For safety assessment, we employ the Surrogate Safety Measure (SSM) to capture conflicting situations. The chosen KPIs are the average network travel time for efficiency and the total number of conflicts for safety. For an individual vehicle, we estimate travel time by calculating the difference between departure and arrival times. Consequently, the average of the compiled travel times for all vehicles in the network represents the overall mean network travel time. Similarly, to estimate the total number of conflicts in the network, each vehicle is equipped with an SSM device that records

TABLE 1: Summary of reviewed simulation-based studies on AVs and CAVs

References	Year	CF model	Assessment criteria	KPIs
[64]	2023	Gipps	Traffic safety	Number of conflicts
[44]	2023	MIXIC	Traffic efficiency and energy consumption	Average travel time, capacity, average electric energy consumption
[65]	2022	Gipps	Capacity analysis	Network capacity
[53]	2022	Krauss, IDM and CACC	Safety of intersections	Number of conflicts
[17]	2021	IDM	Traffic safety and efficiency	TTC, number of conflicts, travel time
[35]	2021	IDM	Throughput and stability	Traffic flow, density
[40]	2021	CACC	Traffic flow	Traffic flow, density, critical speed
[51]	2021	Krauss	Traffic efficiency	Average travel time
[30]	2020	ACC, CACC, and enhanced MIXIC	Traffic flow, and emissions	Throughput, average harmonic speed, and CO_2 per kilometer
[31]	2020	IDM	Capacity analysis	String stability, lane capacity
[54]	2020	Kraus	Traffic efficiency	Average speed
[66]	2020	IDM	Traffic efficiency	Travel time
[67]	2020	Krauss	Capacity analysis	Speed, flow, density
[48]	2019	Wiedemann 99	Traffic safety	Number of conflicts
[41]	2018	CACC	Throughput	Harmonic average speed
[68]	2018	ACC, CACC, and MIXIC	Throughput, and emissions	Average harmonic speed, density, CO_2 and NO_X per kilometer
[45]	2018	Wiedemann 99	Traffic safety	Number of conflicts
[52]	2018	Krauss	Capacity analysis	Flow, density
[69]	2018	CACC	Throughput	Capacity, mean speed
[18]	2016	IDM and CACC	Flow stability and throughput	Platoon size, flow, density
[1]	2016	Wiedemann 99	Traffic efficiency	Average density, travel time, and speed



*The value of first iteration is stored as the initial value of the evaluation function.

FIGURE 1: The methodological framework in this study

interactions or conflicts with other vehicles. This research uses time-to-collision for the analysis of traffic conflicts. TTC represents the time for a collision to occur between two vehicles in follow-lead as well as approaching scenarios. Depending on the situations (as depicted in Figure 2), TTC calculation is defined as:

$$TTC = \begin{cases} \frac{x_l - x_f - L_l}{v_f - v_l}, & if\ v_f > v_l \\ \frac{d_2}{v_2}, & if\ \frac{d_1}{v_1} < \frac{d_2}{v_2} < \frac{d_1+L1+w1}{v_1} \\ \frac{d_1}{v_1}, & if\ \frac{d_2}{v_2} < \frac{d_1}{v_1} < \frac{d_2+L2+w2}{v_2} \end{cases} \quad (1)$$

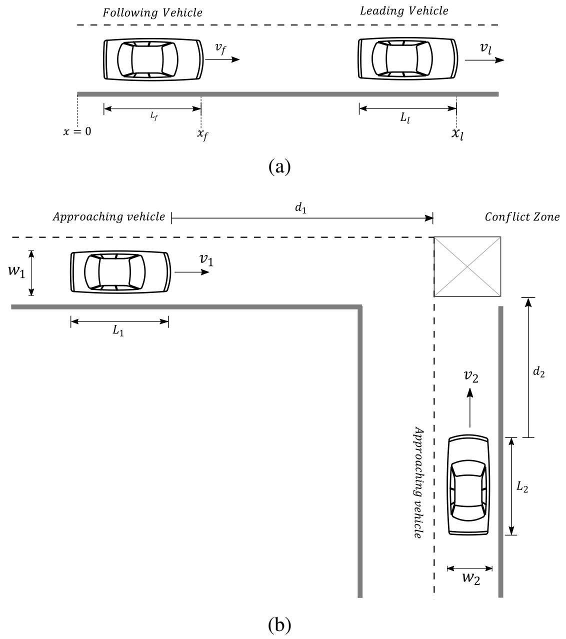


FIGURE 2: Illustration of TTC under (a) follow-lead, and (b) approaching conflicts scenarios

A conflict is identified when the TTC value falls below the specified threshold. In this research, the TTC threshold is set at 1.5 seconds. The cumulative count of conflicts observed throughout the simulation period reflects the total number of conflicts within the network.

The objective function examines diverse combinations of the KPIs by assigning varying importance to each KPI. The aim is to identify the optimized AV CF model parameters for various policies. To account for the differing scales of both KPIs, before using them as the value of the objective function, they are normalized. Depending on the outputs of the simulation and the values of both KPIs, they are normalized to the specified ranges ($0 < T \leq 6$, and $0 < C \leq 12$). These ranges are chosen according to the maximum values observed in the simulation to ensure the data is effectively normalized, allowing for meaningful comparisons. The KPI for the total number of conflicts, which can reach up to 12,000, is normalized to a range of 0 to 12 by dividing by 1,000. Similarly, the KPI for average network travel time, with a maximum value of 600 seconds, is normalized to a range of 0 to 6 by dividing by 100. The KPIs are further weighted by utilizing the weight factor to each normalized KPI as follows:

$$w \cdot T + (1 - w) \cdot C \quad (2)$$

where $0 \leq w \leq 1$ represents the weight of the KPI, T is the normalized mean network travel time, and C denotes the normalized total number of conflicts.

IV. Modelling Car Following Behavior

As mentioned above, in this paper we use IDM, ACC, and Krauss models to replicate the CF behavior of AVs. These models are comprised of set of parameters, where each parameter has some range of values. The proposed framework in this paper, therefore, attempts to find the optimal values of these parameters within the parameters range. Hence, in this section we present each model including their parameters and range of their values in details. Meanwhile, for capturing the CF behavior of human-driven vehicles in our study area, we employ the Wiedemann 99 model. The description of this model is presented in the following section.

A. IDM model

IDM, initially developed by [24], is one of the simplest and accident-free models. Utilizing both desired speed and space headway, the model generates a realistic acceleration profile. IDM excludes reaction time, allowing it to effectively capture the driving behavior of AVs. The basic form of the IDM acceleration function is defined as:

$$a_n(t) = a_{\max}^{(n)} \left[1 - \left(\frac{V_n(t)}{V_0{}^{(n)}(t)} \right)^{\delta} - \left(\frac{S_n{}^*(t)}{S_n} \right)^2 \right] \quad (3)$$

where $a_{\max}$ represents the maximum acceleration or deceleration of the vehicle n, V_n indicates the speed of the following vehicle, $V_0{}^{(n)}$ is the desired speed of the following vehicle, S_n denotes the gap distance between two vehicles, $S_n{}^*$ is the desired distance between two vehicles, and δ is the model parameter. The desired space headway between two vehicles $S_n{}^*$, is determined by the function involving the speed of the following vehicle V_n and the difference of speeds between the leading and following vehicles ΔV_n, as follows:

$$S_n{}^*(t) = S_0{}^{(n)} + V_n(t)\, T_n(t) + \frac{V_n(t)\, \Delta V_n(t)}{2\sqrt{a_{\max}^{(n)} b^{(n)}}} \quad (4)$$

where $S_0{}^{(n)}$ represents the minimum spacing at a standstill condition, T_n denotes the desired (safe) time headway, and $b^{(n)}$ is the desired (comfortable) deceleration, which does not exceed the maximum allowable deceleration.

The basic IDM model is commonly utilized to replicate the driving behavior of AVs in numerous studies. However, the values of the parameters of the model for AVs are not defined and thus several studies employ the IDM parameters from the literature. Table 2 provides an overview of the AVs behavior parameters employed in various simulation studies.

TABLE 2: IDM parameters for AVs modelling [19], [20]

Model parameters	Unit	Values
Desired speed (V_0)	$[km/h]$	120
Model parameter (δ)	[-]	4
Maximum acceleration ($a_{\max}$)	$[m/s^2]$	1.4
Desired deceleration (b)	$[m/s^2]$	2
Minimum gap distance at standstill (S_0)	$[m]$	2
Desired headway (T)	$[s]$	0.6
Maximum deceleration	$[m/s^2]$	2.8

B. ACC Model

ACC model was first developed by [39] and later revised by [62]. The model aims to estimate the speed of an ACC-equipped vehicle in the next step. Since the model utilizes the information gathered by the vehicle's sensors, it is used for AVs modelling in MTMs. The original ACC model consists of two controlling mode namely: (i) speed control mode and, (ii) gap control mode, where the (iii) gap closing control mode was later introduced by [62]. In addition, a fourth control mode (iv) collision avoidance mode is added to avoid rear-end collisions when critical safety conditions occur [75].

First, the speed control mode intends to keep the speed of the following vehicle close to the speed limit. This mode remains active, where there is no leading vehicle in the range of sensors coverage area or where there is leading vehicle in a distance of larger than 120 m. In this mode, the acceleration of the vehicle is controlled by the difference of following vehicle's speed and the speed limit (desired speed) as follows:

$$a = k_1 \left(v_d - v\right) \tag{5}$$

where k_1 is the speed control constant, v is the current speed, and v_d is the desired speed of the vehicle.

Second, the aim of the gap control mode is to keep the desired gap between the two vehicles in a certain range. The acceleration of the following vehicle is controlled by the speed and gap as follows:

$$a = k_2 \left(s - s_d\right) + k_3 \left(v_d - v\right) \tag{6}$$

where k_2 and k_3 represent the gap and speed control constants, respectively, s denotes the current space gap, $(s_d = t_d \cdot v)$ indicates the desired distance between two vehicles, t_d is the desired time headway, and v_d is the desired speed. In this mode the desired speed is referred to the leading vehicle's speed.

Meanwhile, the gap-closing control mode aims to ensure a smooth transition from the speed control model to the gap control mode. This mode activates when the spacing between the following and leading vehicles is less than 100 m. The gap-closing control mode has mathematically the same relation as in gap control mode, however, the coefficients have different values in both modes as shown in Table 3. Finally, the collision avoidance control mode aims to prevent vehicles from rear-end collisions when the critical safety conditions occur. The activation of this mode depends on two conditions: (i) when the spacing to the leading vehicle is less than 100 m, (ii) when the gap deviation is negative.

The modifiable parameters of ACC model to reflect the behavior of AVs are presented in Table 3. The default values indicates the assumed parameters in the literature for approximating the ACC-equipped vehicles. We utilize the range of each parameter (see Table 6) as a search space of the optimization module to reflect the driving behavior of AVs.

TABLE 3: ACC model parameters [19], [62], [75]

Parameters	Symbol	Values
Desired time headway	t_d (tau)	1.0
Speed control gain	k_1	0.4**
Gap control gain space	k_2	0.23
Gap control gain speed	k_3	0.07
Gap-closing control gain space	k_2^*	0.04
Gap-closing control gain speed	k_3^*	0.8
Collision avoidance gain space	k_4	0.8
Collision avoidance gain speed	k_5	0.23

(** = in SUMO this parameter has a negative sign)

C. Krauss Model

The Krauss CF model, introduced by Stephan Krauss in 1997, is a space-continuous model [76]. This model is designed to estimate the safe speed of the vehicle without extracting it from the vehicle's acceleration. In the Krauss model, the safe speed of the following vehicle is expressed as:

$$v_{safe}\left(t\right) = v_l\left(t\right) + \frac{g\left(t\right) - v_l \cdot t_r}{\frac{v_l(t)+v_f(t)}{2b} + t_r} \tag{7}$$

where v_l, v_f denote the speed of leading and following vehicles at time t respectively (see Figure 3), t_r is the reaction time of the driver, b is the maximum comfort deceleration of the vehicle, and $g(t)$ represents the gap between the following and leading vehicles, which is expressed as: $g\left(t\right) = x_l\left(t\right) - x_f\left(t\right) - L$, (x_l, x_f denote the position of the leading and following vehicles, and L is average length of a vehicle).

Furthermore, to compute the desired speed, which is a decisive variable for estimating the speed of the vehicle in the upcoming time step, the model considers the minimum of safe speed, the road speed limit, and the vehicle's maximum

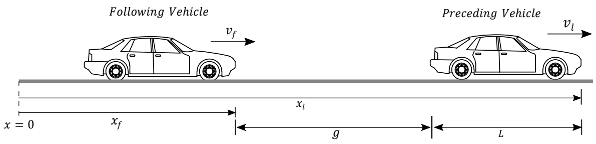


FIGURE 3: Description of the Krauss CF model parameters

capable speed to generate the desired velocity of the vehicles, determined as:

$$v_{des}\left(t\right) = \min[v_{\max}, v\left(t\right) + a \cdot \Delta t, v_{safe}(t)] \quad (8)$$

Finally, the velocity and location of the vehicle at the next time step are calculated as follows:

$$\begin{aligned} v\left(t + \Delta t\right) &= \max[0, v_{des}\left(t\right) - \eta], \\ x_f\left(t + \Delta t\right) &= x_f\left(t\right) + v\left(t + \Delta t\right) \cdot \Delta t \end{aligned} \quad (9)$$

where η is the random perturbation (to mimic the driving imperfection) and Δt is the simulation time step. Based on [77], the η value is assumed to be 0.5 for human-driven vehicles and 0 for CAVs. The assumed parameters' values of Krauss model for reflecting AVs behavior based on [52] are shown in Table 4. The range of values of each parameter is used as the search space of the optimization module.

TABLE 4: Krauss model's parameters [52].

Paramters	Unit	Assumed values
Mingap	$[m]$	0.5
Accel	$[m/s^2]$	3.8
Decel	$[m/s^2]$	4.5
Sigma	[-]	0
Tau	$[s]$	0.6

(sigma = driving imperfection factor, Tau = desired time headway)

D. Wiedemann 99 Model

The Wiedemann 99 model, initially designed for capturing driving behavior on freeways, has seen widespread application, extending to urban traffic scenario in recent studies [78]. The Wiedemann 99 model consists of 10 parameters, as detailed in Table 5. In this research, we utilize the calibrated values of Wiedemann model parameters to capture the CF behavior of human-driven vehicles in the study areas. These parameters are calibrated in another research using the same network and demand characteristics [79]. The calibrated values indicate the mean parameter values. To account for variability in human driving behavior, a normal distribution is applied to these calibrated values within the simulation tool. This approach ensures that the driving behavior of human drivers is not uniform, contributing to the robustness and realism of the simulation results. Worth-mentioning that the base model's demand and traffic assignments are calibrated using Principle Component Analysis (PCA) by [70]. In addition, the behavioral calibration is achieved using Finite Difference Stochastic Approximation (FDSA), a gradient-free stochastic approximation algorithm using several edges travel time data.

V. Experimental Setup

In this research, we develop a SUMO-based simulation platform to systematically simulate and analyze mixed traffic, considering varying deployment scenarios of AVs, since the current resources of CAVs modelling are limited in microscopic simulators. SUMO is selected for its open-accessibility and its widespread use in AV impact assessment studies. Like all traffic models, SUMO has its limitations; however, it provides the capability to simulate large-scale networks while incorporating detailed vehicular behaviors, including CF, and LC configurations [80].

The architecture of the simulation platform consists of three components: (i) Scenario execution, (ii) SUMO environment, and (iii) Output module. For each scenario, a set of inputs, such as demand scale, penetration rate, and OD matrix, are fed into the scenario execution tool. The scenario execution tool assigns trips in the traffic network based on the provided information and runs the SUMO microscopic resolution model. The CF behaviors of AVs and human-driven vehicles serve as the inputs for the SUMO environment to guide the simulation tool on how vehicles should move and interact with each other in the network. Considering the stochasticity in microscopic simulations, we aggregate the outputs (i.e., evaluation indicators) over multiple simulation replications. The study area covers the traffic network of Maxvorstadt, a district in Munich city center (see Figure 4). The network comprises urban road types with morning peak-hour traffic demand. The OD pairs of trips are allocated employing a trip-based stochastic user route choice assignment [21].

A. Human-driven vehicles CF model settings

Since the Wiedemann psychological CF model is a widely used model for replicating driving behavior of human-driven vehicles, in this research we also leverage Wiedemann 99 model to mimic this behavior in our simulation platform. The calibrated parameters of this model are shown in Table 5. We utilize these parameters settings for capturing human-driven vehicles in each simulation scenario.

B. AVs CF model settings

As discussed in section IV, the CF behavior of AVs is modelled using IDM, ACC and Krauss models. The proposed framework uses the initial values of these models' parameters in the simulation platform and searches for the optimized values. The definition of the ranges of each parameter in each model is necessary for the search space of the proposed framework. The ranges for each parameter (see Figure 5 and Table 6) are assumed in a way to capture realistic driving behavior and to include the vehicles capabilities in terms of acceleration and deceleration as well as the comfort driving

TABLE 5: Wiedemann 99 CF model parameters

Parameters	Description	Default value	Calibrated value
CC0	Standstill distance: desired minimum distance between leading and following vehicles [m].	1.50	1.50
CC1	Time gap: desired headway time between leading and following vehicles [s].	0.90	1.50
CC2	Following distance fluctuation: additional distance over the desired safety distance, where at this point following vehicle recognizes a slower leading vehicle [m]	4.00	4.00
CC3	Threshold for entering the deceleration zone: The time before a vehicle starts decelerating to the safety distance [s].	-8.00	-8.00
CC4	Negative following threshold: negative speed variation between following and leading vehicles (the lower the value, the more sensitive the following vehicle's driver)	-0.35	-0.40
CC5	Positive following threshold: a positive speed fluctuation between the following and leading vehicles (the positive value of CC4).	0.35	0.35
CC6	Speed dependency of oscillation: influence of distance of speed variation (the larger the value, the bigger the speed oscillation with increasing distance).	11.44	11.44
CC7	Oscillation acceleration: minimum variation of acceleration or deceleration while following.	0.25	0.25
CC8	Standstill acceleration: desired acceleration when beginning from standstill $[m/s^2]$.	3.50	4.0
CC9	Acceleration at 80 km/h $[m/s^2]$	1.50	1.50

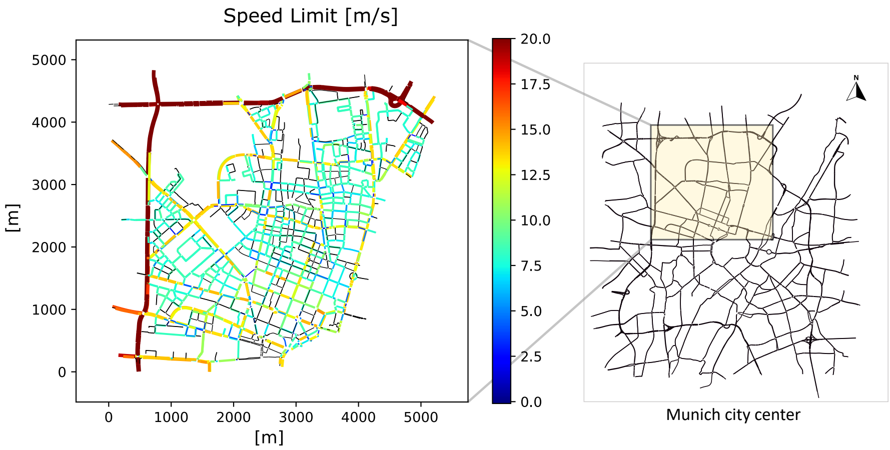


FIGURE 4: Road network of Maxvorstadt district in Munich city center

characteristics. Therefore, this research generates policy-dependent optimized parameters values of IDM, ACC, and Krauss models rather than assumed values. These values could be utilized in future researches to mimic the behavior of AVs instead of assuming them.

C. Study scenarios and simulation settings

In this research, we test the proposed optimization framework under different scenarios with varying demand cases, PRs, and combinations of KPIs. The framework generates a profile of optimized model parameters for capturing AVs CF behavior under each mix traffic conditions and policy settings. We examine the simulation platform with two distinct demand scales: 30% below peak hour traffic and peak hour (morning peak) traffic demand. For each model and demand scale, we analyze scenarios from 0 to 100% PRs with 33% increments. Additionally, the weight coefficient w to weight the policy targets varies from 0 to 1, incremented by 0.33.

TABLE 6: Range of values for ACC model parameters

Parameters	Symbol	Range of values
Desired time headway	tau	0.0 - 1.0
Speed control gain	k_1	0.2 - 0.6
Gap control gain space	k_2	0.2 - 0.3
Gap control gain speed	k_3	0.01 - 0.1
Gap-closing control gain space	k_{2*}	0.01 - 0.06
Gap-closing control gain speed	k_{3*}	0.5 - 1.0
Collision avoidance gain space	k_4	0.5 - 1.0
Collision avoidance gain speed	k_5	0.2 - 0.3

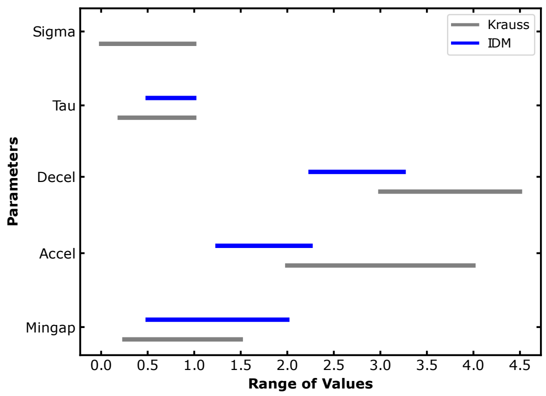


FIGURE 5: Range of IDM and Krauss models' parameters as a search space for DE

The chart below illustrates the overall scenarios space, generating a total of 24 scenarios for AVs under each model. In

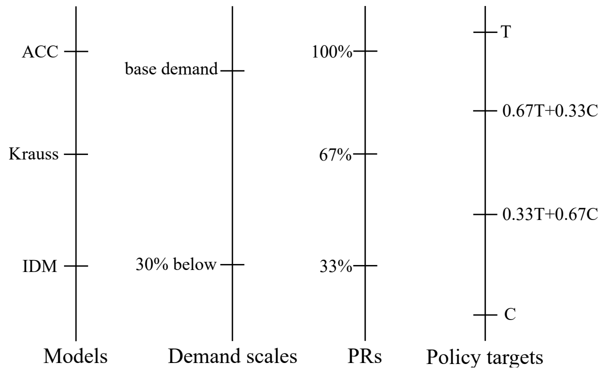


FIGURE 6: Various scenarios for models, demand cases, PRs and policy targets (C: number of conflicts, T: mean network travel time)

each optimization iteration, the evaluation function invokes the simulation module to retrieve the values of the KPIs. Within each call, 12 simulation runs are executed to account for the stochastic nature of the microscopic simulations. The resulting KPIs values represent the average of all simulation runs. A 15 min warm-up time is implemented, during which no data were gathered. Also, it is worth mentioning that based on the DE settings (population size = 10, maximum function evaluation = 1000, mutation = (0.5, 1), etc.), the number of function evaluations for convergence is at least 150 for each AV scenario. Thus, each scenario is simulated more than $150 * 12 = 1800$ times, which is more than $24 * 1800 = 43200$ simulation runs for all AV scenarios and for each model. In total for three models, we run more than $3 * 43200 = 129600$ simulation runs.

D. Parameters sensitivity analysis

To find the most sensitive parameter in each CF model in regards to the policy target, we conduct a sensitivity analysis on the parameters of each model. This study employs one-at-a-time (OAT) sensitivity analysis technique to find the effect of each parameter on the value of the policy targets. The OAT technique analyze the impact of one parameter on the output at a time, keeping other parameters fixed. In this case, we change the values of each parameter within their range (see Figure 5 and Table 6) and the increments of 0.01 to 0.25 (depending on the range of values of each parameter) under different demand scenarios and a full AV environment. The reason for choosing a 100% PRs of AVs is to neglect the effects of human-driven vehicles on the output. Hence, in a 100% PRs of AVs, a change in the value of output could be directly associated with the change of a certain parameter value.

VI. Results and Discussion

The findings and discussion section of this research are structured into four parts. The initial part presents the sensitivity of various policy targets on objective function convergence. Subsequently, the results in the second part illustrate the fluctuation of the optimized values of objective function under different PRs and demand cases. The third part provides a summary of the optimized CF model parameters of AVs across various scenarios. Finally, a parameter sensitivity analysis on the values of each parameter under a 100% PRs of AVs is presented.

A. Convergence analysis

The preliminary findings of this research reveal that in each scenario, the objective function successfully converges and identifies the optimized solution. However, the speed of converges and the objective function fluctuation differ based on the selected policy and CF model. Given that the error term of the objective function corresponds to a policy, a high fluctuation in the values of the objective function shows the influence of the CF model parameters with respect to the policy. Hence, the main aim of this section is to illustrate how a specific policy target is influenced by varying driving behavior (represented by different set of parameters" values) and the selected CF model. Additionally, we investigate the stability of the generated optimized CF parameter values in relation to a policy target.

When assigning the mean network travel time as the objective function, the optimization process terminates after around 250 function evaluations (except for 33% PR) for both IDM and Krauss models. Figure 7(a) and 8(a) show from left to right the convergence plots with different PRs for IDM and Krauss models, respectively. In both models, the objective function variates drastically from function evaluation 1 to 75, where from function evaluation 75 onward, the objective function approaches the optimized value. However, the speed of convergence and objective function fluctuation for the ACC model is slow compared to the IDM and Krauss models. As depicted in Figure 9(a), when selecting average travel time as the policy target, the optimization process terminates after 300 function evaluations, and there is no significant change in the value of the objective function under all AV penetration scenarios. Meanwhile, in all models, lower PRs present a smaller search space for the objective function, leading to a faster termination of the optimization process. The reason is that in lower PRs, the average network travel time is more influenced by human-driven vehicles.

In contrast, for the total number of conflicts as a policy, the optimization process converges after about 300 function evaluations for IDM and Krauss models. As shown in Figure 7(b) and 8(b), the values of the objective function drastically vary with different parameters' sets. The optimized sets of parameters of IDM and Krauss models significantly enhance safety in the network. This improvement is more vital with high demand scales. As displayed in Figure 7(b), in a full AV scenario, the total number of conflicts decreases by approximately 80% from the first iteration until the optimal condition is reached. This high fluctuation of the objective function also demonstrates the high sensitivity of different values of IDM and Krauss model parameters in the safety of the network. Hence, the optimized values of the parameters extracted in this study are stable and ensure the safe CF behavior of AVs under various scenarios. It is worth mentioning that in comparison to the average network travel time, the reduction in the total number of conflicts is significantly high. In addition, the fluctuation of the objective function in higher PRs is larger than in lower PRs, as shown in Figure 7(b) and Figure 8(b), due to larger search space/influence of optimization for higher PRs.

Meanwhile, the ACC model reveals different results when assigning the total number of conflicts as the policy target. In contrast to IDM and Krauss models, the parameters' combination of the ACC model is less sensitive in regards to the change in the total number of conflicts. As shown in Figure 9(b), in a full AV scenario (100% PRs of AVs), the total number of conflicts reduces only around 2% from the first function evaluation until the optimized condition is reached. This is due to the decision-making method of the ACC model, which comprises of four controlling modes. Unlike the IDM and Krauss models, where decisions are based on fewer parameters and rely on simpler formulations to determine the vehicle's acceleration in next step, the ACC model employs multiple decision regimes to estimate a vehicle's acceleration. These controlling modes enable the ACC model to generate a smoother driving profile compared to the IDM and Krauss models. This indicates that the ACC model could well replicate the CF behavior of AVs and optimized values of parameters could be a good candidate to be used in simulation-based impact assessment studies to replicate the CF behavior of AVs.

Furthermore, in Figure 10, we show how the minimization of one policy target (e.g., average network travel time) impacts other KPI (e.g., total number of conflicts in the network) and vice versa. This figure illustrates a detailed view of the function evaluations ranging from 75 to 250, derived from Figures 7-9, under base demand and 100% PR of AVs. The findings reveal that when assigning average network travel time as the policy target, the number conflicts increases significantly as the optimization process converges. This is true for both IDM and Krauss models as shown in Figure 10(a), whereas for ACC model the change on the number of conflicts is not significant. On the other hand, when the number of conflicts is set as a policy target, the average network travel time does not worsen when the optimization process converges as displayed in Figure 10(b).

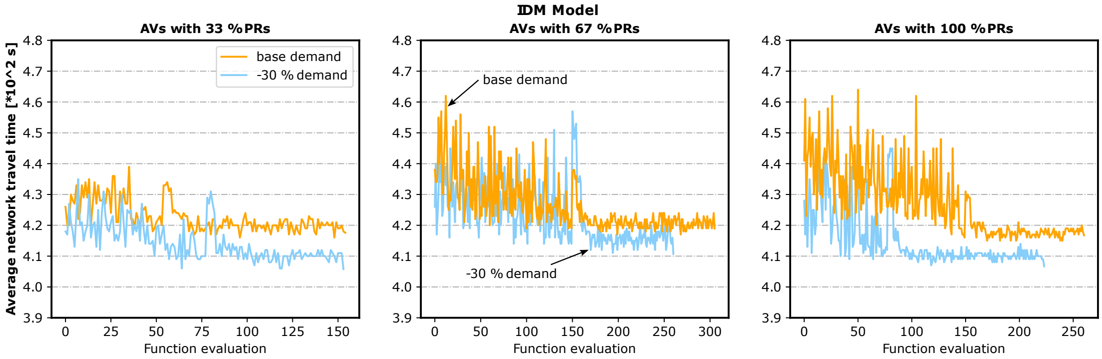
Similarly when choosing both KPIs as the error term of the objective function in all models, the results of the optimization module highlight increased fluctuations in the objective function when safety is prioritized. This reveals that driving behavior parameters are more sensitive to safety compared to efficiency.

B. Traffic efficiency and safety analysis

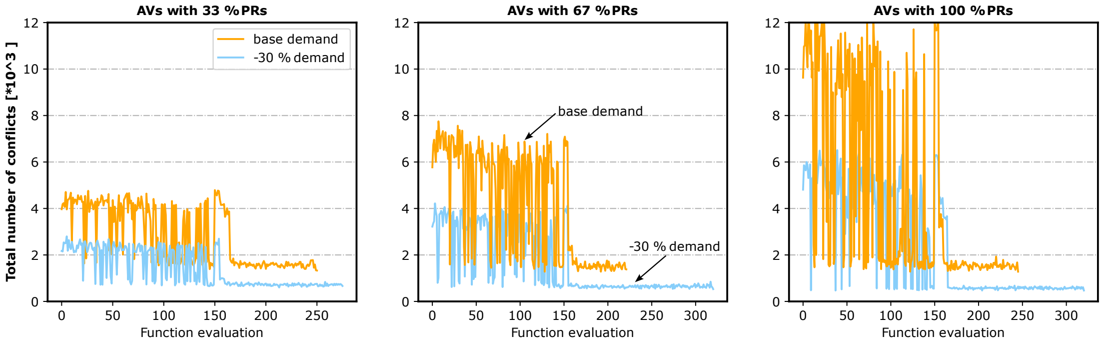
Analyzing the optimized values of the objective function under different PRs and policy targets and their comparison with a fully human-driven vehicles scenario reveals a significant reduction in the total number of conflicts when choosing traffic safety as a policy. Compared to a fully human-driven vehicles environment, the optimized behavior of AVs could potentially reduce the total number of conflicts by approximately 16% in IDM and Krauss models, where the change is not significant in the ACC model as shown in Figure 11. However, when the policy is chosen to enhance traffic efficiency, the situation does not exhibit improvement compared to a fully human-driven vehicles environment in all CF models. The rationale behind this outcome could be that the driving behavior parameters do not exert a significant influence on reducing travel time. The analysis of the convergence plots also shows that the objective function values fluctuate very low when the mean network travel time is selected as a policy. In contrast, the variation in total number of conflicts is considerably high (Figure 7, 8, and 9).

C. Policy-dependent optimized CF model parameters

The results of this study show that the extracted optimized CF model parameters under a full AV scenario could potentially reflect the best parameters values, since the driving behavior of AVs are not influenced by human-driven vehicles, and also the optimization module has a larger search space. Especially, when the total number of conflicts is chosen as a policy target. To have a clear understanding of the parameters change in regards to different policy targets, we show the optimized parameters values of IDM model for all policy targets as depicted in Table 7, whereas for Krauss and ACC



(a)



(b)

FIGURE 7: Convergence plots for 33%, 67%, and 100% PRs of AVs under (a) average network travel time, and (b) total number of conflicts as a policy target for IDM model.

models, only the optimized values for two policy targets (average network travel time, and total number of conflicts) are shown in Table 8 and 9. The arrows in all tables compare the values of parameters of each scenario with the full AV scenario (100% PR).

For the IDM model, when the total number of conflicts is selected as the policy under all demand cases and PRs, the optimization framework derives the optimized values of the CF model parameters. In different scenarios, the values of most of the parameters remain unchanged, as illustrated in Table 7(b). However, when choosing mean network travel time as a policy, generalizing a set of parameters for all PRs becomes challenging. As depicted in Table 7(a), there is a notable fluctuation in mingap for various PRs and demand cases. Additionally, when employing the combined KPIs as a policy, a higher weight assigned to traffic efficiency corresponds to increased variability in the optimized parameters' values across different cases as shown in Table 7(c) and (d).

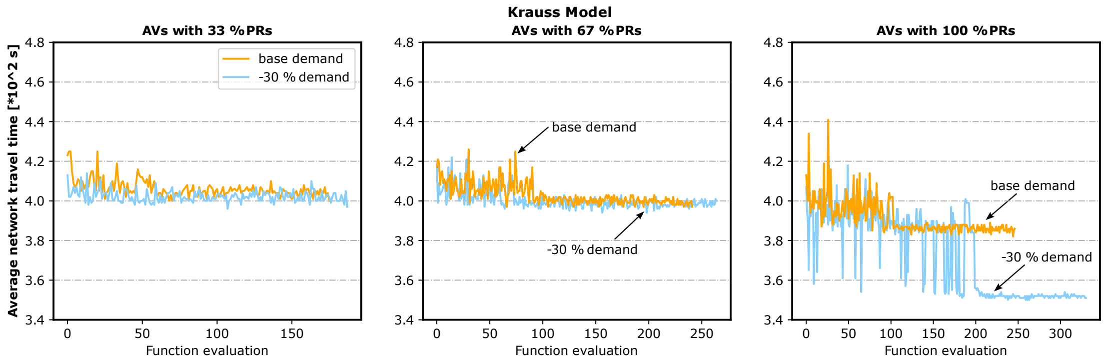
Similarly, for Krauss model, the most stable set of parameters is extracted when total number of conflicts is chosen as the policy target. As shown in Table 8(b), there are less variations in the optimized parameters values in comparison to Table 8(a), where the average network travel time is assigned as a policy target.

On the other hands, the optimized values of the ACC model parameters for both policy targets do not change significantly in almost all scenarios. Among other parameters, tau, and k_1 have comparatively higher variations as shown in Table 9. Still, for total number of conflicts as the policy target, we can generalize a set of parameters (potentially 100% demand scale, and 100% AV PRs) to be used for all AV PRs. Meanwhile, for a full AV scenario, the optimized values of parameters for both demand scales show almost the same values as depicted in Table 9(b).

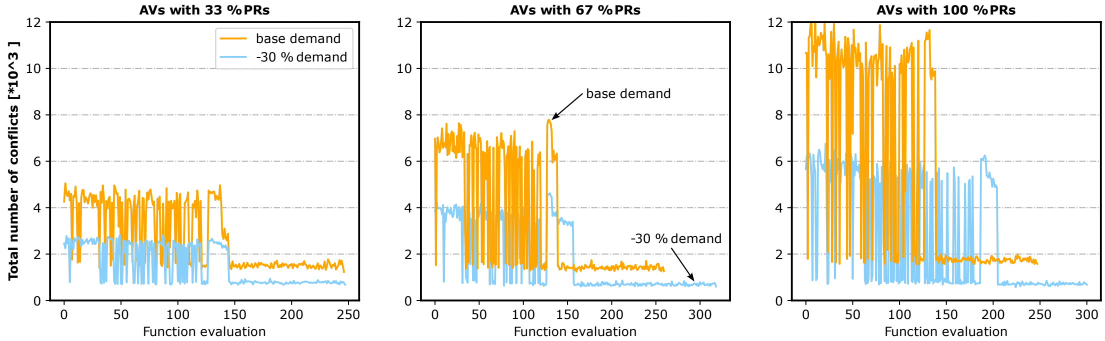
To summarize, the optimized parameters' values of all CF models under a full AV scenario and 100% demand scale could be potentially used in impact assessment studies to approximate the AVs CF behavior.

D. Parameter sensitivity analysis

The results of OAT sensitivity analysis show that for IDM and Krauss models, mingap, and tau are the most sensitive parameters in changing the total number of conflicts in the network (see Figure 12, and 13). For ACC model, however, the parameters of the model except the parameter tau are not



(a)



(b)

FIGURE 8: Convergence plots for 33%, 67%, and 100% PRs of AVs under (a) average network travel time, and (b) total number of conflicts as a policy target for Krauss model.

TABLE 7: The comparison of the optimized AVs IDM model parameters for different policies and under various scenarios

(a) Policy 1: Reduce average network travel time

Demand	PRs	mingap	accel	decel	tau
100%	100%	0.8	2.3	3.1	0.6
	67%	0.6 ↓	2.2 ↓	2.9 ↓	0.5 ↓
	33%	1.1 ↑	2.1 ↓	2.8 ↓	0.6
30% below	100%	1.9	2.3	2.6	0.5
	67%	0.9 ↓	2.3	3.0 ↑	0.6 ↑
	33%	0.5 ↓	2.3	2.6	0.5

(b) Policy 2: Reduce total number of conflicts

Demand	PRs	mingap	accel	decel	tau
100%	100%	1.9	2.0	2.4	1.0
	67%	1.9	2.0	2.4	1.0
	33%	1.7 ↓	2.3 ↑	2.4	1.0
30% below	100%	1.4	1.9	2.3	1.0
	67%	2.0 ↑	1.8 ↓	2.4 ↑	1.0
	33%	1.8 ↑	1.6 ↓	2.4 ↑	1.0

(c) Policy 3: Minimize sum of average network travel time and total number of conflict (33% priority for T and 67% for C)

Demand	PRs	mingap	accel	decel	tau
100%	100%	1.7	2.1	2.3	1.0
	67%	1.7	2.1	2.4 ↑	1.0
	33%	1.6 ↓	2.2 ↑	2.5 ↑	1.0
30% below	100%	1.7	2.0	2.4	1.0
	67%	1.6 ↓	2.1 ↑	2.5 ↑	1.0
	33%	1.6 ↓	2.1 ↑	2.6 ↑	1.0

(d) Policy 4: Minimize sum of average network travel time and number of conflict (67% priority for T and 33% for C)

Demand	PRs	mingap	accel	decel	tau
100%	100%	1.6	2.2	2.5	1.0
	67%	0.9 ↓	2.1 ↓	2.3 ↓	1.0
	33%	1.9 ↑	2.0 ↓	2.2 ↓	1.0
30% below	100%	1.7	2.3	2.5	1.0
	67%	1.4 ↑	2.2 ↓	2.9 ↑	0.8
	33%	1.1 ↓	2.2 ↓	2.7 ↑	0.9

Note: For each demand scale, the arrows compare the optimized values of parameters of each scenario with the full AV scenario (100 % PR).

very sensitive in comparison to other models as displayed in Figure 14.

For IDM model, the lower values of mingap and tau significantly increase the total number of conflicts in the

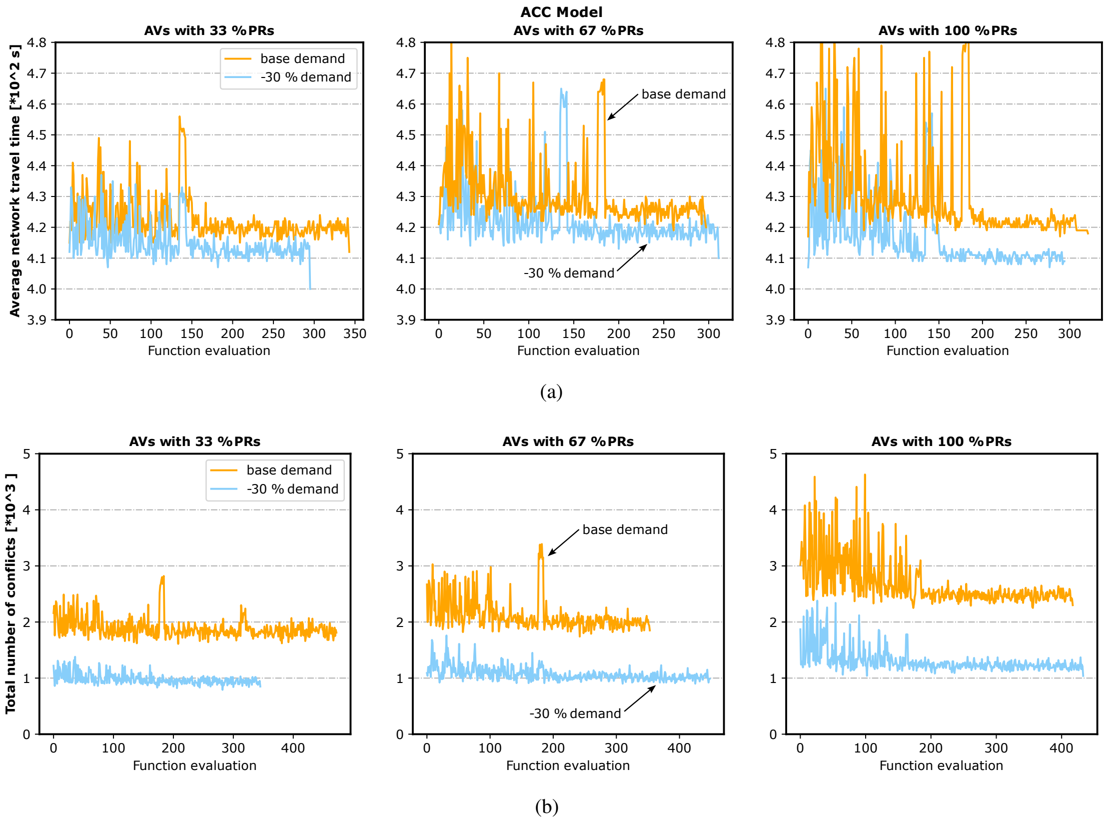


FIGURE 9: Convergence plots for 33%, 67%, and 100% PRs of AVs under (a) average network travel time, and (b) total number of conflicts as a policy target for ACC model.

TABLE 8: The comparison of the optimized AVs Krauss model parameters for (a) average network travel time, and (b) total number of conflicts as policy targets and under various AV PRs.

(a) Policy 1: Reduce average network travel time

Demand	PRs	mingap	accel	decel	tau	sigma
100%	100%	0.3	4.0	3.2	0.2	0.0
	67%	1.1 ↑	3.7 ↓	3.8 ↑	0.2	0.0
	33%	0.3	3.9 ↓	3.3 ↑	0.9 ↑	0.2 ↑
30% below	100%	0.6	3.7	4.3	0.1	0.0
	67%	1.4 ↑	3.6 ↓	4.3	0.7 ↑	0.0
	33%	0.8 ↑	3.2 ↓	3.3 ↓	1.0 ↑	0.1 ↑

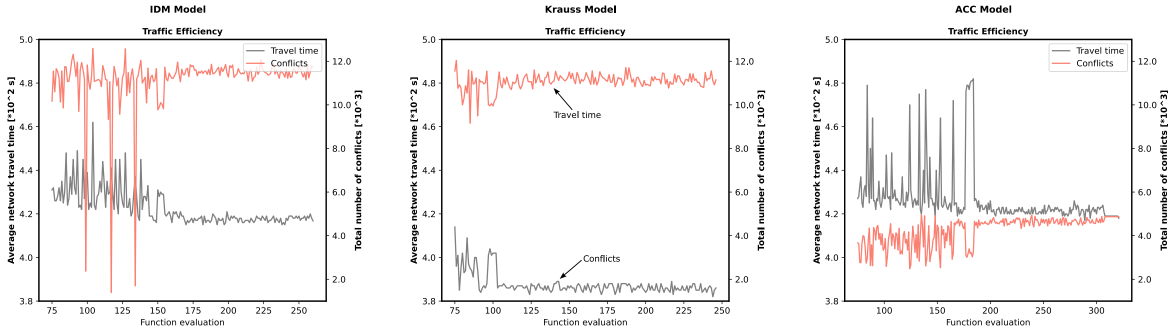
(b) Policy 2: Reduce total number of conflicts

Demand	PRs	mingap	accel	decel	tau	sigma
100%	100%	1.3	2.5	3.6	1.0	0.5
	67%	1.1 ↓	3.4 ↑	3.2 ↓	1.0	0.1 ↓
	33%	1.5 ↑	2.7 ↑	3.7 ↑	0.8 ↓	0.4 ↓
30% below	100%	1.3	2.8	3.0	0.9	0.1
	67%	1.0 ↓	2.6 ↓	3.2 ↑	0.9	0.0 ↓
	33%	1.3	3.2 ↑	4.4 ↑	1.0 ↑	0.2 ↑

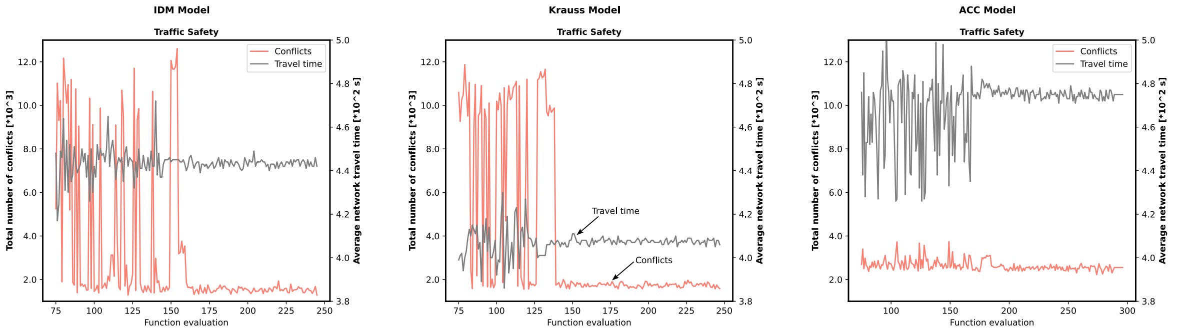
Note: For each demand scale, the arrows compare the optimal values of parameters of each scenario with the full AV scenario (100 % PR).

network. For instance, under a 100% demand scale, when changing the mingap from 0.5 to 2.0, the total number of conflicts in the network reduces around 80%, where for changing the tau from 0.5 to 1.0, the total number of conflicts decrease around 85% as displayed in Figure 12. Similarly, the total number of conflicts shows higher values with lower values of mingap and tau in Krauss model as shown in Figure 13(a). By changing the mingap from 0.25 to 1.5 under 100% demand scale, the total number of conflicts reduces around 82%, where by changing tau from 0.25 to 1.0, the total number of conflicts reduces around 84%. In both IDM and Krauss models, mingap and tau are equally sensitive in regards to the total number of conflicts in the network. Meanwhile, for ACC model, the parameter tau follows the same sensitivity as in IDM and Krauss models in changing the total number of conflicts in the network. However, only a slight change in total number of conflicts is achieved for gap-closing control gap space and gap-closing control gap speed parameters as illustrated in Figure 14. For other parameters, the changes, are not significant.

To summarize, the extracted optimized values in this study contradicts the assumptions made in the literature. For instance, it is assumed in many studies that AVs might drive closer to the leading vehicles [52], [53], where the findings



(a)



(b)

FIGURE 10: Illustration of the impacts of one KPI on the other KPI for each CF model under (a) policy 1: reduce average network travel time, and (b) policy 2: reduce total number of conflicts in the network for 100% PR of AVs and base demand scenario.

TABLE 9: The comparison of the optimized AVs ACC model parameters for (a) average network travel time, and (b) total number of conflicts as policy targets and under various AV PRs.

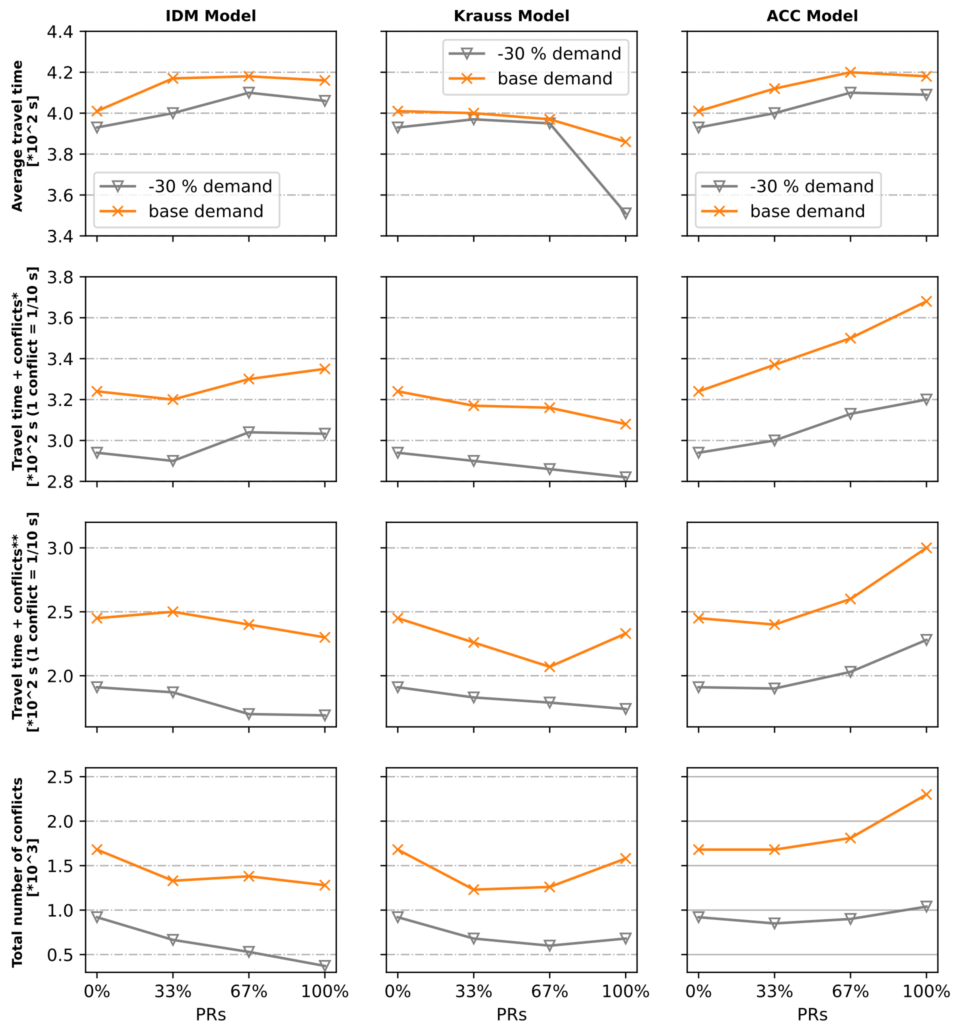
(a) Policy 1: Reduce average network travel time

Demand	PRs	tau	k_1	k_2	k_3	k_2^*	k_3^*	k_4	k_5
100%	100%	0.5	0.5	0.3	0.08	0.06	0.5	0.7	0.2
	67%	0.4 ↓	0.6 ↑	0.3	0.06 ↓	0.05↓	0.5	0.7	0.2
	33%	0.7 ↑	0.2 ↓	0.3	0.08	0.05↓	0.5	0.6 ↓	0.3 ↑
30% below	100%	0.8	0.3	0.3	0.10	0.06	0.6	0.8	0.3
	67%	0.5 ↓	0.3	0.2 ↓	0.06 ↓	0.05 ↓	0.6	0.9 ↑	0.2 ↓
	33%	0.7 ↓	0.6 ↑	0.2 ↓	0.08 ↓	0.05 ↓	0.6	0.8	0.2 ↓

(b) Policy 2: Reduce total number of conflicts

Demand	PRs	tau	k_1	k_2	k_3	k_2^*	k_3^*	k_4	k_5
100%	100%	1.0	0.3	0.3	0.09	0.02	0.9	0.9	0.3
	67%	1.0	0.5 ↑	0.3	0.06 ↓	0.04 ↑	0.9	0.9	0.3
	33%	0.8 ↓	0.3	0.3	0.06 ↓	0.02	0.8 ↓	0.9	0.3
30% below	100%	1.0	0.3	0.3	0.08	0.01	0.8	0.8	0.3
	67%	1.0	0.6 ↑	0.2 ↓	0.09 ↑	0.01	0.8	0.8	0.3
	33%	1.0	0.4 ↑	0.2 ↓	0.07 ↓	0.04 ↑	0.9 ↑	0.9 ↑	0.3

Note: For each demand scale, the arrows compare the optimized values of parameters of each scenario with the full AV scenario (100 % PR).



*Double priority for efficiency, **Double priority for safety

FIGURE 11: The optimum values of the objective function for different policy targets and CF models under two demand scales.

of this study show that the lower mingap results in higher number of conflicts in the network, and the optimized value of mingap is 1.9 for IDM model and 1.25 for Krauss model. Similarly, tau is assumed 0.5 in the literature [19], [20] to replicate the headway of AVs, where our findings show the optimized value around 1.0 for all three models.

VII. Conclusion

AVs are expected to exhibit safe and efficient driving behavior not only in certain traffic conditions but also throughout the entire trip. This research develops an optimization framework to identify the best sets of CF model parameters that generate an optimal driving profile for AVs across various scenarios. The optimization framework utilizes the DE global search algorithm to find the optimal parameter values by sending possible solution sets into the simulation environment. We conducted experiments with different CF models (IDM, Krauss, and ACC), demand scales (peak hour and off-peak hour), PRs (0%, 33%, 67%, and 100%), and policy targets (efficiency, safety, and combinations of both) was conducted to validate the proposed framework.

The convergence analysis of the objective function reveals that, when choosing the total number of conflicts as a policy, the objective function shows significant variability until the optimized (minimal) solution is reached. This indicates that an optimized set of CF parameters could considerably enhance the safety (minimum number of conflicts in the network). However, the convergence speed and fluctuation

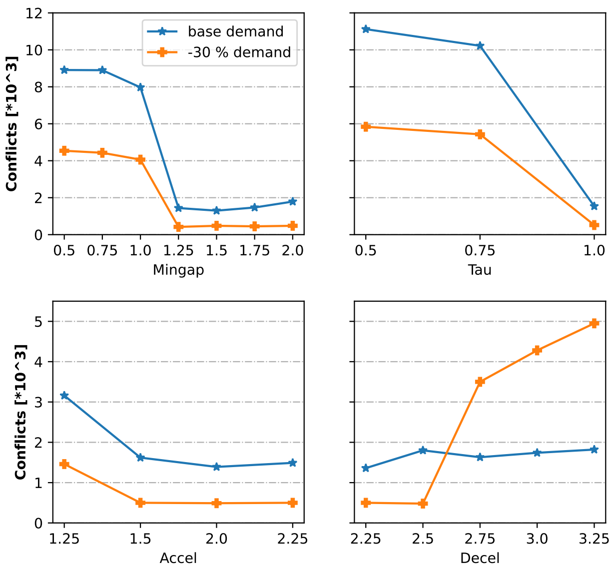


FIGURE 12: Sensitivity analysis of IDM model's parameters in regards to the total number of conflicts under two different demand scales

differ by CF model; IDM and Krauss show high sensitivity to the total number of conflict, while the ACC model is more stable (less fluctuation). Higher PRs also lead to greater fluctuations, likely due to a larger search space or increased optimization impact on the KPIs. In comparison, when the mean network travel time is set as a policy, the objective function variation is smoother. Meanwhile, the findings reveal that when assigning the average network travel time as the policy target, the number of conflicts increases significantly as the optimization process converges. This is true for both IDM and Krauss models; however, for the ACC model, the change is not huge. Similarly, when the number of conflicts is chosen as a policy target, the average network travel time does not worsen in all CF models while the optimization process terminates.

The analysis of the optimized values of the objective function (policy target) reveals that choosing the total number of conflicts as the policy target leads to a significant reduction in the number of conflicts as the PRs of AVs increase. In contrast, when the average network travel time is considered as the policy, no significant improvements are achieved compared to a fully human-driven vehicles scenario. In addition, the investigation of the parameter values determines that choosing the number of conflicts as a policy generates generalized parameter values that could be used for all demand scales and PRs in all CF models. Finally, the findings of sensitivity analysis show that the minimum gap (mingap) is the most sensitive parameter for IDM and Krauss models, where time headway (tau) is the most sensitive parameter for all three models in changing the total number of conflicts in the network. Other parameters do not have a magnificent influence on changing the policy targets.

The proposed optimization framework finds the optimal set of AVs' CF model parameters that could be potentially utilized in impact assessment studies instead of using assumed parameter values. However, one of the limitations of this study was to test the framework in one study area. While the experimental findings of this research could be applicable to similar case studies and demand patterns, further work will be needed to generalize these findings. This involves testing the proposed framework in different study areas, demand patterns, and unpredictable traffic situations, and extracting correspondingly optimized CF model parameters. Second, in this research, we utilized the Wiedemann model to replicate human-driven vehicles. However, it is interesting to model both human-driven vehicles and AVs using the same CF model and extract the optimal AV CF parameters. This will lead to a more accurate investigation of the impacts of different PRs of AVs on the network. In addition, a comprehensive impact assessment of AVs PRs on a network level using the extracted optimized CF parameters of this study will be part of our future work. Meanwhile, in this research we extracted the AV CF parameters, where the following vehicle communicates only with the leading vehicle through its sensors. A study using our methodological framework is needed to investigate and generate the optimal CF parameters for CAVs. This could be done using a CF model integrated into a simulation model, e.g., modified IDM model as in [28], which considers various vehicles into account for following the leading vehicle. Finally, a research to generate the optimal driving parameters considering both CF and LC models would be also part of our future work.

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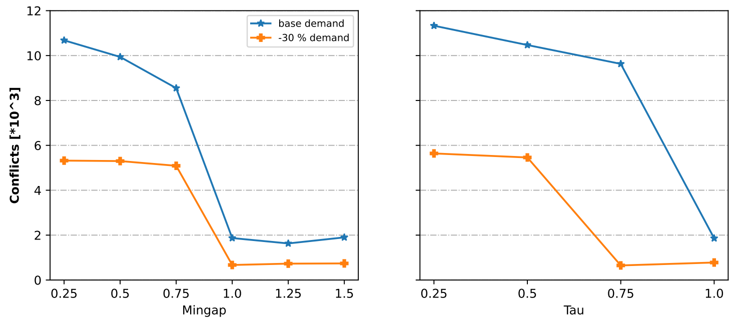
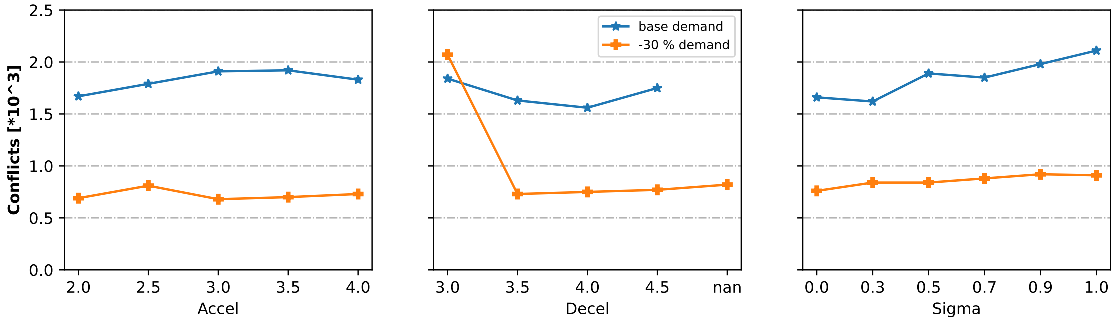


(a) High Sensitivity



(b) Low sensitivity

FIGURE 13: OAT sensitivity analysis of Krauss model's parameters in regards to the total number of conflicts

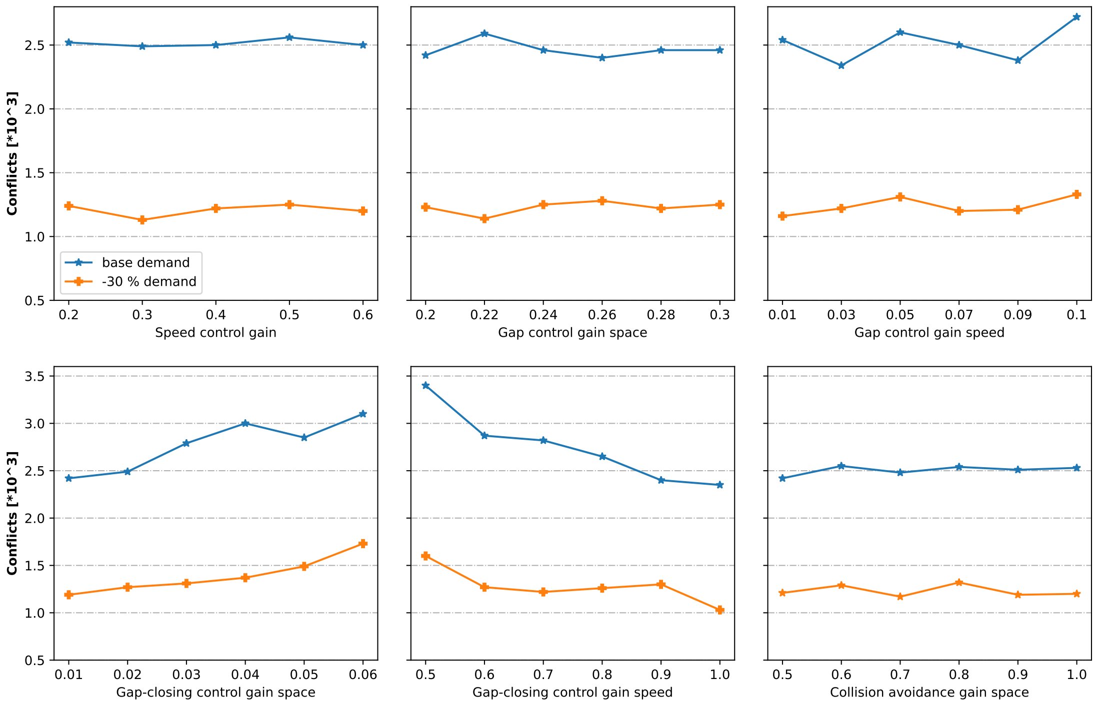


FIGURE 14: Sensitivity analysis of ACC model's parameters in regards to the total number of conflicts under two different demand scales (the parameter tau follows the same sensitivity as in IDM and Krauss models).

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C Sadid and Antoniou (2024). Dynamic Spatio-temporal Graph Neural Network for Surrounding-aware Trajectory Prediction of Autonomous Vehicles

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Dynamic Spatio-temporal Graph Neural Network for Surrounding-aware Trajectory Prediction of Autonomous Vehicles

Hashmatullah Sadid[1], and Constantinos Antoniou[1]

***Abstract*—Trajectory prediction is a critical aspect of understanding and estimating the motion of dynamic systems, including robotics and autonomous vehicles (AVs). For safe and efficient driving behavior, an AV should predict its own motion and the motions of surrounding vehicles in the upcoming time steps. To achieve this, understanding the interaction among vehicles is crucial for accurate trajectory prediction. In this research, we implement a dynamic Spatio-temporal graph convolutional network to predict the trajectory distribution of vehicles in a traffic scene. We perform the graph convolutional network (GCN) operation on directed graphs to capture the spatial dependencies among vehicles in each traffic scene. To accurately replicate the interaction among vehicles, we propose a novel weighted adjacency matrix derived by the strategic positions of vehicles (angular encoding) and the reciprocal of distances among vehicles in a traffic scene. Additionally, we employ the temporal convolution network (TCN) to learn the temporal dependencies of a trajectory sequence and decode the future driving status using historic trajectories. We test the model with a naturalistic trajectory dataset (HighD) and conduct performance evaluation. The findings reveal that the proposed model could significantly improve accuracy compared to existing state-of-the-art models. Meanwhile, we conduct transfer learning to test the generalizability of our model on low data availability scenario using NGSIM (US-101) dataset. The results show that the relearned model perform comparability well and depicts competing performance in comparison to the state-of-the-art methods.**

***Index Terms*—Trajectory prediction, dynamic Spatio-temporal graph neural network, autonomous vehicles**

I. Introduction

Trajectory prediction with its wide applications in autonomous driving [1]–[3], robot navigation [4], [5], and surveillance systems [6]–[8], has attracted significant attentions in recent years. In the field of autonomous driving, an autonomous vehicle (AV) should predict the possible future motion and trajectory of the surrounding vehicles for its own safe and efficient driving actions in the next time steps. This is possible for AVs, since they have the ability to detect the surrounding environment using their advanced sensing technologies (e.g., Lidar, Radar). The more advanced version of AVs, so-called connected AVs (CAVs), are capable of exchanging driving information (i.e., speed, acceleration, position, and more) not only with nearby connected vehicles (V2V) but also with connected vehicles in their communication range, as well as infrastructure (V2I) [9]. Trajectory prediction is not important only for the motion prediction of AVs, but also for capturing their driving behaviors in terms of car-following and lane-changing. An accurate trajectory prediction model could be potentially integrated with a simulation tool to replicate the driving behavior of AVs and conduct a simulation-based impact assessment of AVs deployment scenarios in a traffic network [9].

In a traffic scene, a vehicle continuously tries to act in such a way to have safe and efficient movement. The movement of a vehicle is related to its own past actions as well as its nearby vehicles' motions. Understanding other drivers' intentions is essential to predicting a vehicle's future positions and actions. The availability of the open source trajectory datasets such as HighD [10], NGSIM [11], pNEUMA [12], Waymo [13], and nuScenes [14], and the success of deep learning algorithms make it possible to accurately replicate the interaction among vehicles in a traffic scene and predict their movements in the next time steps.

There are two aspects in mimicking the trajectory of vehicles, namely, the temporal dependency of a vehicle's actions and the spatial dependency of a vehicle's actions with respect to its interaction with neighboring vehicles and map information (e.g., road geometry, speed limits, traffic lights). There are many attempts to capture the temporal dependency using recurrent neural networks (RNN) [15], Long short-term memory (LSTM) networks [16]–[18], and temporal Convolution neural network (CNN) [19], [20]. Among them, LSTM networks have shown significant success in capturing complex temporal dependencies. Some works also coupled LSTM-based methods together with pooling mechanisms to capture both temporal and interaction dependencies by aggregating a vehicle's neighbors past trajectories as an additional input to predict a target vehicle's trajectory [21]–[23]. In addition, attempts have been made to model the spatial dependencies among moving vehicles and capture the dynamic spatial interactions using LSTM-based methods [24], [25]. However, a key limitation of the LSTM-based methods is that they assume a grid structure for a traffic scene to capture the spatial dependency. Since the spatial relation of vehicles are non-Euclidean, this makes it a challenging task for LSTM-based methods to interpret and explain the model decisions.

Graph-based methods where vehicles are represented as nodes of a graph and the interaction among them are shown

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as edges of the graph could accurately and meaningfully replicate a traffic scene and predict a vehicle's future trajectory. Researchers utilize a graph neural network (GCN) to capture the spatial dependencies among vehicles, where temporal extractors such as GRU (Gated recurrent unit), LSTM, and temporal CNN are used to mimic the temporal dependencies. A combination of GCN with a temporal module is also called a spatio-temporal graph convolution network(STGCN). Several researchers utilized STGCN methods to predict the trajectory of vehicles as well as pedestrians [26]–[33]. In these methods, the interaction among vehicles are captured using weighted adjacency matrices.

In graph-based trajectory prediction studies, constructing an adjacency matrix and the defining the effects of nearby vehicles on the target vehicle play an important role. In many studies, when learning the spatial dependencies among vehicles, researchers only consider the direct distance among vehicles as a weight factor to construct the adjacency matrix [27], [31]–[33]. Using the weighted adjacency matrix, the aim is to distinguish the respective effects of the neighboring vehicles on the target vehicle. However, this approach contradicts real-world driving behavior. The driving actions of a vehicle is more influenced by the leading vehicle than a vehicle on the back. Assuming the same distance between a target vehicle and the vehicle on the front and back, the target vehicle might highly consider the front vehicle for safe and efficient driving. Similarly, the right-lane vehicles might have less influence on the driving behavior of a vehicle that, for instance, drives in the middle lane of a three-lane highway. Considering equal importance for all vehicles around the target vehicle does not match with the real driving behavior and introduces noises. Therefore, to accurately distinguish the true effects of the surrounding vehicles on the target vehicle, consideration of the driving position (e.g., leading, following, right-lane, left-lane, etc.) we call it strategic position in addition to direct distance is crucial.

The second challenge is that the adjacency matrix among vehicles in a scene is not symmetric and follows a directed graph structure. A leading vehicle highly impacts the actions of the following vehicle, whereas the following vehicle might also have lower effects on the actions of the leading vehicle. Third, the strategic position of the nearby vehicles might change in each scene. For instance, a vehicle on the back of the target vehicle might speed up, change its lane, and become the left lane alongside for the target vehicle. Similarly, nearby vehicles may loss their strategic positions by either existing the road, or new vehicles might take their positions. This brings a dynamic variation on the adjacency matrix not only in the positioning of the nearby vehicles but also creation of new interactions with new vehicles under different frames.

To address the above-mentioned limitations, this research implements a dynamic STGCN to simultaneously predict the motion and trajectory of all surrounding vehicles considering their strategic positions in a driving scene. We implement GCN to learn the spatial dependencies among vehicles in each scene considering the dynamic behavior of the graph structure. For constructing the adjacency matrix for embedding into the spatial GCN, we propose a two-step process which considers both the strategic position and location of nearby vehicles. For capturing the temporal correlation of the driving status, we employ the temporal convolution network (TCN) to decode the future driving status using the historic trajectories.

The main contributions of this research work are as follows: (i) We introduce a novel approach that incorporates the strategic positions of vehicles into the dynamic STGCN model. Unlike traditional methods that rely solely on distance-based adjacency matrices, our approach considers the relative positions and strategic orientations of vehicles to capture their spatial relationships more accurately. (ii) The implementation of a dynamic STGCN model on a directed graph structure, to predict simultaneously the trajectories of all vehicles in a traffic scene. By leveraging the directed graph topology, our approach captures the intricate interdependencies among vehicles, allowing for comprehensive trajectory predictions that consider the evolving dynamics of the entire traffic scenario.

The remainder of this paper is structured as follows: In the following section, we review the related work on trajectory prediction methods. In section III, we formulate the trajectory prediction problem description. Section IV describes the overall model architecture of the dynamic STGCN model including the proposed weighted adjacency matrix generation method. In section V, we conduct experiment and present the results of this research. Finally, a conclusion in Section VI explains the overall contribution of this article alongside further research directions.

II. Related Works

Over the past years, there have been many methods developed for trajectory prediction. According to [34], these methods are categorized into physics-based models, learning-based techniques, and planning-based methods. Physics-based models such as kinematic models [35], Kalman filtering [36], and Monto-Carlo methods are computationally efficient for trajectory prediction. These models can provide relatively better short-term predictions compared to long-term, when the vehicle's dynamics are well-understood and predictable. However, they struggle in rapidly changing traffic scenarios, where the dynamics of other vehicles are difficult to predict, and hence they are unreliable for long-term predictions [37].

Learning-based methods often driven by machine learning and deep learning techniques, leverage historical data to predict vehicle trajectories. These methods often employ techniques such as RNN [15], CNN [19], [20], LSTM [16]–[18] methods, Transformer models [38]–[41], and graph-based deep learning methods [27], [32], to capture the complex dependencies in vehicle's trajectory in a wide driving scenarios. Meanwhile, the planning-based methods aim to find optimal trajectories through algorithm solutions and optimizations. These methods are efficient in long-term prediction by explicitly optimizing vehicle trajectories, however, they could be computationally intensive [42], [43]. The current sate-of-the-art shows that learning-based models have been successful in trajectory prediction problem. These models are computationally efficient and benefit from the availability of open source trajectory datasets.

The trajectory prediction problem could be divided into two sub-tasks: (i) how a vehicle's past actions influence its future movement and (ii) how the interaction of a target vehicle with its neighbors affects its own future movements. Thus, trajectory prediction requires capturing both the temporal and spatial (interaction) dependencies. With the success of the LSTM-based methods in capturing the sequential data, researchers widely utilized LSTM to predict vehicles' and pedestrians' trajectories. We can categorize LSTM methods based on whether they account for vehicle interactions or not. Early works such as [17], [18], [44] utilized a single-layer LSTM by using the past trajectories of each vehicle in a traffic scene to predict their future trajectories without considering the interaction among vehicles. To address this limitation, some works introduced pooling mechanisms to capture the influence of other vehicles' on a target vehicle [21]–[23]. For instance, [23] proposed a single-layer LSTM that takes the past trajectories of the nearby vehicles as an additional input to mimic the trajectory of the target vehicle. However, the pooling mechanism in these studies only aggregates the trajectory information of all vehicles but does not distinguish the different impacts of nearby vehicles on the target vehicle. To further improve LSTM-based methods and capture spatio-temporal dependencies, recent methodological works consider the trajectories of surrounding vehicles when predicting the target vehicle's trajectory using a multi-layer LSTM. For instance [25] proposed a two-layer LSTM to learn the interaction among vehicles in a traffic scene by sharing the states of vehicles with each other. Although the latter method improved the accuracy of trajectory prediction, it is still challenging to interpret and explain model decisions.

Meanwhile, the Transformer model, originally developed for natural language processing (NLP) tasks [45], has been widely applied to various tasks, including object detection [46], image classification [47], posture estimation [48], and trajectory prediction [38]–[40], [49]. The attention mechanism allows Transformer models to capture both long-range and short-range dependencies simultaneously. In addition, a Transformer model's ability to process sequence data in parallel rather than sequentially accelerates both training and inference. Several studies utilized Transformer models for the trajectory prediction task. Some consider only the temporal dependency of a vehicle's driving actions [41], [50], whereas others also consider the interaction among vehicles in a traffic scene [38]–[40]. For instance, [41] utilized a Transformer model for pedestrian trajectory prediction, considering the past trajectories of pedestrians without modelling the interaction among them. Similarly, [50] used the modification of a standard Transformer, incorporating past trajectories as input features extracted from aerial view photo datasets. In contrast, [40] applied stacked transformers with a focus on defining dynamic variations in social behavior and representing interactions between vehicles using a graph attention module. [39] proposed a novel framework for multi-agent motion prediction using a hierarchical vector Transformer to mimic both the interaction among agents and the long-term dependencies of their driving actions. Although Transformer models have shown potential improvements in trajectory prediction tasks, they require substantial computational resources, and interpretability can be challenging due to the complex interactions learned by the self-attention mechanism [51].

The successful implementation of LSTM-based methods in trajectory prediction, and the interpretability challenge in Transformer models paved the road for researchers to further explore the trajectory prediction problem, emphasizing the spatial interaction of vehicles in a traffic scene. Hence, graph-based models, especially GCN-based models, have attracted attention for trajectory prediction problem, as they could accurately capture the spatial dependencies of vehicles in a traffic scene using a graph structure (i.e., vehicles as nodes of the graph and connection among them as edges of the graph) [30], [52], [53].

GCN is the most popular graph neural network (GNN) type extracted from the idea of the normal convolutional network. GCN can handle the cyclic mutual dependencies architecturally using a pre-defined number of layers with different weights in each layer. There are two types of GCN proposed in the literature, namely spectral-based and spatial-based GCN. The first spectral-based method was proposed by [54]. In this approach, graph convolution is defined by introducing filters from the view of graph signal processing. The information propagation in spectral GCN could be similar to signal propagation along the nodes. In spectral GCN, the convolution operation is defined in the Fourier domain by calculating the Eigen-decomposition of graph Laplacian matrix (for in-depth details, the reader is referred to [55]). On the other hand, spatial-based approaches consider the information propagation by operating on spatially close neighbors to define graph convolution. In the method proposed by [56], a symmetric-normalized aggregation with self-loop update operation is employed.

In vehicle trajectory prediction, GCN aggregates the features of the neighboring vehicles in a traffic scene using the adjacency matrix to predict the target vehicle's trajectory. GCN can well mimic the spatial dependencies among vehicles in traffic scenes; however, to capture the temporal dependencies and predict the future trajectories, temporal extractors such as GRU, LSTM, or TCN are combined with the GCN model, which is called the STGCN model.

The implementation of a STGCN model for trajectory prediction requires (i) the representation of a traffic scene as a graph, (ii) the construction of the adjacency matrix, and (iii) the selection of a temporal extractor. The graph structure is dynamic since the position and interaction of vehicles vary over time in traffic scenes. Second, the adjacency matrix is constructed in such a way as to distinguish the effects of vehicles on each other. Third, the temporal extractor is mainly used to capture the temporal dependency of a vehicle's movements in the past time horizon and use the knowledge to predict the trajectories in the future. The selection of a temporal extractor depends on its computational efficiency as well as whether it can predict the trajectories of all vehicles in a traffic scene at the same time. Recent works on vehicle trajectory prediction show that researchers used TCN to extract temporal dependencies in a STGCN architecture [27], [32], [33]. The reason is that TCN could predict the trajectories of all vehicles in a traffic scene simultaneously, whereas most LSTM-based methods predict the trajectory of each vehicle at a time. In real-time decision-making by AVs, it is necessary to predict the future trajectories of all nearby vehicles at the same time.

Several studies utilized a STGCN architecture for trajectory prediction. For instance, [27] developed the Social-STGCN model to predict the pedestrians' trajectory. This research used distance among pedestrians to create the weighted adjacency matrix and provide prior knowledge about the social relations between pedestrians. In this study, time-extrapolate CNN (TXP-CNN) is considered for temporal dependency extraction and future trajectory prediction. Similarly, [32] used STGCN to predict the vehicle trajectory. In their research, the reciprocal of direct distance among vehicles is used to construct the adjacency matrix and conduct convolution operation. In addition, the TCN model is utilized to extract the temporal dependency. Moreover, [33] utilized a STGCN framework to predict pedestrians' trajectory. This study is based on the Social-STGCN by modifying the model hyper-parameters and conducting more experiments. It is worth mentioning that some works also used gated attention networks (GAT) to capture the spatial dependency among vehicles. GAT utilizes the attention mechanism to allocate different weights to different nodes. For instance, [30] utilized a GAT model together with a TCN for pedestrian trajectory prediction. Inspired by the successful results of the STGCN model, in this research, we utilize the STGCN model similar to [27] for predicting vehicles' trajectory by constructing the weighted adjacency matrix based on vehicles' strategic position and their distances.

III. Problem Description

Trajectory prediction is the core task of the decision-making unit of AVs. The aim of the trajectory prediction is to predict the future motion of all nearby vehicles of a target AV in order to decide for its own future actions. This could be achieved using the past trajectories of all vehicles available in a traffic scene. The interaction among vehicles vary in each traffic scene, depending on the motion features of each vehicle. As shown in Figure 1, the relation between the target vehicle (the black colored vehicle) and nearby vehicles, both in terms of their strategic position and distance, change over time. This makes the trajectory prediction problem dynamic both in temporal and spatial dimensions. To formulate the trajectory prediction problem, we define N as the number of vehicles observed in a traffic scene with t_{obs} steps, where the attribute of a single vehicle $i \in \{1, \ldots, N\}$ at the time step $t \in \{1, ..., t_{obs}\}$ is denoted as:

$$X_i{}^t = \left[(x_i^t, y_i^t), (v_{xi}^t, v_{yi}^t), (a_{xi}^t, a_{yi}^t), \ldots\right]$$

Given the observed attributes of the vehicle X_i as $X_i^{1:t_{\text{obs}}} = [X_i^1, X_i^2, \ldots, X_i^{t_{\text{obs}}}]$, the aim is to simultaneously predict the future attributes of all vehicles denoted as Y_i^t for a prediction horizon, where $t \in \{t_{obs}, t_{obs+1}, \ldots t_{pred}\}$.

IV. Dynamic STGCN Model

In this research, the proposed model consists of two main components: the Spatio-temporal Graph Convolution Network (STGCN) and Temporal Convolution Network (TCN) modules. The STGCN module performs Spatio-temporal convolution operations on the graph representation of the vehicles trajectories to embed the driving features. These features are a compact embeddings of the historical vehicle trajectory observations. TCN module extracts the temporal dependency of vehicles trajectories and extrapolate the future trajectories of all vehicles simultaneously using these historical trajectory observations. An illustration of the overall framework is shown in Figure 2.

A. Spatio-Temporal Graph Representation

Considering the main elements of a graph (node and edge), the interaction among vehicles could be represented as a graph. Since the structure and the features of the vehicle trajectory graph changes over time, we name it dynamic Spatio-temporal graph. A dynamic Spatio-temporal graph could be defined as set of spatial graph G_t, where $t \in \{1, ..., t_{obs}\}$ representing the spatial dependencies of vehicles at time t. Considering N vehicles in a traffic scene, a spatial graph is defined as $G_t = (V_t, E_t)$, where $V_t = \{v_i^t \,|\, \forall i \in \{1, \ldots, N\}\}$ is the set of vertices (nodes) of the graph G_t. Each node v_i^t represents a vehicle in a frame with the relevant features $\{x_i^t, y_i^t\}$. E_t is the set of edges (connectors) within the graph G_t, which is defined as $E_t = \left\{e_{ij}^t \,\middle|\, \forall i, j \in \{1, \ldots, N\}\right\}$. In case of a connection between node i and j at time t, $e_{ij}^t = 1$, otherwise $e_{ij}^t = 0$.

The information whether two nodes are connected to each other does not reveal how strongly a node affects another node. Hence, to capture the magnitude of interaction between two vehicles, we attach weights to edges of the graph at each time t. These weights are organized into the weighted adjacency matrix A_t. In this research work, we define two types of adjacency matrix: the Euclidean distance-based adjacency matrix, and positional angular encoding adjacency matrix. The combination of both adjacency matrix types result in the final adjacency matrix which is used for the training of the model.

Euclidean Distance-based Edges

The first step for construction of the weighted adjacency matrix is to calculate the Euclidean distance between any two connected nodes. The closer the distance indicate the stronger interaction among vehicles. We use the equation (1) to measure the distance function (reciprocal of the distance) between two nodes and to give higher weight for closer vehicles as follows:

$$d(p_i^t, p_j^t) = \frac{1}{\sqrt{(p_{ix}^t - p_{jx}^t)^2 + (p_{iy}^t - p_{jy}^t)^2}} \tag{1}$$

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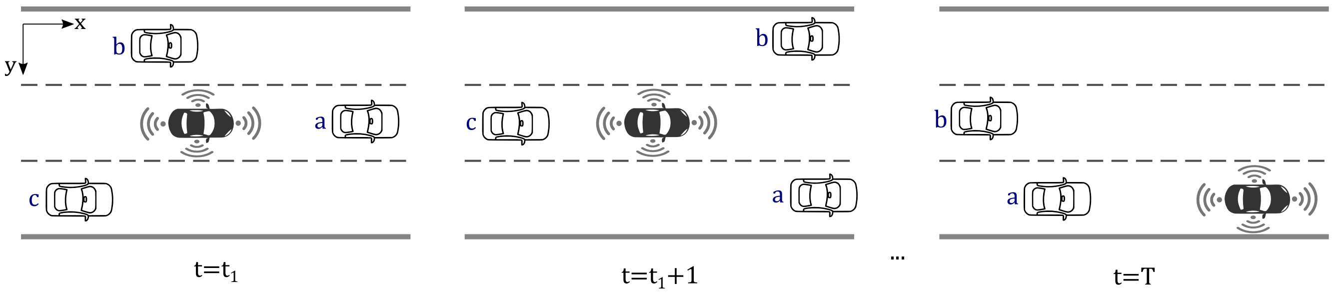

Fig. 1: The illustration of the interaction among vehicles over time; both the strategic position and distance of vehicles in respect to the target vehicle changes over time.

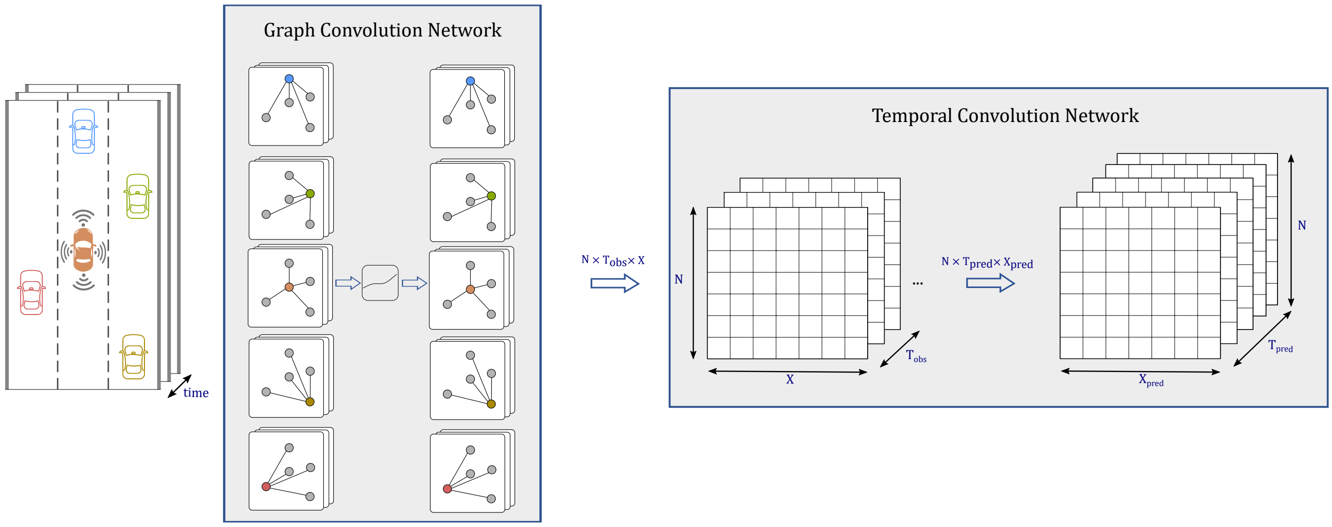

Fig. 2: The overall architecture of the proposed dynamic STGCN architecture. In each traffic scene, GCN takes the trajectories of vehicles as input and learns the spatial dependencies among them. This is done for all traffic scenes, and the results are mapped on the features maps. The TCN module then operates on the features maps to extract the temporal dependencies and predict the future trajectories.

where $p_i^t = (x_i^t, y_i^t)$ and $p_j^t = (x_j^t, y_j^t)$ are the coordinates of the vehicles i and j at the time t. The Euclidean distance-based weighted adjacency matrix is presented as:

$$A'^{\,t}_{ij} = \begin{cases} d(p_i^t, p_j^t), & \text{if edge } e_{ij}^t = 1 \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

Positional Angular Encoding-based Edges

The Euclidean distance-based adjacency matrix only provides information on how close two vehicles are. However, it does not reveal the strategic position of the vehicle with respect to the target vehicle. Therefore, we construct the angular positional encoding of the nearby vehicles with respect to the target vehicle to capture the strategic position of the surrounding vehicles. For this, the cosine function is used to distinguish the preceding vehicles (front, right, left) from the following vehicles (back, right, left) of the target vehicle. Consider a traffic scene, where the upper left corner represents the origin of the coordinate system as illustrated in Figure 3. The x-axis depicts the longitudinal direction of the travel of vehicles and increases to the right, and y-axis indicates the lateral movement of vehicles, which grows downwards. In case of a curvature, the x-axis remains horizontal, whereas the deviation in the value of y-axis could capture the curvature of the road and thus the curved trajectory of a vehicle. The strategic position of a vehicle with respect to other vehicles is estimated based on the coordinates of the vehicles, which are taken from the upper left corner of their bounding boxes. For instance, in Figure 3, the blue-colored vehicle is located in the preceding left position of the brown-colored vehicle, indicating that the blue-colored vehicle has a positive strategic position with respect to the brown-colored vehicle. Thus, the angle between two vehicles i and j can be derived as follows:

$$\theta_{ij}^t = \theta(p_i^t, p_j^t) = \arctan\left(\frac{p_{iy}^t - p_{jy}^t}{p_{ix}^t - p_{jx}^t}\right) \tag{3}$$

where $p_i^t = (x_i^t, y_i^t)$, and $p_j^t = (x_j^t, y_j^t)$ are the coordinates of the vehicles at the time t. The weighted adjacency matrix based on the the angular position of the nearby vehicles in respect to the target vehicle is defined as:

$$A''^{\,t}_{ij} = \begin{cases} cos(\theta_{ij}^t), & \text{if edge } e_{ij}^t = 1 \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

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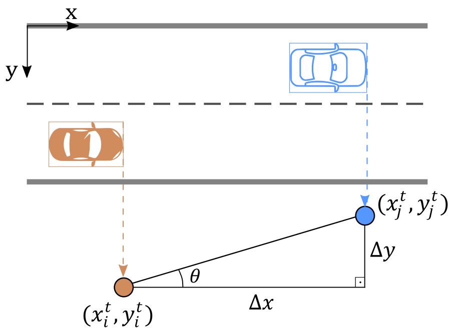

Fig. 3: The illustration of the angle calculation between two vehicles in a traffic scene. The upper left corner of the traffic scene corresponds to the origin of the coordinate system, and the upper left corner of the vehicles' bounding box represents the coordinates of vehicles with respect to the origin.

The elements of the angular position-based adjacency matrix takes values between $[-1, +1]$, where positive values indicate that the vehicle locates in the preceding positions of the target vehicle, and negative values shows its location in the following positions of the target vehicle. A value of $+1$ means that the vehicle is in front of the target vehicle, where -1 depicts that the vehicle is in the back of the target vehicle. Since the elements of an adjacency matrix can not have a negative value, we re-scale it to [0,+1] by multiplying the original cosine range by 0.5 and adding it by +0.5. In this context, the edge value of 0 indicates that a vehicle is on the back of the target vehicle.

The element-wise sum of both reciprocal distance adjacency matrix and angualr positional encoding adjacency matrix is the final weighted adjacency matrix.

$$A_{ij}^t = {A'_{ij}}^t + {A''_{ij}}^t = \begin{cases} d(p_i^t, p_j^t) + cos(\theta_{ij}^t), & \text{if edge } e_{ij}^t = 1 \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

B. Graph Convolution Network

The graph representation of the vehicle trajectory contains the spatial and temporal information of the vehicles' motions. In the spatial dimension, a vehicle's future state is highly related to its own state and its nearby vehicles' states. To capture the spatial dependencies among vehicles in each time step, we implement the GCN method proposed by [56]. GCN is a powerful method to aggregate and map the hidden representation of each node with its neighbors. The convolution operation to extract the features of nodes in each layer is expressed as:

$$H^{(l+1)} = \sigma(\hat{D_t}^{-1/2} \hat{A}_t \hat{D_t}^{-1/2} H^{(l)} \mathbf{W}^{(l)}) \tag{6}$$

where $H^{(l)}$ is the feature matrix of nodes in layer l, σ denotes the activation function, $\hat{A}_t = A_t + I$ is the adjacency matrix with I as identity matrix, $\hat{D}_t$ is the diagonal node degree matrix of $\hat{A}_t$, and the $\mathbf{W}^{(l)}$ represents the trainable parameters matrix in layer l. According to [56], the $\hat{D_t}^{-1/2} \hat{A}_t \hat{D_t}^{-1/2}$ aims to normalized the symmetric adjacency matrix and make the learning process of GCN faster. Since, in our proposed approach, the adjacency matrix is non-symmetric, therefore, we implement row-normalization technique similar to [57] to normalize the adjacency matrix. Thus, the term $\hat{D_t}^{-1/2} \hat{A}_t \hat{D_t}^{-1/2}$ in equation (6) become $\hat{D_t}^{-1} \hat{A}_t$.

In each layer, the GCN operation aggregates the features of the neighboring nodes and adds it to the features of the target vehicle. The updated features' vector of the target node is then passed to the next layer. This operation is conducted to each node and the features vector of any node in the next layer contains the aggregated information from the previous layer.

C. Spatio-Temporal Graph Convolution Neural Network

In GCN, we capture the spatial dependencies among vehicles in each scene (time step) and embed the features of each node based on its own features and its nearby vehicles. The output of the GCN operation is the set of features for each node in each time step. The STGCN contains the set of all graphs G_t, where the features and adjacency matrix changes over time.

Since, a vehicle's motion is highly dependent on its own past actions, we need to define a method to capture temporal dependencies. Several existing works have implemented LSTM to capture the temporal dependencies in STGCN. However, due to computational deficiency of LSTM, CNN-based temporal dependency extractor is used for trajectory prediction. Building upon the approach introduced by [27], we conduct both the temporal dependency extraction and future motion prediction using the TCN module.

D. Temporal Convolution Network

Following the operation of the STGCN module, the resulting output is the spatio-temporal embedding of each node from the input graph. As shown in Figure 2, the extracted spatio-temporal features is a three-dimensional tensor $H \in \mathbb{R}^{C' \times T \times N}$, where C' is the vehicles' features space, T is the number of time steps, and N is the number of vehicles. The TCN module operates on the temporal dimension of the graph embedding to capture the temporal dependency as well as to extent it for future trajectory prediction. TCN takes the $H' \in \mathbb{R}^{T \times C' \times N}$, which is generated from H by transposing dimensions, as input to learn the temporal dependency of a vehicle's past motions and the interaction with its neighbors. TCN considers the past time dimension as feature channels. In addition, TCN is constructed with a series of residual connected CNNs, where the residual connections are used to pass information through the layers. However, there is an exception for the first layer, since it receives input from the STGCN embedding output. The output of the TCN module is a tensor with the dimension $F \times C' \times N$. We conduct an ablation analysis to determine the number of layers in TCN for optimal performance of the model.

E. Model Transferability

To further examine the generalization ability of the proposed model with a different dataset characterized by variations in collection date, data size, and study area, we use transfer learning method. Transfer learning involves leveraging knowledge gained from source domain to a target domain. While trajectory datasets may share common feature sets and label types, it's crucial to note that the marginal distributions of features and conditional probability distributions of labels could differ significantly. For example, trajectory sequences may vary notably between different locations, highlighting the need for robust transferability to adapt to such variations. Hence, in this research, we select the best-trained model on the source data (large dataset) and directly apply it to the target data (small dataset) using transductive transfer learning. This implies that the parameters' weights in the pre-trained model serve as priors or initial values when transitioning to the target task. Moreover, the model can seamlessly be applied to the target task without necessitating any modifications, retraining, or fine-tuning on a subset of the target data.

V. Experiment and Results

A. Dataset

In this research, we utilize HighD trajectory dataset to evaluate the proposed model. The HighD dataset is a naturalistic trajectory dataset recorded on German highway using drone videography and with a frequency of 25 Hz. The dataset contains 60 recordings of straight highway sections of over 16.5 hours from six different locations and in various traffic conditions. Most of the HighD dataset is collected in the last season of the year 2017, and five out of 60 recordings are gathered in 2018. The dataset includes more than 110,500 vehicles (81% cars and 19% trucks) with 44,500 driven kilometers. In HighD dataset, a vehicle's trajectory attributes include it's type, width and length, coordinates, lateral and longitudinal velocity and acceleration, as well as other extracted information such as surrounding vehicles' positions, time headway (THW) or time-to-collision (TTC) and lane change maneuver.

In our experiment, we evaluate the model by splitting the dataset into 80% for training, 10% for validation, and 10% for testing. In addition, we follow the widely used setting for trajectory extraction using 8 seconds segment (3 seconds to observe trajectory, and 5 seconds to predict the trajectory). Furthermore, for model transferability analysis, we use portion of the US-101 in NGSIM dataset. The NGSIM dataset contains video recordings of traffic scenes, typically captured by cameras at strategic locations such as intersections or highways. These recordings provide detailed information about vehicle movements, including their trajectories, speeds, accelerations, and lane changes with a frequency of 10 Hz in real traffic scenarios. The dataset includes vehicle trajectories recorded under mild, moderate, and heavy traffic conditions, each spanning a duration of 45 minutes. Both datasets are downsampled to 5 Hz frequency, ensuring consistency in temporal resolution across our experimental setup.

B. Evaluation Module

In this research, we use the root mean square error (RMSE) to evaluate the performance of the proposed model. RMSE estimates the square root of the squared difference between predicted and ground truth trajectories. We calculate RMSE based on the average dispacement error (ADE) and the final displacement error (FDE). ADE-based RMSE compute the average square root error between the predicted trajectory and the ground truth trajectory over a specified time horizon, where FDE-based RMSE measures the error in the final points. Mathematically, ADE-based and FDE-based RMSE are defined in equations (7), and (8) as follows:

$$RMSE_{ADE} = \sqrt{\frac{1}{N \cdot t_{\text{pred}}} \sum_{n \in N} \sum_{t \in t_{\text{pred}}} (\hat{x}_t^n - x_t^n)^2 + (\hat{y}_t^n - y_t^n)^2} \tag{7}$$

$$RMSE_{FDE} = \sqrt{\frac{1}{N} \sum_{n \in N} (\hat{x}_t^n - x_t^n)^2 + (\hat{y}_t^n - y_t^n)^2} \tag{8}$$

where $p_t^n = (x_t^n, y_t^n)$, and $\hat{p}_t^n = (\hat{x}_t^n, \hat{y}_t^n)$ represents the ground truth and predicted attributes of the vehicle n at time t respectively. To consider the probability distributions of the predicted trajectories rather than mean values, we follow the work of [21] and [27], which 10 samples are generated based on the predicted distribution. The closest sample to the ground truth is then used to calculate the RMSE.

C. Model Implementation and Configuration Settings

We utilize PyTorch deep learning framework to implement the proposed model. Given that the trajectory prediction model generates the probability distribution of the trajectories, we train the model by minimizing the negative log-likelihood loss, defined as:

$$\mathcal{L} = -\sum_{n=1}^{N} \sum_{t=1+T}^{T+T_{pred}} \log \mathcal{P}(x_t^n, y_t^t | \hat{\mu}_t^n, \hat{\sigma}_t^n, \hat{\rho}_t^n) \tag{9}$$

where $\mathcal{P}(x_t^n, y_t^t | \hat{\mu}_t^n, \hat{\sigma}_t^n, \hat{\rho}_t^n)$ represents the likelihood of the ground truth position (x_t^n, y_t^t) within the predicted probability distribution, and $\hat{\mu}_t^n$, $\hat{\sigma}_t^n$, and $\hat{\rho}_t^n$ are the estimated mean, variance of the distribution, and correlation coefficient, respectively.

Throughout the training process, we employ a batch size of 128 and conduct the training for 100 epochs using a Stochastic Gradient Descent (SGD) optimizer. The initial learning rate is set to 0.01 and is subsequently adjusted to 0.002 after 70 epochs to expedite the convergence process. Meanwhile, the resulting output from each STGCN layer is passed through a dropout layer with a dropout ratio of 0.3. In addition, based on the findings of the ablation study, we select the appropriate number of layers for both STGCN and TCN modules ensuring the best performance of the model. It is worth-mentioning that the development of our model involved modifications to the original code created by [27].

D. Ablation Analysis

In this research, we conduct several experiments to understand the contribution of different components on the overall performance of the model. The ablation study includes (i) the impact of various combinations of the number of layers for the STGCN and TCN modules, (ii) the investigation of the effectiveness of different weighted adjacency matrices, (iii) the effect of the connected AVs distinguished by their communication ranges, and (iv) the performance of the model with both ADE- and FDE-based RMSE evaluation matrices.

First, we assess our model with varying number of layers for STGCN and TCN modules. The aims is to find the best model configuration as well as to assess how the performance of the model changes with varying the number of spatial and temporal layers. As displayed in Table I, a model with one layer of STGCN and five layers of TCN shows the lowest FDE-based RMSE value for 5 seconds prediction horizon and could be potentially used for further evaluations. Meanwhile, the increase in the number of STGCN layer detriotes the performance of the model under varying combinations with the number of TCN layers, whereas, by increasing the number of TCN layers (until 5), the model depict improved performance.

TABLE I: Comparison of the RMSE values for different combinations of STGCN and TCN layers.

STGCN layers \ TCN layers	1	3	5	7
1	1.08	0.61	**0.55**	0.70
3	1.48	0.70	0.93	0.78
5	1.88	2.80	0.81	1.01

Second, in graph-based trajectory models, the representation of the adjacency matrix plays a vital role in capturing the interactions among vehicles, which gives a prior knowledge to the model about the importance of the surrounding vehicles on the decision of the target vehicle. As discussed in section IV-A, our approach considers the combination of the relative angular position of the surrounding vehicles as well as their reciprocal distance to the target vehicle. We conduct several experiments to compare the performance of our approach with other kernel functions (e.g., direct distance, reciprocal of distance). The findings of this ablation study indicate that the best performance is achieved through our approach as shown in Table II. This indicates that the prior knowledge for the model can significantly improve the performance of the model. In comparison to the direct distance-based adjacency matrix, our approach shows around 42% reduction in average error. Similarly, our model depicts 30% and 31% reduction in error compared to reciprocal of distance and angular position encoding approaches respectively.

Third, we initially set the AVs detection range to 100 meters around the target vehicle. Since our data includes the trajectories of vehicles on Motorway, we only consider the

TABLE II: The performance comparison of the model under different weighted adjacency matrix.

Prediction Horizon [s]	Direct distance	Reciprocal of distance	Angular position	Combined*
1	0.18	0.15	0.13	**0.09**
2	0.32	0.28	0.27	**0.19**
3	0.54	0.46	0.43	**0.30**
4	0.72	0.56	0.61	**0.42**
5	0.92	0.75	0.83	**0.55**
Mean	0.54	0.44	0.45	**0.31**

vehicles in the same direction of the target vehicle. Thus, the target vehicle can detect the motion of the longitudinal vehicles within the range of 100 meters, and all surrounding lateral vehicles. Additionally, CAVs in practice could use the V2V communication to observe the motion of vehicles within the communication range of a CAV. Thus, we test the performance of our model with different communication ranges including 200, 300, and 400 meters. As illustrated in Table III, the model performance detriotes when increasing the detection range. This can attributed to the nature of the HighD dataset, which predominantly comprises data from human-driven vehicles. In such scenarios, driving decisions often rely on interactions with nearby vehicles, leading to optimized performance within limited detection ranges. However, it's important to note that these findings may vary significantly with datasets involving CAVs. Given the distinct behavioral patterns of CAVs, particularly in terms of communication and interaction, the model's performance under larger detection ranges might yield contrasting results.

TABLE III: Comparison of the RMSE values for different communication range and under various prediction horizons.

	Detection Range [m]			
Prediction Horizon [s]	100	200	300	400
1	0.09	0.11	0.12	0.13
2	0.19	0.21	0.25	0.27
3	0.30	0.34	0.42	0.45
4	0.42	0.49	0.61	0.66
5	0.55	0.64	0.80	0.86
Mean	0.31	0.36	0.44	0.47

Finally, we investigate the performance of our model with both evaluation matrices (ADE- and FDE-based RMSE). As shown in Table IV, the ADE-based RMSE shows lower values compared to the FDE-based RMSE. The reason is that ADE-based RMSE considers the past errors and generates the average error, whereas for FDE-based RMSE, only the final error of the last time step is reported.

E. Baselines

To verify the performance of the proposed model, we compare the results of our model with the state-of-art methods for HighD dataset. These state-of-the-art methods includes prediction models proposed from 2016 to 2023. For a fair

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TABLE IV: The performance comparison of the model with different evaluation matrices.

Prediction Horizon [s]	ADE-based RMSE	FDE-based RMSE
1	0.13	0.09
2	0.21	0.19
3	0.29	0.30
4	0.37	0.42
5	0.45	0.55
Mean	0.29	0.31

comparison, we report the FDE-based RMSE similar to existing methods. The baseline methods in this research are as follows:

- Social-LSTM (S-LSTM) [21]: This model is designed for predicting the future trajectories of multiple interacting agents (pedestrians or vehicles) in a dynamic environment. A LSTM is used for each trajectory and the resulting output is shared among LSTMS (of all trajectories) using the fully connected pooling layer.
- Social Generative Adversarial Networks (S-GAN) [64]: This model employs adversarial learning, with a generator and discriminator trained in opposition. The generator, featuring an encoder-decoder structure, predicts future trajectories from past trajectories and uses a social pooling layer to account for agent interactions, ensuring socially acceptable paths. The discriminator evaluates these trajectories, promoting realistic and diverse predictions.
- Convolutional Social Pooling (CS-LSTM) [58]: This LSTM-based model employs convolutional social pooling layers to address spatial interactions. It focuses on predicting multi-modal trajectory distributions for the target vehicle, with predictions informed by maneuver-based considerations.
- Non-local Social Pooling (NLS-LSTM) [59]: The NLS-LSTM model introduces non-local social pooling layer, which integrates both local and non-local information. The non-local multi-head attention mechanism captures the significance of each vehicle in relation to the observed vehicle.
- Dual Learning Model (DLM) [60]: The DLM utilizes the lane occupancy and risk maps for accurate vehicle trajectory prediction.
- Environment-Attention Network (EA-Net) [61]: This model introduces a novel parallel structure, containing a graph attention network and convolutional social pooling with a squeeze-and-extraction mechanism. This innovative architecture serves as the environmental feature extraction module and is embedded within the LSTM encoder-decoder framework.
- Multi-head Attention Social Pooling (MHA-LSTM) [63]: The model employs multi-head attention to extract intricate features from both the target vehicle and its surrounding vehicles using dot product attention.
- BRAM-ED [62]: This model considers the change of driving behavior in trajectory prediction. This framework consists of driving behavior recognition module, behavior attention mechanism trajectory encoder, and behavior adaptive future trajectory decoder.
- Spatial-temporal dynamic attention network (STDAN) [65]: This model adopts a hierarchical structure for feature extraction and fusion. It considers motion states, social interactions, and temporal correlations between interactions when predicting trajectories, benefiting from the utilization of LSTM and attention mechanisms.
- Wave Superposition Inspired Pooling (WSiP) [66]: This model uses a novel wave-pooling method by modeling each vehicle as a wave characterized by amplitude and phase. This wave representation allows for the dynamic aggregation of interactions among vehicles, effectively capturing high-order interactions by superimposing their waves. Integrated into an encoder-decoder framework, the model processes historical trajectory data and current vehicle states to predict future movements.
- Dual Transformer-based Prediction (DTP) [67]: This model employs two Transformers to capture the vehicles' intentions and predict their trajectories. The intention prediction module aims to extract the vehicles' states and outputs the intention probability vector. The trajectory prediction Transformer uses the intention probability vector as a prior knowledge to predict the future trajectories.
- Adaptive Multi-Modal Vehicle Trajectory Prediction (DACR-AMTP) [68]: This model predicts vehicle trajectories in complex traffic scenarios by learning drivers' intentions and behaviors while considering dynamic relationships among vehicles. It consists of five modules: line boundary constraints, dynamic drivable area determination, historical trajectory encoding, multi-headed attention mechanism, and adaptive multimodal prediction. These modules capture geographic, interaction, and intention constraints, enabling accurate trajectory prediction.
- Surrounding-aware STGCN (SA-STGCN): The model proposed in this research.

F. Performance Analysis

The findings of the experiment reveal that our SA-STGCN model outperforms the existing methods across all prediction horizons. As shown in Table V, our model consistently achieves the lowest average error over all prediction horizons. For a prediction horizon of 5 seconds, our model reveals a 34% reduction in error compared with strongest baseline model, resulting in an error reduction to 0.55 m. Moreover, when comparing the mean error over all prediction horizons, our approach achieves a RMSE value of 0.31 m, representing approximately 28% reduction compared to the best existing model. This clearly indicates that the prior knowledge to the model by means of the weighted adjacency matrix could play a vital role in improving the trajectory prediction.

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TABLE V: The comparison of the RMSE value for different state-of-the-art methods with our model (HighD dataset).

Prediction Horizon [s]	S-LSTM [21]	S-GAN [64]	CS-LSTM [58]	NLS-LSTM [59]	DLM [60]	EA-Net [61]	MHA-LSTM [63]	BRAM-ED [62]	STDAN [65]	WSiP [66]	DTP [67]	DACR-AMTP [68]	SA-STGCN
1	0.22	0.30	0.22	0.20	0.22	0.15	0.19	0.10	0.19	0.20	0.41	0.10	**0.09**
2	0.62	0.78	0.61	0.57	0.61	0.26	0.55	0.25	0.27	0.60	0.79	**0.17**	0.19
3	1.27	1.46	1.24	1.14	1.16	0.43	1.10	0.43	0.48	1.21	1.11	0.31	**0.30**
4	2.15	2.34	2.10	1.90	1.80	0.78	1.84	0.56	0.91	2.07	1.40	0.54	**0.42**
5	3.41	3.41	3.27	2.91	2.80	1.32	2.78	1.01	1.66	3.14	-	1.01	**0.55**
Mean	1.53	1.66	1.49	1.34	1.32	0.59	1.29	0.43	0.70	1.55	0.93	0.42	**0.31**

G. Model Transferability

Table VI presents the analysis of model transferability onto a target dataset. The size of the target dataset (US-101 NGSIM) is relatively low (<10%). When utilizing the target data for training, the baseline model with the randomly initialized parameters yields a RMSE of 2.73. However, unfreezing the layers of the pre-trained model on the target data leads to the best RMSE values across all prediction horizons, as illustrated in the Table VI. This highlights the importance of fine-tuning when transferring knowledge from the source to the target domain. The necessity arises from the distinct temporal patterns observed between the target and source datasets. Thus, the model undergoes relearning of network patterns specific to the target dataset.

TABLE VI: Performance comparison between training new model and fine-tuning pre-trained model.

	RMSE [m]	
Prediction Horizon [s]	Baseline model*	Transfer model**
1	0.47	0.34
2	0.91	0.65
3	1.47	0.97
4	2.10	1.14
5	2.73	1.55
Mean	1.53	0.93

Weight initialization:*random, **pre-trained

Furthermore, comparing the performance of the transfer learning model with the existing methods reveals that our model competes with almost all methods as depicted in Table VII. Despite the relatively small size of the target data used for transfer learning, our relearned model exhibits comparable performance to existing state-of-the-art models that are trained and tested on much larger datasets. Hence, transfer learning is prominent in scenarios with low data availability.

H. Inference Speed and Model Size

Computational efficiency is a crucial aspect of the real-time application of a trajectory prediction model in automated driving. In this research, we analyze the deployability of our model in autonomous vehicles based on its model size and inference speed. We compare our model inference speed and parameter counts with GRIP [73] and GSTCN [32] models. Both models predict the trajectories of all vehicles simultaneously. The findings reveal that our model has the least parameter size, as shown in Table VIII. Regarding the inference time, our model takes an average of 0.037 ms to predict one vehicle's trajectory. This is significantly faster than the GRIP model, with a speed improvement of 8.7 times. When compared to the GSTCN model, our model also performs better in terms of inference speed. These improvements are associated with the architecture of our model by employing the GCN and CNN, which overcame the limitations of recurrent architecture and aggregation mechanisms.

TABLE VIII: The comparison of the model sizes and inferences speeds of different models.

Model	Parameters count	Inference time* (ms)
GRIP	496.3K (15×)	0.322 (8.7×)
GSTCN	48.9K (1.5×)	0.044
SA-STGCN (ours)	**31.8K**	**0.037**

*: mean inference time per vehicle

I. Qualitative Analysis

Figure 4 illustrates the visualization of several representative predicted trajectories under no interacting, mild, moderate, and congested traffic scenes. The model observes the 3 seconds trajectories of vehicles in a traffic scene (shown as solid blue line), and predicts the upcoming 5 seconds trajectories (illustrated as red dashed line). The dash-dotted line (in green) depicts the ground truth 5 seconds trajectories of vehicles. Under all traffic conditions, the model demonstrates the ability to predict vehicle trajectories closely aligned with the ground truth, indicating the generalizability of our approach across diverse traffic scenes.

VI. Conclusion and Research Gaps

In this research, we implement a dynamic STGCN model to simultaneously predict the motion and trajectories of vehicles in a traffic scene. The model combines GCN operation to capture the spatial (interaction) dependencies among vehicles on a directed graph and a TCN module to extract the temporal dependency in trajectory sequences, enabling accurate predictions of future vehicle movements. Within the GCN operation, we propose a novel method for building the weighted adjacency matrix considering each vehicle's strategic position and distance to the target vehicle. The aim is to provide

TABLE VII: The comparison of the RMSE value for different state-of-the-art methods with fine-turning our pre-trained model (NGSIM US-101 dataset).

Prediction Horizon [s]	CV [69]	V-LSTM [70]	C-VGMM +VIM [71]	CS-LSTM [58]	GSTCN [32]	DAM [72]	BRAM-ED [62]	STDAN [65]	WSiP [66]	DACR-AMTP [68]	Transfer Model
1	0.73	0.66	0.66	1.03	0.42	0.50	0.36	0.42	0.56	0.57	**0.34**
2	1.78	1.62	1.56	1.13	0.81	1.11	0.82	1.01	1.23	1.07	**0.65**
3	3.13	2.94	2.75	1.61	1.29	1.78	0.94	1.69	2.05	1.68	0.97
4	4.78	4.63	4.24	2.31	1.97	2.69	1.19	2.56	3.08	2.53	**1.14**
5	6.68	6.63	5.99	3.21	2.95	3.93	1.28	3.67	4.34	3.40	1.55
Mean	3.42	3.30	3.04	1.86	1.49	2.00	0.92	1.87	0.56	1.85	0.93

prior knowledge to the model and to capture the impacts of the nearby vehicles on a target vehicle. The combination of angular encoding and the reciprocal of the distance of each vehicle to target vehicles is used to construct the adjacency matrix.

To evaluate the performance of the proposed model, we conduct an experimental setup using the HighD dataset. Additionally, we perform transfer learning to examine the generalization ability of the proposed model using the NGSIM (US-101) dataset. The findings of this research reveal that our model outperforms the existing state-of-the-art methods under different prediction horizons. For a prediction horizon of 5 seconds, the model shows a 34% reduction in error compared with the strongest baseline model. Similarly, the results of transfer learning depict that the relearned model performs comparability well and depicts competing performance in comparison to the existing methods.

This research also raises new lines of work to further extend the implementation of the proposed model. First, in this research, we utilized the HighD dataset to train the model, given that the HighD dataset is gathered from the German highways and includes only cars and trucks. However, the model could be tested with different datasets, preferably in urban areas that include multi-road users. Second, in our research, we only considered the past trajectories involving the coordinates of AVs; further exploration could consider investigating the integration of additional data sources, such as LiDAR or Radar with more features, to enhance the model's accuracy and robustness in diverse traffic scenarios. Third, our proposed model could be potentially utilized in lane-free traffic scenarios. We can assess the efficacy of our model using a dataset that involves lane-free traffic, paving the way for the potential development of a motion planning algorithm grounded in our model's predictions. Finally, there is a potential to integrate the proposed model into a microscopic simulation tool to replicate the driving behavior of AVs under varying traffic conditions and conduct impact assessment. This will generate plausible findings on the potential impacts of AVs deployment scenarios.

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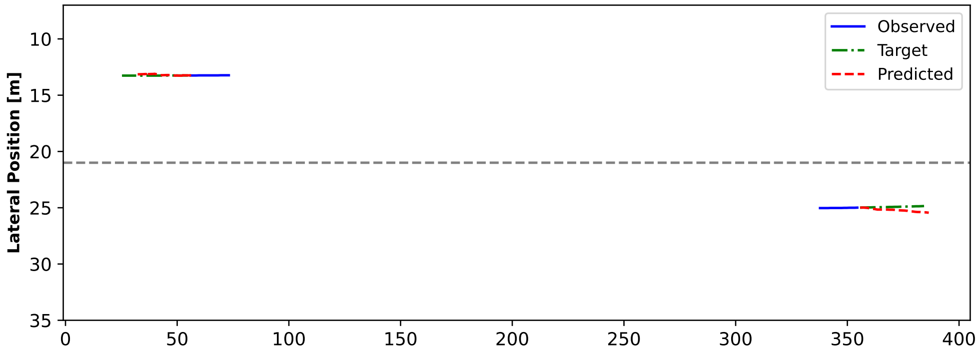
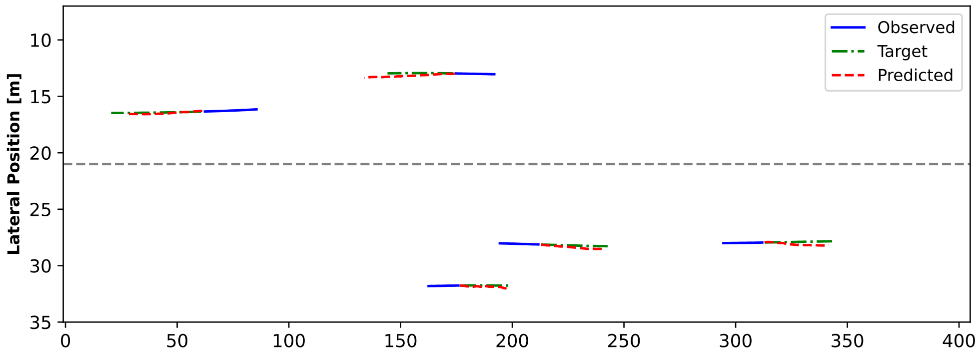
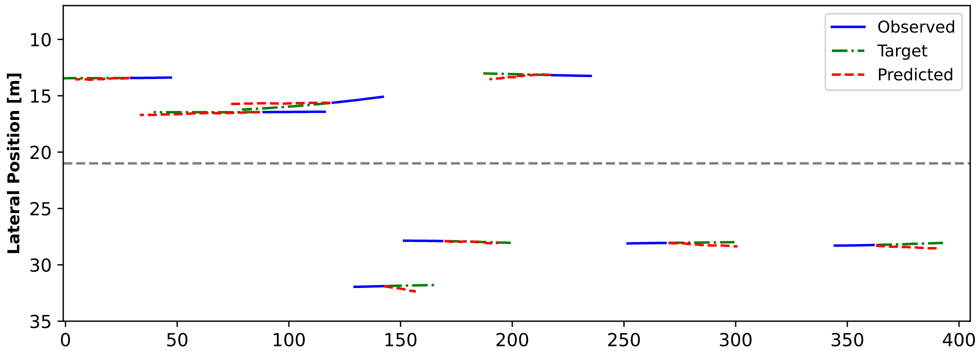


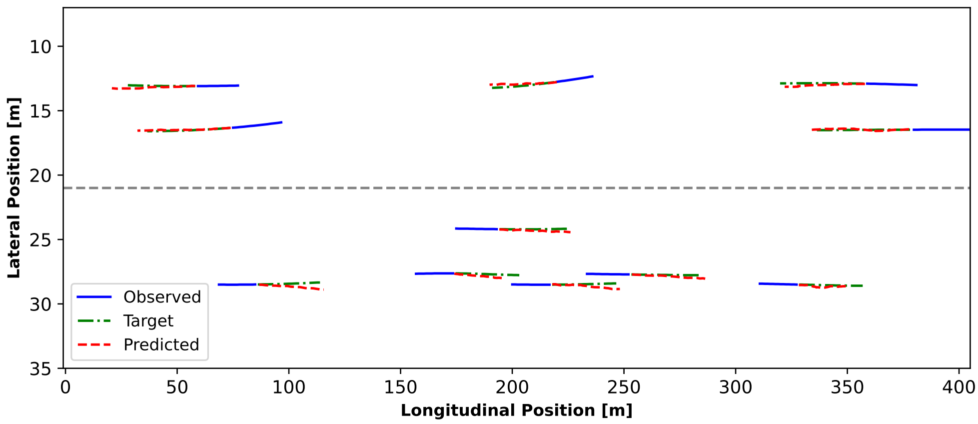
(a) No interacting traffic scene



(b) Mild traffic scene



(c) Moderate traffic scene



(d) Congested traffic scene

Fig. 4: Illustration of predicted, target, and observed trajectories under no interacting, mild, moderate and congested traffic scenes.

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A simulation-based impact assessment of autonomous vehicles in urban networks

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Abstract

The behavioural differences between autonomous vehicles (AVs) and human-driven vehicles (HDVs) can significantly impact traffic efficiency, safety, and emissions. Simulation-based impact assessments using microscopic traffic models often modify car-following (CF) and lane-changing (LC) configurations to differentiate AVs from HDVs. Typically, researchers adjust CF model parameters to replicate AV driving behaviour, but these assumptions can lead to varying conclusions on AV impacts. The scope of each study (e.g., freeways, highways, urban links, intersections) also influences the outcomes. This research conducts an impact assessment utilizing optimized AV driving behavior rather than assumptions on a city network level (Munich) using a simulation-based platform. The particle swarm optimization (PSO) algorithm is used to calibrate the base model and run simulation experiments under various penetration rates (PRs) and demand scenarios. Results show significant safety improvements throughout the network under higher PRs, while lower PRs might lead to deteriorating safety. At 100% AV PR, the total number of conflicts decreased by around 25% compared to a fully HDV environment. Considering AVs' sensing capabilities, additional safety improvements are found in almost any AV PR. However, AVs might not improve traffic efficiency; in some cases, they may slightly increase average network travel time, though this change is minimal.

1 | INTRODUCTION

Fully automated vehicles, also called autonomous or self-driving vehicles, will gradually enter the market. There are optimistic and pessimistic views about the mass deployment of autonomous vehicles (AVs). From an optimistic perspective, predictions are toward significant impacts of AVs on traffic safety improvement [1, 2], congestion reduction [3], fuel savings [4–6], vehicle emissions reduction [5], and driving restrictions [7, 8]. On the other hand, the pessimistic view challenges the penetration of AVs on the market due to their potential technical failures [9, 10], social acceptance [11], costs [12], induced traffic demand [13], years of testing, and regulatory approvals. Since new technological innovations have rapidly entered the market, it is expected that AVs might experience the same trend. We will eventually witness a situation where AVs interact with human-driven vehicles (HDVs), cyclists, and pedestrians [14].

From a transportation perspective, AVs might have different driving behaviour than HDVs. These differences are due to AVs' sensing and communication capabilities. AVs can detect the precise picture of the surrounding environment using advanced sensing technologies (e.g. radar and lidar) and react accordingly with the help of a trained decision processing unit (DPU). Meanwhile, AVs are capable of exchanging driving status (i.e. speed, acceleration, position, and more) with other connected vehicles and infrastructure (thanks to V2V and V2I), which are labelled as connected autonomous vehicles (CAVs) [15, 16].

AVs and CAVs are expected to bring significant changes in mobility, safety, and emissions. Many researchers have conducted simulation-based studies to quantify these potential changes in transportation systems. Microscopic traffic models (MTMs) are widely used to predict the impact of AVs and CAVs on safety and efficiency. The general findings of most studies reveal that higher penetration rates (PRs) of AVs and/or CAVs could have more considerable impacts on efficiency and safety [17–23]. More optimistic views are for CAVs in comparison to AVs [22, 24–26]. However, the magnitude of changes differs among various studies. It is also reported that higher demands for CAVs could lead to substantial changes in the network [25, 27]. In contrast, some studies reported different findings on the impacts of AVs and CAVs. For instance, [26] reported that compared to HDVs and with the constant demand, any PRs of AVs do not improve the traffic flow efficiency; however, CAVs enhance the condition. They also reported that in lower traffic demands, HDVs always outperform CAVs.

To design an experimental setup for evaluating the impacts of AVs deployment scenarios, replicating the AVs' driving behaviour is crucial. In MTMs, the driving behaviour of vehicles is modelled both in terms of their longitudinal (car-following) and lateral (lane-changing) configurations. Several studies have attempted to approximate the accurate characteristics of these behaviours (especially CF behaviour) for AVs and CAVs in MTMs [17, 22, 28–30]. Although there are many state-of-the-art modelling methods for the CF behaviour of AVs and CAVs, they require defining a certain set of parameters. The values of these parameters are often based on assumptions or estimated using limited trajectory data from field experiments involving AVs and CAVs. The use of various CF models with researchers' assumptions for model parameters leads to different findings regarding the impacts of AV deployment scenarios. To address this challenge, two possible solutions could be employed: first, utilization of mass real-world AV data to calibrate a specific CF model; second, use the optimal driving behaviour of AVs and extract the optimized parameters of a CF model. By adopting either of these approaches, researchers can ensure a more accurate replication of AV driving behaviour in MTMs, leading to more reliable evaluations of AV deployment scenarios.

The first approach, which involves the utilization of mass real-world AV data to calibrate a CF model, faces significant challenges due to the lack of extensive field data for AVs. The available data are often limited to specific locations and driving behaviours, making them non-generalizable. Therefore, the second approach, involving the optimization of AV driving behaviour and extraction of optimized CF model parameters, could be more feasible and effective in MTMs for mimicking the driving behaviour of AVs.

It is expected that the DPU of the AVs contains pre-trained complex deep learning algorithms that regulate the AV to react in any traffic situation while keeping safe and efficient driving manoeuvres [31]. In MTMs, we can regulate AVs to generate optimal trajectories from origin to destination, considering all driving constraints. A CF model that generates such an optimal driving manoeuvre for AVs is referred to as optimized CF behaviour. In our previous work in [31], we developed a framework that finds a set of optimized driving parameters of AVs under various PRs, demand scale, and optimization functions. The extracted optimized CF behaviour could be used in a simulation-based impact assessment study to give more realistic results on the potential impacts of AVs rather than weak assumptions. Hence, the main aim of this research is to investigate the impacts of AVs on mobility and safety using the optimal driving behaviour of AVs. Furthermore, most AV impact assessment studies focus on intersections [17, 32], urban links [18, 19, 33], and freeways [22, 27, 34–36], whereas limited studies are conducted at the network level; therefore, our research focuses on impact assessment in a traffic network.

The main contributions of this research are: (i) to assess the potential impacts of AVs deployment scenarios in a traffic network, and (ii) to study the influencing factors on the potential impacts of AVs using generalized estimating equation (GEE) and zero-truncated Poisson (ZTP) regression models. This paper investigates how the behavioural difference of AVs with optimized driving behaviour could bring changes on the efficiency and safety of a network, where other factors, such as infrastructure, speed limit, intersection controllers, and more, play a vital role in the performance of traffic flow and safety.

The remainder of this paper is structured as follows. In the following section, we review the recent literature on microscopic simulation tools utilized for AVs impact assessment. In Section 3, we introduce the methodology of this research, including a calibration scheme, the modelling method for replicating AVs' longitudinal driving behaviour, the evaluation areas, and the design of an experimental setup. The experimental setup aims to run different AVs deployment scenarios in a city-scale network with calibrated and validated features. The findings of this research and the results of regression analysis (run on achieved results) are presented in Section 4, which is followed by a discussion in Section 5. Finally, a conclusion in Section 6 explains the overall contribution of this article alongside further research directions.

2 | LITERATURE REVIEW

A wide range of simulation-based studies focus on identifying the potential impacts of AVs on the transportation system. In a simulation-based study, three aspects are essential for setting up an experiment and conducting impact assessment, namely (i) the calibration of the base model, and the selection of an appropriate CF model, including the adopted parameters to replicate the driving behaviour of AVs, (ii) defining the assessment areas and key performance indicators (KPIs) to quantify the impacts, and (iii) the choice of a powerful traffic simulation tool. In the following subsections, we present each aspect in detail.

2.1 | Modelling and calibration of the car following behaviour

CF models play a crucial role in MTMs and simulation tools. These models describe how individual vehicles behave while following each other on roads, considering factors like speed, distance, acceleration, and reaction to changes in the environment. Replication of vehicular CF behaviour has been a continuous research focus in the field of traffic modelling and simulation. CF models are generally categorized into mathematical and data-driven models. Mathematical models rely on fundamental principles of physics and mathematics to describe how vehicles interact with each other on the road under different traffic situations. On the other hand, data-driven models are developed directly from observed data on vehicle trajectories and behaviour collected from real-world traffic conditions. These models use statistical techniques and machine learning algorithms to analyse patterns in the data and develop mathematical representations of typical CF behaviour. Although data-driven models outperform many mathematical models in replicating the CF behaviour of vehicles, they are not widely used in impact assessment studies.

Mathematical models are initially developed to replicate the driving behaviour of HDVs and have been widely used in simulation tools. These models comprise methods focusing on a driver's physical actions, such as desired speed, acceleration, deceleration, i.e. Gazis–Herman–Rothery (GHR) model [37], Gipps model [38], intelligent driver model (IDM) [39], optimal velocity model (OVM) [40]; however, some also consider the psychological inputs of the drivers, such as the Wiedemann model [41]. These models are comprised of modifiable parameters that mimic the driving behaviour and are often calibrated with mass field driving data of vehicles. The behavioural calibration of a CF model involves the fine-tuning of its modifiable parameters to minimize the discrepancies between real-world driving configurations and the simulated environment. Several methods have been implemented to calibrate a CF model in the literature. These methods include genetic algorithm (GA) [42–47], particle swarm optimization (PSO) [48, 49], machine learning-based methods [50], and combination of various optimization techniques [51, 52]. For instance, [42] employed the GA to calibrate the parameters of IDM, Gipps, Wiedemann, GHR, and FVD (full velocity difference) [53] models. [49] used the PSO algorithm to extract the calibrated parameters of a psychophysical CF model in a microsimulation. Meanwhile, [50] implemented an artificial neural network (ANN)-based model to calibrate the parameters of the Wiedemann model. On the other hand, [51] proposed the combination of the PSO and machine learning-based approach to calibrate the default CF model of the Transmodeler simulation tool. Given that this research conducts impact assessment of AVs deployment scenarios in mixed traffic, we need to calibrate the base model (fully HDVs environment) to accurately approximate the driving behaviour of HDVs in real-world traffic conditions. Hence, in this research, we employ PSO for behavioural calibration.

Furthermore, for AVs, there are no established mathematical models, and researchers often employ conventional mathematical models to mimic the CF behaviour of AVs. According to [54], IDM, MIXIC, Wiedemann 99, and Krauss models are frequently used CF models for mimicking the driving behaviour of AVs in literature. The selection of a specific CF model for replicating the driving behaviour of AVs in simulation-based impact assessment studies depends first on whether the model can replicate the potential driving behaviour of AVs and second on whether it is well-integrated in a widely used simulation tool. For instance, Wiedemann 99 is the default CF model of VISSIM; therefore, many studies utilized Wiedemann 99 to mimic the CF behaviour of AVs and conduct impact assessment using VISSIM. An overview of the simulation tools and their CF models is presented in Section 2.3.

Given the current impracticality of large-scale AV testing and the limitations of available AV-related data, which are restricted to specific locations and driving behaviours, accurately calibrating a CF model to replicate AV driving behaviour is not feasible. Consequently, impact assessment studies often rely on the assumed driving behaviours of AVs. Some studies assume AVs will drive more cautiously with larger headway gaps, while others assume a more aggressive driving style. These differing assumptions lead to conflicting findings, particularly regarding the number of conflicts and overall safety. In contrast, this research employs the optimal driving behaviour of AVs to conduct network-wide impact assessment [54].

2.2 | Assessment areas and KPIs

In simulation-based impact assessment, the selection of assessment areas and their relevant KPIs is important for constructing an effective experimental setup. These choices ensure that the simulation can comprehensively evaluate the potential impacts of AVs across various dimensions. A review of previous studies reveals that the majority of researchers conduct impact assessments of AVs and CAVs for safety and traffic efficiency, where some also evaluate the environmental effects (e.g. energy consumption and emissions) [54]. For each assessment area, various KPIs are chosen depending on the scope of the study. For efficiency assessment, most researchers employed KPIs such as traffic flow (e.g. traffic flow, density), average travel time, string stability, average velocity, and more [22, 29, 30, 34]. For instance, [18] studied the impact of CACC-equipped vehicles on traffic efficiency in urban roads with congested sections. This study selects traffic capacity, waiting time, queue length, and total travel time as the main KPIs. The findings of this study indicate that in comparison to conventional vehicles, CACC-equipped vehicles with a PR of 100% can increase the traffic capacity by more than 2.6 times. The study claims that by increasing the PR of CACC-equipped vehicles, the waiting time on congested roads decreases.

Similarly, for safety evaluation, researchers use the surrogate safety measure (SSM) model to quantify the potential conflicting situations and to assess the impact of AVs PRs on traffic safety. Most studies used time-to-collision (TTC), post-encroachment time (PET), and number of conflicts (using certain TTC and PET thresholds) as KPIs for safety assessment in the literature [17, 22, 28, 55]. A recent study by [28] explored the impacts of CAVs on the safety of a motorway section. In this study, the number of conflicts is used as a KPI. The results revealed that higher PRs of CAVs reduce traffic conflicts. Similarly, [17] investigated the effects of CAVs on the safety of signalized and unsignalized intersections. The findings of this study showed that CAVs can significantly reduce the number of conflicts at both intersections. In addition, it is claimed that a 100% PR of CAVs could eliminate any crossing conflicts between vehicles.

Finally, for emission assessment, the amount of CO_2 and NOx emissions per kilometres g/kg are used as KPIs [24, 25].

One important note is that most studies assume the same energy consumption and emissions factors used for existing HDVs and for AVs. [25] conducted a simulation-based study to investigate the impact of (C)AVs on throughput and emissions in a ring road. CO_2 and emissions per kilometre are selected as KPIs for environmental impacts. The findings of this study highlighted that in free-flow traffic, where vehicles are not bound to speed limits, human-driven vehicles exhibit the highest emissions. Conversely, any PRs of CAVs could lead to low emissions. The study also claimed that AVs drive at low speeds and thus force the engine to work less efficiently. Hence, in comparison to CAVs, AVs increase emissions.

2.3 | Microscopic traffic simulators

Microscopic traffic simulators are highly detailed and complex tools that capture the driving behaviour of a single vehicle, including following behaviour, lane change behaviour, and its interaction with other road users. Given the availability of numerous traffic simulators in the market, each with its features and functionalities, it is vital to have a comprehensive understanding of these characteristics. Generally, microscopic traffic simulators are divided into commercial and open-source tools. Commercial traffic simulators are generally user-friendly and less complex products that offer a wide range of user support. Open-source simulators, in comparison, are typically free to use, open, and collaborative, while they have limited user support and are complex for new users. Among many traffic simulators (i.e. VISSIM, AIMSUN, PARAMICS, CORSIM, SUMO), PTV VISSIM, and AIMSUN are the commonly used commercial tools for modelling and simulation of AVs, where SUMO is the open-sources simulator for this purpose.

PTV VISSIM is a multi-modal traffic simulator developed by PTV Group in Karlsruhe, Germany [56]. This widely used tool includes simulating individual vehicles, public transport, bikes, and pedestrians based on the driving behaviour models, control devices, and road network characteristics. VISSIM employs the Wiedemann psychological model [41] to mimic the CF behaviour of vehicles. Modifying the model's parameters allows us to replicate AVs' driving behaviour and conduct impact assessment. The parameters of this model have already been extracted within the CoEXist project to capture the driving behaviour of AVs; however, the calibration of these parameters is based on a few AVs trajectories [57]. VISSIM also gives the option to override the default CF model and control the driving behaviour of AVs externally through the COM interface. The COM interface allows user-developed applications to access network topology, signal control, path flows, and vehicle behaviour. This enables VISSIM to model intricate control logic and advanced transportation systems and components. In addition, the output module of VISSIM enables users to gather a wide range of simulation outputs, including link, node, and network-level traffic data.

AIMSUN (advanced interactive microscopic simulator for urban and non-urban networks), developed by AIMSUN Inc., is a powerful simulation tool allowing both microscopic and mesoscopic simulation capabilities [58]. It offers various tools for traffic demand modelling, network calibration, and performance analysis. AIMSUN Next is well-known for modelling traffic dynamic assignments, incident management, and other ITS applications. AIMSUN Next has the flexibility to model the detailed driving behaviour of vehicles in its microscopic model, which makes it a good candidate for replicating the driving behaviour of AVs. AIMSUN Next supports modelling various modes, including private vehicles, public transport, pedestrian, and bicycles. The default CF model of AIMSUN Next is based on the Gipps' safety distance model [38]. In addition, AIMSUN Next can be further extended with Python scripts, allowing it to automate the simulation with different scenarios, including CF parameter adjustments. The external agent interface (EAI) makes it possible to override the controlling logic of vehicles in the simulation environment both for HDVs and AVs.

SUMO (simulation of urban mobility) developed by German Aerospace (DLR), is an open-source and highly portable microscopic traffic simulation tool [59]. It allows the design and simulation of large-scale networks with detailed vehicular behaviour, including CF, LC, and interactions with traffic controllers and other vehicles. SUMO is widely used in academia for its flexibility, extensibility, and availability of various traffic demand scenario generation tools. In SUMO, each vehicle is modelled explicitly with its own route and runs individually through the network. Several modules, each with its unique function like NETEDIT, TraCi (traffic control interface), SUMO-GUI, routing algorithms, visualization, network import and emission calculation, and more, make SUMO a powerful simulation tool. Regarding CF models, SUMO contains most of the widely used mathematical CF models, including Krauss [60], IDM [39], Gipps [38], and Wiedemann [41] models. SUMO also provides the possibility to model ACC (adaptive cruise control) [61] and CACC (cooperative ACC) [62] equipped vehicles. For the simulation of AVs, researchers either modify the parameters of the available CF model or override any CF logic externally using SUMO's API. Additionally, a mesoscopic simulation mode has been added to SUMO. This mode allows running simulations with less detailed precision, i.e. potentially sacrificing some modelling accuracy, but significantly speeding up the process and reducing computational requirements. This feature enables e.g. the option to initially run numerous scenarios to find a rough optimal solution for a specific problem before utilizing the microscopic version for the final series of runs.

Table 1 provides a summary of different characteristics of the traffic simulators. All three tools simulate traffic in a continuous manner and can replicate AVs driving behaviour by modifying the parameters of the CF models. VISSIM and AIMSUN are user-friendly tools with strong visualization capabilities, but they are commercial, and therefore, their widespread usage in academia is limited. In contrast, SUMO is relatively complex; however, it has high flexibility in generating different scenarios. In addition, since it is open-source, it is a suitable option for various applications, particularly in AVs impact assessment.

TABLE 1 The comparison of widely used traffic simulation tools for AVs modelling.

Criteria/Tool	VISSIM	AIMSUN	SUMO
License	Commercial	Commercial	Open-source
Developer	PTV group	Aimsun Inc.	SUMO Community & DLR Institute
Simulation level	Microscopic	Micro/mesoscopic	Micro/mesoscopic
Visualization	2D and 3D	2D and 3D	2D
Customization	Highly customizable	Customizable	Extensible through plugins and scripting
Supported languages	C++, Java, Python	C++, Java, Python	Python, any programming language for XML config
GUI support	High	Moderate	Moderate
Complexity	Simple	Moderate	Complex
CF models	Wiedemann (74 and 99)	Gipps	Krauss (default), IDM, Gipps, Wiedemann (74 and 99), ACC, and CACC
Modelling of AVs	Customizable to simulate AV behaviour	Supports AV behaviour modelling	Customizable to simulate AV behaviour

Meanwhile, the findings of the literature review show that all three tools are widely used in AV impact assessment studies. The scope of each study in these simulation tools differs from intersections, links to part of a network, as well as freeways. Recent researches, such as [26, 29, 32, 35, 55], utilized PTV VISSIM to evaluate the potential impacts of AV deployment scenarios on traffic efficiency and safety. For instance, [29] investigated the impacts of ACC and CACC-equipped vehicles on traffic efficiency and energy consumption in an ideal expressway. In their research, the MIXIC (microscopic model for simulation of intelligent cruise control) model was used to mimic the driving behaviour of ACC and CACC vehicles in VISSIM. In addition, [35] studied the impacts of AV deployment scenarios on the capacity of a freeway in VISSIM. They utilized the Krauss model to mimic the driving behaviour of AVs by overriding the default Wiedemann model using the COM interface. Similarly, [55] studied the impact of CAV PRs on safety in a Motorway in VISSIM using the default Wiedemann 99 model. Other studies, including [22, 26, 28, 30] used AIMSUN for AVs impact assessment. [28] and [30] used the default Gipps model in AIMSUN to evaluate the safety and efficiency impacts of AVs, respectively. Meanwhile, [22] and [26] used IDM and CACC models in AIMSUN, respectively, by overriding the default CF model to assess the impacts of AV PRs. Finally, many studies also used SUMO for AVs impact assessment [17, 21, 23, 33, 34, 63]. For example, [17] used Krauss, IDM, and CACC models in SUMO to investigate the effects of CAVs on the safety of signalized and un-signalized intersections. [34] studied the impacts of commercially available ACC vehicles on traffic stability and throughput in SUMO. This study used IDM to capture the CF behaviour of theoretical ACC and commercially available ACC vehicles.

In Table 2, the summary of reviewed simulation-based studies is presented, which explains specific information on the CF model, assessment criteria, KPIs, network type, and simulation tools. The table is sorted based on the publication date of the citations, which are displayed in reverse chronological order (newest to oldest).

3 | METHODOLOGICAL FRAMEWORK

3.1 | Approach

In this research, we develop a framework to systematically model and simulate the CF behaviour of AVs under different PRs and conduct a network-wide impact assessment under various demand scenarios. The framework is comprised of three components, namely, a scenario generation module, a simulation environment, and an output module. In the scenario generation module, the corresponding optimized CF parameters are passed into the simulation environment for a certain PR of AVs. There, AVs behave according to these optimized parameters' settings. Since it is expected that AVs might have different driving behaviour than HDVs, the magnitude of these differences might also vary depending on the PR. For instance, AVs might behave similar to HDVs in lower PRs, whereas in higher PRs, their behaviour may be significantly different. Therefore, our framework models AVs with different CF parameter settings depending on the PRs of AVs. The optimized CF parameters' settings under various PRs are extracted using the proposed optimization framework in [31]. Meanwhile, the simulation environment runs multiple simulation replications under the set conditions and outputs the predefined assessment criteria. The output data are further analysed to investigate the potential impacts of AVs. A schematic diagram of the main methodology of this research is depicted in Figure 1. Additionally, for ease of reference, a list of symbols used in the following subsections is provided in Table 3.

3.2 | Modelling CF behaviour of human-driven vehicles

In this research, we choose IDM to replicate the CF behaviour of HDVs since it has been widely used in the literature to accurately replicate drivers' driving behaviour. IDM, first developed

TABLE 2 Summary of reviewed simulation-based studies on AVs including their CF model, assessment criteria, KPIs, network type, and traffic simulator.

Reference	Year	CF model	Assessment criteria	KPIs	Network	Simulator
[28]	2023	Gipps	Traffic safety	Number of conflicts	Freeway	AIMSUN
[29]	2023	MIXIC	Traffic efficiency and energy consumption	Average travel time, capacity, average electric energy consumption	Expressway	VISSIM
[17]	2022	Krauss, IDM, and CACC	Traffic safety	Number of conflicts	Intersection	SUMO
[30]	2022	Gipps	Capacity analysis	Network capacity	City	AIMSUN
[22]	2021	IDM	Traffic safety and efficiency	Time-to-collision (TTC), number of conflicts, travel time	Freeway	AIMSUN
[34]	2021	IDM	Throughput and stability	Traffic flow, density	Freeway	SUMO
[18]	2021	CACC	Traffic efficiency	Traffic flow, density, critical speed	Urban road	Numerical simulator
[21]	2021	Krauss	Traffic efficiency	Traffic flow, travel time	City	SUMO
[35]	2020	Krauss	Capacity analysis	String stability, lane capacity	Freeway	VISSIM
[23]	2020	IDM	Traffic efficiency	Travel time	Freeway	SUMO
[63]	2020	Krauss	Capacity analysis	Speed, flow, density	Urban road	SUMO
[55]	2019	Wiedemann 99	Safety analysis	Number of conflicts	Motorway	VISSIM
[26]	2018	CACC	Throughput	Harmonic average speed	Ring road	AIMSUN
[64]	2018	Wiedemann 99	Traffic safety	Number of conflicts	Roundabout	VISSIM
[32]	2018	Wiedemann 99	Safety analysis	Number of conflicts	Signalized intersection and roundabout	VISSIM
[33]	2018	Krauss	Capacity analysis	Flow, density	Grid network	SUMO
[65]	2016	Wiedemann 99	Traffic efficiency	Average density, travel time, and speed	Autobahn	VISSIM

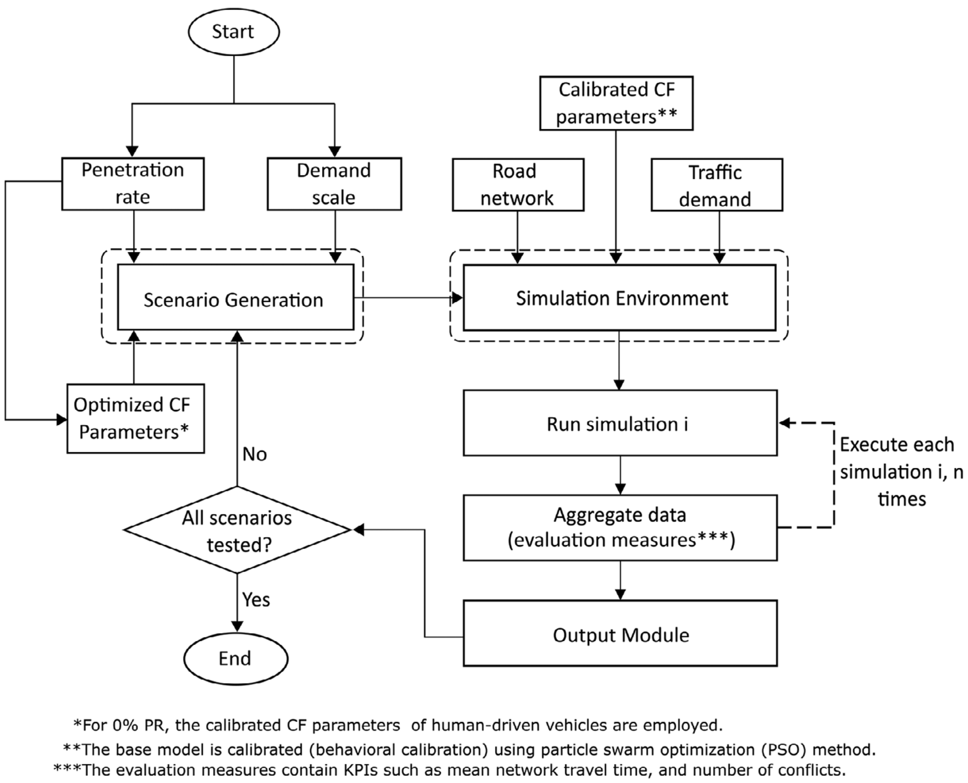

FIGURE 1 The methodological framework in this study.

TABLE 3 The list of symbols used in this research.

Category	Symbol	Description
IDM	$a_n(t)$	Acceleration of vehicle n
	$a_{\max}$	Maximum acceleration/deceleration of the vehicle
	V_n, $V_0^{(n)}$	Speed, and desired speed of the following vehicle
	S_n	The gap distance between two vehicles
	S_n^*	Desired spacing between two vehicles
	δ	Model parameter
	ΔV_n	Speed difference between following and leading vehicles
	$S_0^{(n)}$	Minimum spacing at a standstill situation
	T_n	Desired (safe) time headway
	$b^{(n)}$	Desired (comfortable) deceleration
Krauss	v_{safe}	Safe velocity of the following vehicle
	v_{l}	Speed of the leading vehicle
	v_{f}	Speed of the following vehicle
	t_{r}	Reaction time of the driver
	b	Maximum comfort deceleration
	$g(t)$	Gap between the leading and the following vehicles
	x_{l}	Position of the leading vehicle
	x_{f}	Position of the following vehicle
	L	Average length of a vehicle
	v_{des}	Desired speed of the following vehicle
GEE	K	Number of clusters
	n_i	Observations in cluster i
	Y_{ij}	Response for jth observation in cluster i
	X_{ij}	Covariate vector for jth observation in cluster i
	μ_{ij}	Mean for jth observation in cluster i
	β	Regression coefficients
	$R_i(\alpha)$	Working correlation matrix for cluster i
	α	Correlation parameter
	ϕ	Scale parameter
ZTP	y	Observed count in a time interval
	λ	Mean parameter of the Poisson distribution
	$E(y)$	Expected count
	$\text{Var}(y)$	Variance
	$g(\lambda)$	Link function in the ZTP regression model
	$\hat{\lambda}$	Estimated mean parameter
	$\mathbf{X}$	Design matrix
	β	Vector of regression coefficients
	ϵ	Random error with a standard logistic distribution

by [39], is one of the simplest and accident-free models, which utilizes both the desired speed and space headway to generate a realistic acceleration profile. The basic form of the IDM acceleration function is expressed as:

$$a_n(t) = a_{\max}^{(n)}\left[1 - \left(\frac{V_n(t)}{V_0^{(n)}(t)}\right)^{\delta} - \left(\frac{S_n^{\,*}(t)}{S_n}\right)^{2}\right] \tag{1}$$

where $a_{\max}$ represents the maximum acceleration or deceleration of the vehicle n, V_n is the speed of the following vehicle, $V_0^{(n)}$ is the desired speed of the following vehicle, S_n is the gap distance between two vehicles, $S_n^{\,*}$ is the desired spacing between two vehicles, and δ denotes the model parameter. The desired space headway between two vehicles $S_n^{\,*}$ is a function of the following vehicle speed V_n and the speed difference between the leading and following vehicles ΔV_n, which can be estimated as follows:

$$S_n^{\,*}(t) = S_0^{(n)} + V_n(t)T_n(t) + \frac{V_n(t)\Delta V_n(t)}{2\sqrt{a_{\max}^{(n)} b^{(n)}}} \tag{2}$$

where $S_0^{(n)}$ is the minimum spacing at a standstill situation, T_n is the desired (safe) time headway, and $b^{(n)}$ is the desired (comfortable) deceleration.

The IDM model parameters are calibrated (behavioural calibration) based on the real-field travel time data. Since we utilize a dynamic traffic assignment-based simulation model in SUMO, the route choice is already calibrated in another study employing the same demand and network characteristics [66]. Thus, we only conduct behavioural calibration to match the simulated travel times with the real-field travel times of links in the network, keeping the traffic assignments unchanged. The data include the peak-hour travel time information along several major roads in Munich city center network. This research uses the PSO algorithm to calibrate the IDM parameters. PSO is a metaheuristic, stochastic, and population-based optimization algorithm inspired by the behaviour of bird flocking or fish schooling. It is used to find the global optimal solution by iteratively updating a population of candidate solutions (particles) in a search space [67]. The algorithm iteratively searches for the design space to improve a candidate solution with regard to an objective function. Unlike gradient-based optimization methods, PSO does not require the objective function to be differentiable, divisible, and continuous. The choice of PSO in this research is associated with its convergence speed and computational efficiency [68, 69].

In PSO, each particle represents a candidate solution and moves through the search space by adjusting its position based on its own experience and the collective knowledge of the entire population. The particles' movements are influenced by two key factors: their own best-known status (pbest) and the best-known position of the whole population (known as gbest) [70]. By incorporating these references, particles are directed toward regions of the search space that exhibit promising solutions,

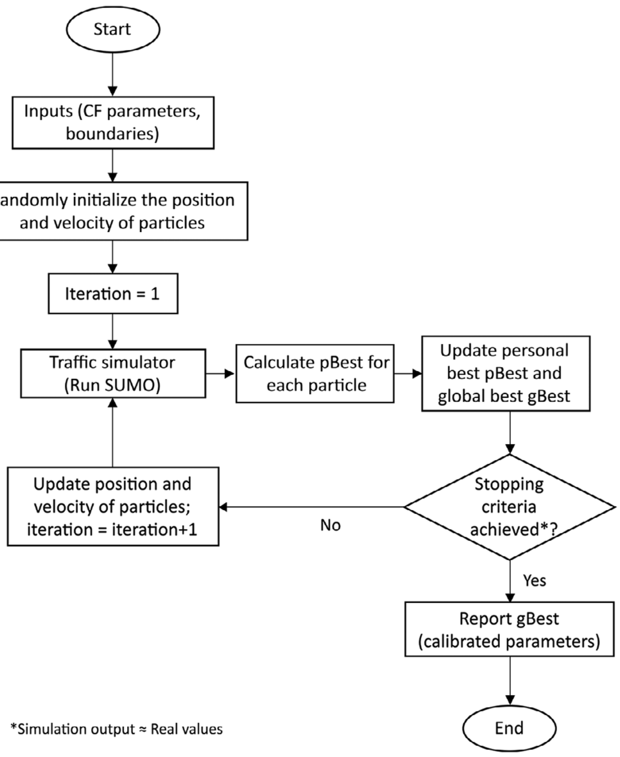

FIGURE 2 Illustration of PSO calibration method.

allowing for effective exploration and exploitation during optimization. This paper uses the root mean square normalized (RMSN) as an objective function to minimize the dispersion between the simulated and true travel times, where the input variables are the CF model parameters. PSO tries to change the parameters of the CF model within their boundary conditions (i.e. realistic driving behaviour, acceleration and deceleration capability, comfort driving etc.), aiming to find the minimum RMSN. The overall process of the PSO algorithm integrated with SUMO traffic simulator is illustrated in Figure 2.

3.3 | Modelling CF behaviour of AVs

In this research, we utilize the Krauss CF model to replicate the longitudinal driving behaviour of AVs. This model is widely used in modelling the CF behaviour of AVs in MTMs, and is the default CF model in SUMO. The Krauss CF model developed by Stephan Krauss in 1997 is a space-continuous model [60].

TABLE 4 Krauss model's optimized AV parameters [31].

PRs [%]	Mingap [m]	Accel [m/s^2]	Decel [m/s^2]	Sigma [-]	Tau [s]
20	1.6	2.6	3.6	0.4	0.8
40	1.5	2.7	3.7	0.4	0.8
60	1.1	3.4	3.2	0.1	1.0
80	1.2	3.0	3.4	0.4	1.0
100	1.3	2.5	3.6	0.5	1.0

(Sigma = driving imperfection factor, Tau = desired time headway).

Krauss model estimates the safe speed of the vehicle without deriving it from the acceleration profile of the vehicle. In Krauss model, the safe velocity of the following vehicle is calculated as follows:

$$v_{\text{safe}}(t) = v_l(t) + \frac{g(t) - v_l \cdot t_r}{\frac{v_l(t)+v_f(t)}{2b} + t_r} \tag{3}$$

where v_l, v_f are the speed of leading and following vehicles at time t respectively (see Figure 3), t_r is the reaction time of the driver, b is the maximum comfort deceleration of the vehicle, and $g(t)$ is the gap between the following and leading vehicles, which is computed as: $g(t) = x_l(t) - x_f(t) - L$, ($x_l$, x_f are the position of the leading and following vehicles, and L is the average length of a vehicle).

Meanwhile, to estimate the desired speed, which is a decisive variable for determining the speed of the vehicle in the next time step, the model takes the minimum of safe velocity, the road speed limit, and the vehicle's maximum capable speed to generate the desired speed of the vehicles, expressed as:

$$v_{\text{des}}(t) = \min[v_{\max}, v(t) + a \cdot \Delta t, v_{\text{safe}}(t)] \tag{4}$$

Finally, the velocity and location of the vehicle at the next time step are computed as follows:

$$\begin{aligned} v(t+\Delta t) &= \max[0, v_{\text{des}}(t) - \eta], \\ x_f(t+\Delta t) &= x_f(t) + v(t+\Delta t) \cdot \Delta t \end{aligned} \tag{5}$$

where η is the random perturbation (to capture the driving imperfection) and Δt is the simulation time step. The optimized parameter of the Krauss CF model was already extracted in [31] as depicted in Table 4.

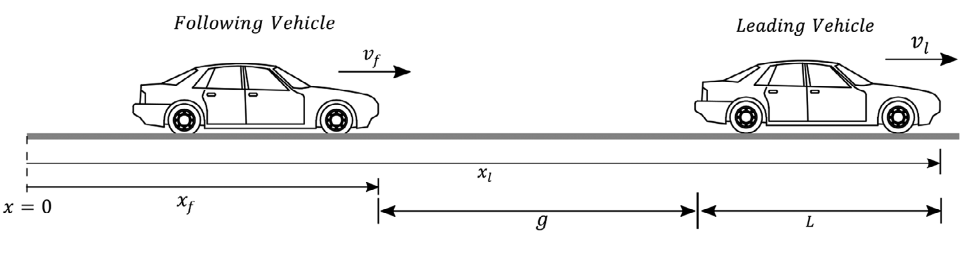

FIGURE 3 Description of the Krauss CF model parameters.

3.4 | Evaluation areas

In this research, we select traffic efficiency and safety as evaluation areas to estimate the impacts of AVs deployment scenarios on transport network performance. Traffic data, including edge-related, intersection-level, and network-wide information, are collected for the evaluation of efficiency. For safety assessment, we utilize the surrogate safety measure (SSM).

3.4.1 | Traffic efficiency assessment

Traffic data is collected from the simulation environment in 5-min intervals for each link, intersection, and overall network. Depending on the assessment criteria, we utilize various KPIs, such as travel time, flow, occupancy, speed, density, time loss, and queue length, for traffic efficiency analysis. To make sure the outputs of simulation runs under different AV scenarios are significantly different, we employ a one-way ANOVA (analysis of variance) statistical approach. Meanwhile, to investigate whether each pair of scenarios is different from the other, we apply Tukey's HSD (honestly significant difference) test.

First, we investigate the traffic flow elements (average volume, speed, occupancy, density, average travel time) through specific segments (edges) of the network under various scenarios. The data gathered from the loop detectors installed on edges are further used to study the specific impacts of different AVs scenarios on links. Second, to analyse the effects of AV PRs on the traffic situation of signalized intersections, average passing speed, and average time loss are utilized as KPIs. We collect this information using area detectors around each signalized intersection. Finally, for analysis of the network performance, the average network travel time is calculated under different AV PRs using every vehicle's travel time. For a single vehicle, the travel time is estimated using the difference between the departure and arrival times. Hence, the mean of aggregated travel times of all vehicles in the network corresponds to the average network travel time.

Furthermore, to investigate the relationship between the potential impacts, PRs, and other relevant factors (e.g. flow, speed etc.), we implement the generalized estimating equation (GEE) regression method. GEE is a statistical method that is used for analysing data with correlated or clustered observations. GEE is an extension of generalized linear models (GLMs), which is used in longitudinal studies (repeated observations) and clustered data (data collected from different clusters or groups) [71]. In our case, edge travel time is collected in 5-min intervals during the simulation period. Thus, each edge segment is considered as a cluster, and the repeated observation is the travel time.

Suppose the datasets (travel time) of repeated observations involving K clusters of edges. Each cluster i (where $i = 1, 2, \dots, K$) is associated with n_i observations denoted as response vector Y_{ij} (travel time) of the jth response ($j = 1, 2, \dots, n_i$). Furthermore, let X_{ij} represent a $p \times 1$ vector of explanatory variables (covariates) corresponding to each observation. We can define the response vector for the ith cluster as $Yi = (Y_{i1}, Y_{i2}, \dots, Y_{i(n_i)})$ and its mean vector as $\mu_i = (\mu_{i1}, \mu_{i2}, \dots, \mu_{i(n_i)})$, where μ_{ij} denotes the mean value for the jth response. The means μ_{ij} are related to the p dimensional regression vector X_{ij} by the $p \times n_i$ mean-link function g as follows:

$$g(\mu_{ij}) = X_{ij}^{\top} \cdot \beta \tag{6}$$

where β is the unknown $p \times 1$ vector of regression coefficient with the true value β_0. In addition, let the conditional variance of Y_{ij} given X_{ij} be:

$$\mathrm{Var}(Y_{ij} \mid X_{ij}) = v(\mu_{ij})\phi \tag{7}$$

where v is a known variance function of μ_{ij}, and ϕ is the scale parameter. Both v and ϕ are associated with the distribution of the responses. For instance, in case Y_{ij} follows a Gaussian distribution, μ_{ij} is specified as 1, and if it shows Poisson distribution, then $\mu_{ij} = \mu_{ij}$. Also, let the $R_i(\alpha)$ be the working correlation matrix ($n_i \times n_i$) or the pattern of measures within a cluster which is described by the vector parameter α, then the variance-covariance matrix for Y_i is expressed as:

$$V_i = \phi A_i^{\frac{1}{2}} R_i(\alpha) A_i^{\frac{1}{2}} \tag{8}$$

where $A_i^{\frac{1}{2}}$ is a ($n_i \times n_i$) diagonal matrix with entries $v(\mu_{ij})$ as the jth diagonal element. The GEE for estimation of the ($p \times 1$) β is obtained by solving the following equation:

$$\sum_{i=1}^{K} \frac{\partial \mu_i}{\partial \beta}^{\top} V_i^{-1} (Y_i - \mu_i(\beta)) = 0 \tag{9}$$

where $\frac{\partial \mu_i}{\partial \beta}^{\top}$ is a ($p \times ni$) matrix of the partial derivative of the mean in regard to the regression parameter of the ith cluster, which is obtained as follows:

$$\frac{\partial \mu_i}{\partial \beta}^{\top} = \begin{bmatrix} \frac{x_{i11}}{g'(\mu_{i1})} & \cdots & \frac{x_{ini1}}{g'(\mu_{ini})} \\ \vdots & & \vdots \\ \frac{x_{i1p}}{g'(\mu_{i1})} & \cdots & \frac{x_{inip}}{g'(\mu_{ini})} \end{bmatrix} \tag{10}$$

[71] propose utilizing consistent moment estimates for both parameters, ϕ and α. This results in an iterative process that alternates between estimating β for fixed values of $\hat{\phi}$ and $\hat{\alpha}$, and estimating ϕ and α for fixed values of $\hat{\beta}$. This approach results in a consistent estimate for β. According to [71], this also holds if the working correlation structure $R_i(\alpha)$ is misspecified.

Meanwhile, there are many different structures for working correlation matrix, including independent, exchangeable, k-dependent, autoregressive, Toeplitz, and unstructured; in this paper, we select independent and exchangeable for GEE analysis.

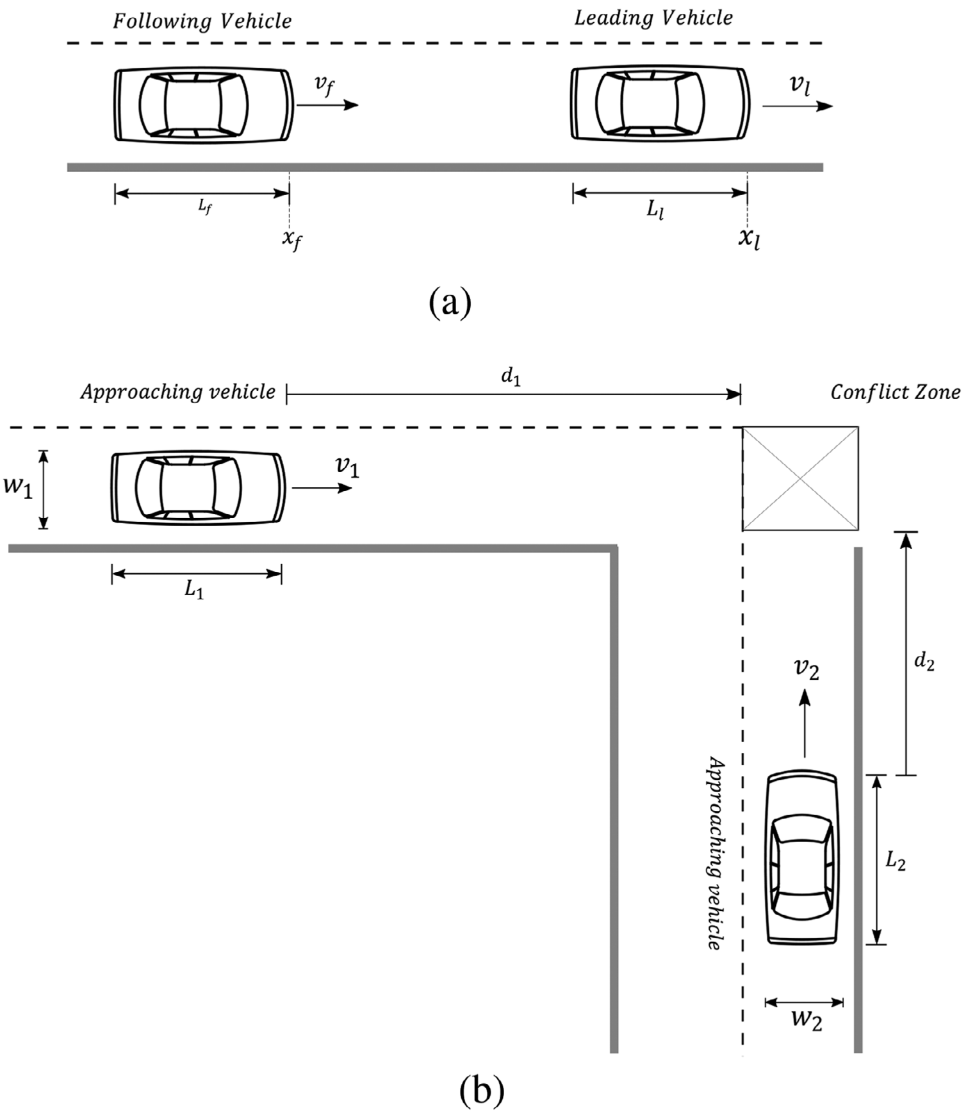

FIGURE 4 Illustration of TTC under (a) follow–lead, and (b) approaching conflicts scenarios.

- Independent R: within a cluster, the observations are independent.

$$\mathrm{Corr}(Y_{ij}, Y_{ik}) = \begin{cases} 1 & j = k \\ 0 & j \neq k \end{cases}, \qquad \text{e.g.} \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \tag{11}$$

- Exchangeable R: within a cluster, the observations hold a constant correlation.

$$\mathrm{Corr}(Y_{ij}, Y_{ik}) = \begin{cases} 1 & j = k \\ \alpha & j \neq k \end{cases}, \qquad \text{e.g.} \begin{pmatrix} 1 & \alpha & \alpha \\ \alpha & 1 & \alpha \\ \alpha & \alpha & 1 \end{pmatrix} \tag{12}$$

3.4.2 | Safety assessment

For safety evaluation, the SSM is used to approximate the number of conflicts in the network. For this purpose, each vehicle is equipped with an SSM device, which logs the conflicts of the vehicle with other vehicles. In this research, time-to-collision (TTC) is used for the traffic conflict analysis. TTC is the time required to collide between two vehicles in follow–lead as well as approaching situations. Depending on the scenarios (as depicted in Figure 4), TTC calculation is expressed as:

$$\mathrm{TTC} = \begin{cases} \frac{x_l - x_f - L_f}{v_f - v_l}, & \text{if } v_l > v_f \\ \frac{d_2}{v_2}, & \text{if } \frac{d_1}{v_1} < \frac{d_2}{v_2} < \frac{d_1 + L1 + w1}{v_1} \\ \frac{d_1}{v_1}, & \text{if } \frac{d_2}{v_2} < \frac{d_1}{v_1} < \frac{d_2 + L2 + w2}{v_2} \end{cases} \tag{13}$$

A conflict is considered when the TTC value is less than the specified threshold. A TTC value of 1.5 s or less is considered as unsafe condition; hence, in this research, we set the TTC threshold to 1.5 s. The sum of all conflicts noticed during the simulation period indicates the total number of conflicts in the network. Similarly, we apply the one-way ANOVA statistical approach to check whether the total number of conflicts among scenarios are significantly different. In addition, to investigate whether each pair of scenarios is different from each other, we implement Tukey's HSD test [72].

Meanwhile, since AVs sensing technologies could potentially detect and respond to a conflicting situation much faster than HDVs, the unsafe TTC threshold might be lower for AV-AV and AV-HDV interactions. Hence, we conduct a sensitivity analysis to check how different PRs of AVs affect the total number of conflicts under various TTC thresholds.

Furthermore, to model the relationship between traffic characteristics, PRs, and the total number of conflicts in the network, we utilize a zero truncated Poisson (ZTP) regression model. The ZTP is a statistical approach used for analysing count data, excluding zero values from the dataset [73, 74]. Since this research employ the total number of conflict in the network for analysis, the zero number of conflicts in the network is not practical. The probability mass function (PMF) of the ZTP distribution is expressed as follows:

$$P(y;\lambda) = \frac{\lambda^y}{y!(e^{-\lambda}-1)}, \qquad y = 1, 2, 3, \ldots \tag{14}$$

where y is the observed count in a time interval, and λ is the mean parameter of the Poisson distribution. In addition, the expected counts and the variance for given λ can be expressed as follows:

$$E(y) = \frac{\lambda e^{\lambda}}{e^{\lambda}-1}, \qquad \mathrm{Var}(y) = \frac{\lambda e^{\lambda}}{e^{\lambda}-1}\left(1-\frac{\lambda}{e^{\lambda}-1}\right) \tag{15}$$

Finally, the ZTP regression model (link function) is as follows:

$$g(\lambda) = \log(\hat{\lambda}) = \mathbf{X}\beta + \epsilon \tag{16}$$

where X is the design matrix, β is the vector of regression coefficients, and ϵ is the random error that has the standard logistic distribution. In this model, we take different PRs of AVs, the standard deviation of the average network speed, and the average throughput in the network.

3.5 | Experimental setup

In this research, we develop a SUMO-based simulation platform to systematically simulate and analyse mixed traffic, considering varying deployment scenarios of AVs, since the current resources of CAVs modelling are limited in microscopic simulators. The architecture of the simulation platform consists of three components: (i) scenario generation, (ii) simulation environment, and (iii) output module. For each scenario, the scenario generation tool utilizes inputs such as demand scale, PR, and OD matrix. This tool assigns trips in the traffic network based on the provided information and runs the SUMO microscopic resolution model. The CF behaviours of AVs and HDVs serve as inputs to guide vehicles movement and interactions within the SUMO environment. For LC configurations, we maintain the default settings of SUMO for both AVs and HDVs. Considering the stochasticity in microscopic simulations, we aggregate the outputs (i.e. evaluation indicators) over multiple simulation runs. The study area covers the traffic network of Munich city center as shown in Figure 5, which includes urban road types with morning peak-hour traffic demand. The OD pairs are allocated using a trip-based stochastic user route choice assignment.

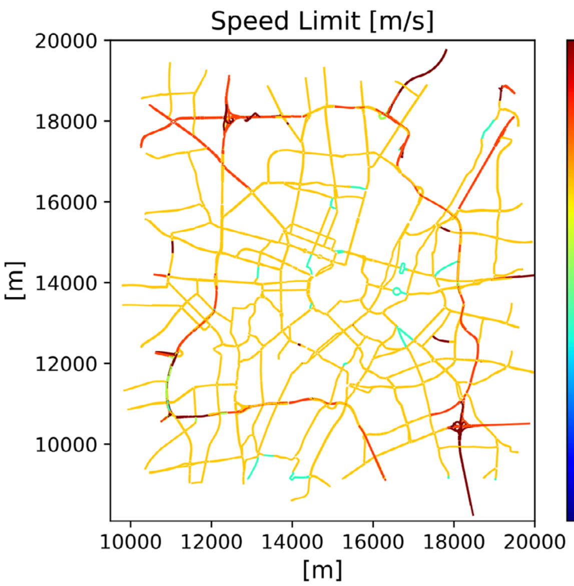

FIGURE 5 Transport network of Munich city center.

TABLE 5 IDM model's parameters range and calibrated values.

Parameters	Unit	Range of values	Calibrated value
Mingap	[m]	0.5–2.0	1.2
Accel	[m/s^2]	1.5–2.5	2.3
Decel	[m/s^2]	2.5–3.5	2.6
Tau	[s]	0.5–1.5	1.0

Meanwhile, as discussed in Section 3.2, we use IDM to calibrate the base model. The definition of the range of each parameter is necessary for the search space of the PSO. Hence, the range of each parameter of the IDM is assumed to replicate realistic driving behaviour and include the vehicle's capabilities in terms of acceleration and deceleration, as well as the comfort driving characteristics. The result of the calibration process, considering 12 simulation runs for each PSO iteration and a 15-min warm-up time is depicted in Table 5.

Additionally, in this research, we conduct impact assessment under different scenarios varying by demand fluctuations and PRs. We examine the simulation platform with two demand cases, namely, 30% below peak hour traffic and peak hour traffic demand. For each demand scale, we investigate scenarios with 0 to 100% PRs with 20% increments. Considering the overall scenario space for each demand scale, a total of 5 scenarios for AVs are generated. Meanwhile, to account for the inherent stochastic nature of microscopic simulations, we execute each scenario a total of 12 times. The resulting KPIs values are derived from the mean of all 12 simulation runs. Additionally, a 15-min warm-up period is implemented, during which no data are collected. In total, 12 scenarios (including 0% PR of AV) are executed, leading to a cumulative 144 simulation runs (12 runs for each of the 12 scenarios).

4 | RESULTS

The results section of this paper is structured into three segments. The first part describes the influences of AVs on traffic efficiency. It discusses the specific mobility effects of different AV PRs on links, intersections and overall network. The second part reveals the findings of safety assessments conducted across diverse scenarios within the Munich city network. Lastly, we present the outcomes of statistical analysis of the travel time- and conflicts-based regression models.

4.1 | Traffic efficiency

To explore the effects of different AV deployment scenarios on traffic efficiency, we employ a range of KPIs depending on the assessment area. For assessing the impacts on the overall network, we consider KPIs such as average network travel time, average waiting time, number of stops per vehicle throughout the trip, and mean time loss per vehicle. The average waiting time per vehicle is defined as the duration when the speed of a vehicle is less than 0.1 m/s, while the mean time loss per vehicle represents the time during which a vehicle operates below the ideal speed. Additionally, to investigate impacts on intersections, we use average time loss per vehicle and average intersection passing speed as indicators.

Analysing the mean network travel time in each AV scenario and comparing it with a fully HDV environment reveals a slight increase in average network time up to 40% AV PRs. Beyond this point, there is a reduction in travel time, as illustrated in Figure 6a. The results of the ANOVA test indicate that the F-value (5.741) for all AV scenarios under base demand exceeds the critical F-value (3.856) at a 95% confidence interval. This holds true for 30% below demand, where the F-value (5.506) for all AV scenarios, including 0% PR, surpasses the F-critical value (3.856). While the one-way ANOVA test reports different means among AV PRs for both demand scales, the Tukey HSD test demonstrates statistically significant changes between a fully HDV environment (0% PR) and (20%, 40%, and 60% PRs), as well as among (20%, 40% PRs) and a fully AV environment (100% PR) under the 30% below demand scale. With the base demand, only (20% and 40% PRs) exhibit significant differences from 0% PR and 100% PR.

As illustrated in Figure 6a, when the AV PRs range from 20% to 40%, the average network travel time experiences an approximately 10% increase compared to a fully HDV environment under both demand scales. This rise is primarily attributed to the behavioural changes of AVs in the network, leading to additional delays throughout the system. However, as the AV PR increases beyond 40% up to 100%, there is a subsequent reduction in average travel time, approaching levels comparable to a fully HDV scenario. This trend is consistent across other KPIs, as depicted in Figure 6b–d. This suggests that AVs do not substantially alter the overall network performance, as various influencing factors such as infrastructure, speed limits, and intersection control impose limitations on the effects of behavioural changes among vehicles in the network.

Similarly, the results of AVs impacts on the state of intersections reveal that the change in average time loss per vehicle per intersection with different AV PRs is not significantly different when compared to a fully HDVs scenario, as depicted in Figure 7. This outcome is attributed to the unchanged controlling algorithms of the traffic signals within the study area. In addition, the average passing speed per intersection remains almost the same for all AV scenarios. Hence, the behavioural difference in AVs driving configuration may not lead to substantial changes in both the mean time loss per vehicle and the average passing speed per intersection.

4.2 | Traffic safety

We use the total number of conflicts as the KPI to analyse the potential safety implications of AV PRs in the study area. A conflict is identified when the TTC value between two vehicles is less than or equal to a specific threshold set at 1.5 s in this study. Additionally, we vary the TTC threshold values for conflicts involving AV-AV and HDV interactions to explore the influence of AVs' sensing capabilities on the overall number of conflicts. This approach provides insight into how safety is affected by different AV PRs and the varying thresholds for conflict detection.

The summary statistics for traffic conflicts at different PRs of AVs are presented in Table 6, encompassing mean, minimum, and maximum values, as well as standard deviation. Initial findings indicate that, under both demand scales, increasing the PR of AVs up to 40% results in a concurrent increase in the total number of conflicts. This increase is directly linked to the distinct driving behaviour of AVs. Although in small PRs, the driving behaviour of AVs is influenced by HDVs, the change in parameters of the CF model results in a higher number of conflicts. This could also be expected in real-world scenarios where a limited PR of AVs might impact the driving behaviour of HDVs, prompting frequent adjustments in CF behaviour. Similarly, by increasing the PRs of AVs from 40% onward, there is a notable reduction in total number of conflicts. In a fully AV scenario, the total number of conflicts is around 25% lower than in a fully HDV environment. This indicates that

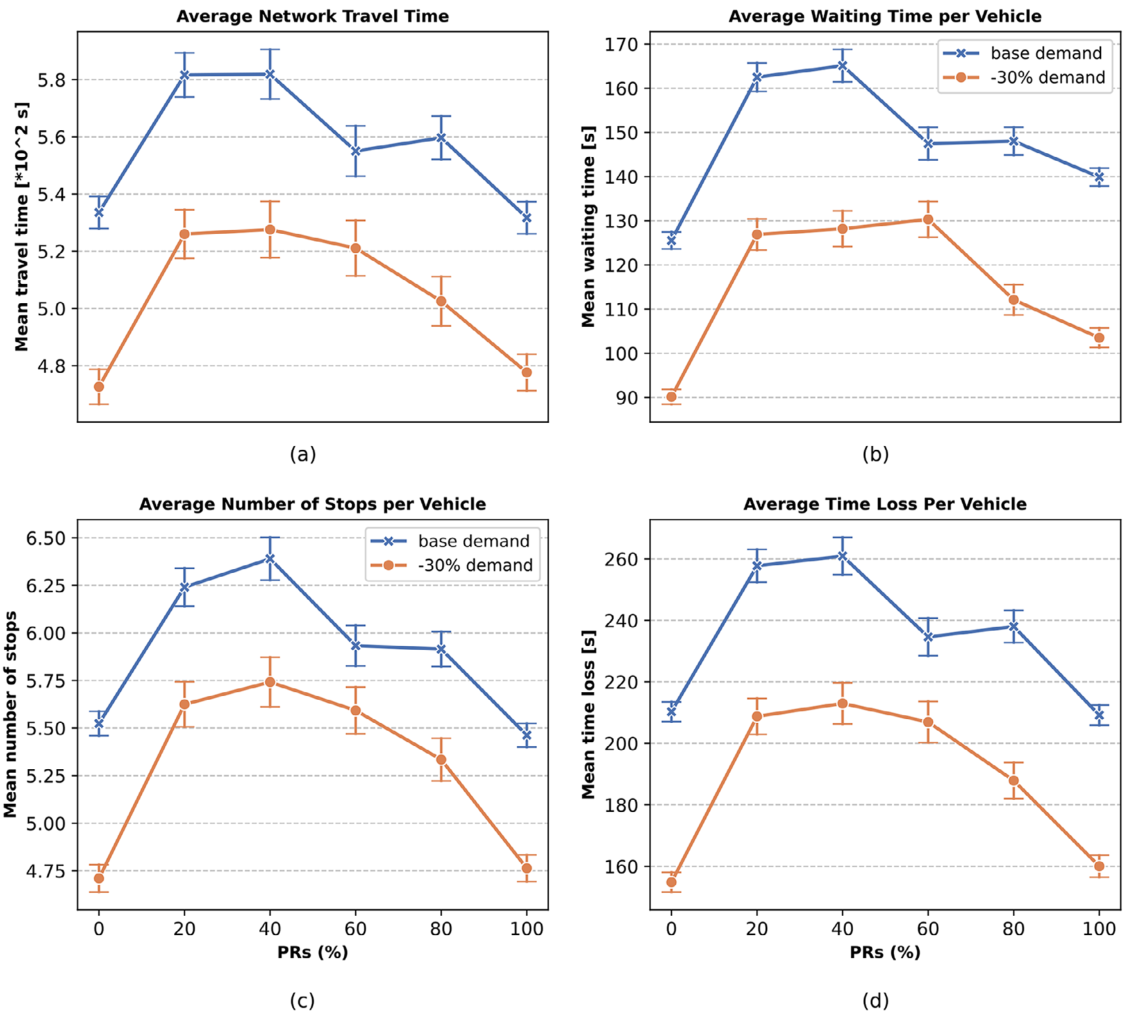

FIGURE 6 The impacts of AV PRs on (a) average network travel time, (b) average waiting time per vehicle, (c) mean number of stops per vehicle, and (d) average time loss per vehicle (the error bars show the variability of data around the mean).

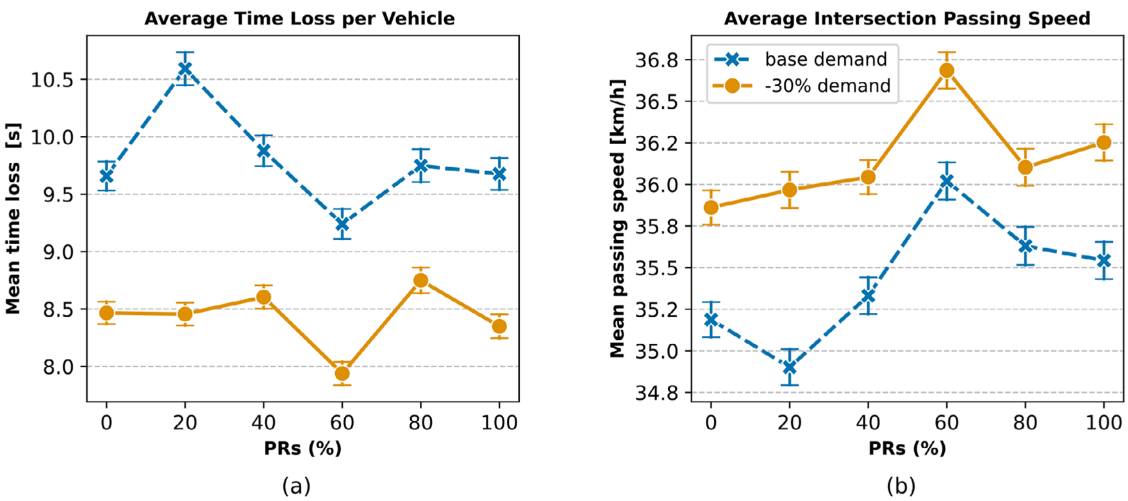

FIGURE 7 Illustration of the potential impacts of AV PRs on (a) average time loss per vehicle per intersection, and (b) average intersection passing speed (the error bars show the variability of data around the mean).

TABLE 6 Summary statistics of traffic conflicts (TTC = 1.5 s) under different PRs and demand scales.

Demand	PRs	Mean	Minimum	Maximum	Std deviation
100 %	0%	16,455	15,575	16,517	302.38
	20%	22,154	21,970	23,836	623.51
	40%	27,661	26,422	28,689	664.93
	60%	26,586	26,298	28,294	683.35
	80%	17,985	17,410	18,660	384.31
	100%	12,413	11,653	13,157	495.63
30% below	0%	8,894	8,576	9,331	250.06
	20%	13,721	13,205	15,528	619.78
	40%	17,596	16,271	18,190	521.31
	60%	17,031	16,530	17,854	365.55
	80%	10,927	9,832	11,663	485.29
	100%	6,592	6,252	7,202	286.47

AVs' CF behaviour could significantly change safety; however, in higher PRs.

Moreover, the results of the one-way ANOVA test indicate a significant variation in the total number of conflicts across all AV deployment scenarios in both demand scales. The F-value (9.974) for all AV scenarios under base demand exceeds the critical F-value (3.911) at a 95% confidence interval. Similarly, for the 30% below demand scale, the F-value (4.493) for all AV scenarios, including 0% PR, surpasses the F-critical value (3.911). Furthermore, the Tukey HSD test reveals a significant variation between all pairs of AV PRs except for 40% and 60% PRs under both demand scales.

Meanwhile, the sensing capabilities enable AVs to react faster than HDVs in conflict situations. Therefore, it is arguable that the TTC threshold for HDVs' conflicts could be set to 1.5 s, where the HDV is the following (ego) agent either in an HDV–HDV or HDV–AV situations. However, for AV–AV and AV–HDV conflicts, we can set the TTC threshold to 1.25, 1.0, and 0.75 s. In comparison to the initial scenario, where TTC is set to 1.5 s for all conflict types (Figure 8a), the total number of conflicts is significantly lower for other TTC thresholds, as depicted in Figure 8b–d. When setting the TTC threshold to 1.25 s for AV-related conflicts, the total number of conflicts in 100% PR reduces around 61% in comparison to 0%

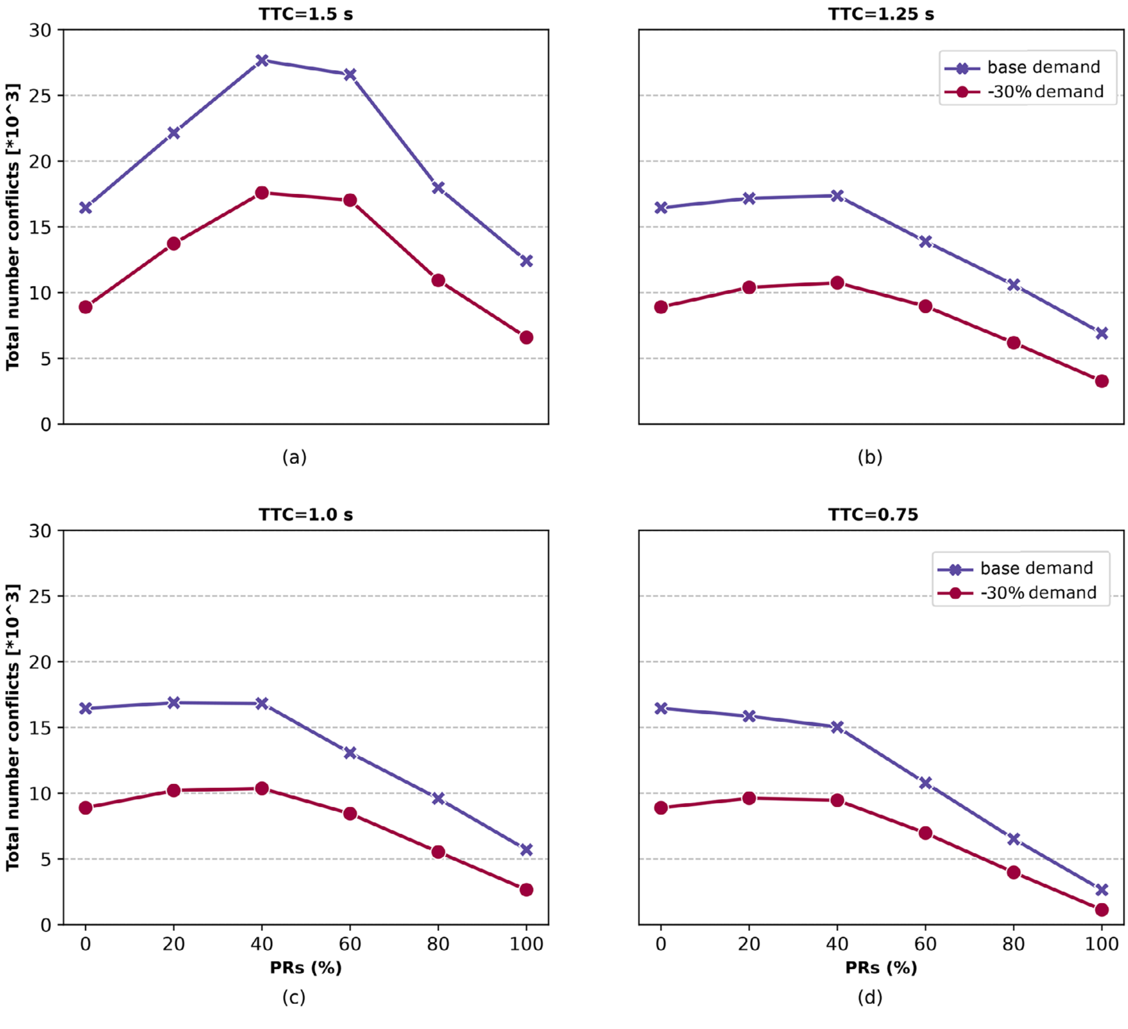

FIGURE 8 The comparison of the total number of conflicts under various TTC thresholds.

TABLE 7 The contribution of vehicle types on conflicts generation under various TTC thresholds and scenarios.

(a) TTC threshold = 1.5 s							(b) TTC threshold = 1.25 s						
Demand	**PRs**	**AV-AV**	**AV-HDV**	**HDV-HDV**	**HDV-AV**	**Sum**	**Demand**	**PRs**	**AV-AV**	**AV-HDV**	**HDV-HDV**	**HDV-AV**	**Sum**
100%	0%	0	0	16,455	0	16,455	100%	0%	0	0	16,455	0	16,455
	40%	7,214	7,109	6,218	7,120	27,661		40%	1,721	2,305	6,218	7,120	17,364
	80%	10,328	3,220	1,259	3178	17,985		80%	4,562	1,589	1,259	3,178	10,588
	100%	12,413	0	0	0	12,413		100%	6,914	0	0	0	6,914
30% below	0%	0	0	8,894	0	8,894	30% below	0%	0	0	8,894	0	8,894
	40%	4,683	4,429	4,003	4,481	17,596		40%	950	1,312	4,003	4,481	10,746
	80%	6,169	2,022	846	1,890	10,927		80%	2,480	966	846	1,890	6,182
	100%	6,592	0	0	0	6,592		100%	3,264	0	0	0	3,264
(c) TTC threshold = 1.0 s							**(d) TTC threshold = 0.75 s**						
Demand	**PRs**	**AV-AV**	**AV-HDV**	**HDV-HDV**	**HDV-AV**	**Sum**	**Demand**	**PRs**	**AV-AV**	**AV-HDV**	**HDV-HDV**	**HDV-AV**	**Sum**
100%	0%	0	0	16,455	0	16,455	100%	0%	0	0	16,455	0	16,455
	40%	1,508	1,986	6,218	7,120	16,832		40%	707	993	6,218	7,120	15,038
	80%	3,787	1,376	1,259	3,178	9,600		80%	1,515	569	1,259	3,178	6,521
	100%	5,704	0	0	0	5,704		100%	2,648	0	0	0	2,648
30% below	0%	0	0	8,894	0	8,894	30% below	0%	0	0	8,894	0	8,894
	40%	782	1,109	4,003	4481	10,375		40%	408	577	4,003	4,481	9,469
	80%	1,980	812	846	1,890	5,528		80%	816	424	846	1,890	3,976
	100%	2,651	0	0	0	2,651		100%	1,126	0	0	0	1,126

PR under both demand scenarios, where for TTC threshold 1.0 and 0.75 s, these figures show approximately 67% and 85%, respectively.

In addition, to gain a deeper understanding of the contribution of vehicle types in generating conflicts in the network, we distinguish AV and HDV-related conflicts under each TTC threshold, AV PR, and demand scale scenarios. As shown in Table 7, when setting the TTC threshold to 1.5 s, AV-related conflicts (AV-AV and AV-HDV) are higher than HDV-related conflicts under 40% PRs for both demand scenarios. The selection of a 40% PR allows us to assess the contribution of AV conflicts in a scenario where the presence of HDVs in the network is predominant. However, for lower TTC thresholds, the contribution of HDV-related conflicts is higher under 40% PR for both demand scale scenarios.

4.3 | Regression analysis

To better investigate the potential benefits of AV PRs on traffic efficiency and safety, we implement GEE and ZTP regression models, respectively, to relate the impacts with the influencing factors. For the GEE model, we use edge travel time per kilometre as a dependent variable and AV PRs, flow, length of edge, flows, and speed limit as independent variables. Whereas for the ZTP regression model, the total number of conflicts is set to the dependent variable, AV PRs, flow, and standard deviation of speed as independent variables.

4.3.1 | Travel time regression analysis

The results of the regression model with two correlation structures (independent and exchangeable) are shown in Table 8. For comparison of model goodness of fit under different correlation structures, we also use the AIC (Akaike Information Criterion) parameter (the lower value of AIC indicates a better model fit). As depicted in Table 8, the value of AIC is smaller for the independent working correlation structure, making it a better fit compared to the exchangeable correlation structure. In addition, there are differences in the coefficient and standard errors of the variables in both working correlation structures. For instance, the variable AV60 (60% PR of AV) is significant (p-value = 0.001) under the independent correlation structure, whereas it is not statistically significant (p-value = 0.132) under the exchangeable correlation structure. Meanwhile, the value of the estimated correlation matrix in the exchangeable structure is 0.754.

The investigation of the coefficient estimates of AV PRs reveals that under the independent structure, AV20, AV40, and AV80 are significant in changing edge travel time per kilometre, whereas under the exchangeable correlation structure, only AV20 and AV40 are statistically significant. The positive sign of the coefficients indicates that any AV PR increases the edge travel time per kilometre compared to a fully HDV environment; however, the magnitude of this increase is different in each AV PR. In a mixed environment, where AVs interact with HDVs, there might be frequent driving behaviour adjustments

TABLE 8 Regression-based edge travel time per kilometre analysis.

	Independent				Exchangeable			
Variable	**Coeff.**	**Std. Err.**	**z value**	**$Pr(>\|z\|)$**	**Coeff.**	**Std. Err.**	**z value**	**$Pr(>\|z\|)$**
Intercept	18.004**	3.753	4.797	<0.001	12.263**	3.845	3.189	0.001
AV20	0.931**	0.250	3.717	<0.001	0.531**	0.224	3.265	0.001
AV40	1.178**	0.277	4.262	<0.001	0.633**	0.292	2.166	0.030
AV60	0.913**	0.268	3.410	0.001	0.367	0.244	1.507	0.132
AV80	0.455	0.257	1.772	0.076	0.036	0.218	0.167	0.867
AV100	0.086	0.237	0.362	0.717	−0.289	0.180	−1.609	0.108
Edge length	0.068**	0.001	58.005	<0.001	0.071**	0.002	41.448	<0.001
Flow	0.014**	0.003	5.078	<0.001	0.030**	0.006	4.872	<0.001
Speed limit	−0.948**	0.274	−3.464	0.001	−0.765**	0.254	−3.016	0.003
AIC	500645.98				505287.27			

**Significance at 0.05 level.

toward safe manoeuvres, and this may lead to increased edge travel time per kilometre. In lower PRs, there is less driving behaviour oscillation compared to a fair share of both AVs and HDVs (e.g. 50%). Similarly, in higher PRs, the driving behaviour is influenced by AVs, and therefore, the driving actions are less disturbed for both AVs and HDVs compared with a 50% PR. As depicted in Table 8, under the independent correlation structure, the coefficient estimates of AV PR initially increase from 0.931 (AV20) to 1.178 (AV40) and then reduces gradually to 0.086 (AV100). Meanwhile, compared to the base scenario (0% PR), the travel time value per kilometre is higher in a fully AV environment (100% PR); however, the coefficient estimate is not significant, and thus, the safe driving behaviour of AVs could potentially improve safety without deteriorating traffic efficiency.

Furthermore, traffic flow significantly affects edge travel time per kilometre under both correlation structures. The higher flow results in increased travel time per kilometre. Similarly, the coefficient estimate of the speed limit is negative, which indicates that the travel time per kilometre at an urban road with higher speed limit is less compared to the same urban road with lower speed limit.

4.3.2 | Conflicts regression analysis

The findings of the conflicts-based regression model are presented in Table 9. Based on the estimated coefficients, AV PRs (except AV80) are found to be significant in affecting the total number of conflicts in the network. The signs of AV20, AV40, and AV60 are positive, whereas AV80 and AV100 have negative signs. The differences in the driving behaviour of AVs and HDVs result in increased conflicting situations. The higher the interactions among AVs and HDVs, the higher is the total number of conflicts. In scenarios with both low and high AV PRs, the total number of conflicts tends to be lower compared to situations with an equal mix of AVs and HDVs (e.g. 50% AV PR). In lower PRs, the number of conflicts tends to be like

TABLE 9 Regression-based conflicts analysis.

Variable	**Coeff.**	**Std. Err.**	**z value**	**$Pr(>\|z\|)$**
Intercept	2.484**	0.058	42.740	<0.001
AV20	0.044**	0.010	4.237	<0.001
AV40	0.124**	0.010	11.924	<0.001
AV60	0.074**	0.011	6.676	<0.001
AV80	−0.001	0.011	−0.077	0.939
AV100	−0.695**	0.022	−31.590	<0.001
Log (flow)	0.305**	0.005	60.739	<0.001
Speed Std	0.142**	0.003	43.078	<0.001

**Significance at 0.05 level.

the fully HDV scenario since the driving behaviour of AVs is influenced by HDVs. Similarly, in higher PRs, the number of conflicts is associated to AVs and tends toward a fully AV scenario. By increasing the PR up to 50%, the total number of conflicts increases, where with higher PRs (>50%), the change in the total number of conflicts in comparison to a fully HDV scenario reduces. When the PR reaches 80%, the change in the total number of conflicts compared to the based scenario is insignificant. However, in a 100% PR, the total number of conflicts reduces significantly. Therefore the coefficient estimates increase from 0.044 (AV20) to 0.124 (AV40), and then reduces to −0.008 (AV80) and finally to −0.695 (AV100).

Additionally, the standard deviation of speed is a significant variable in changing the total number of conflicts in the network. Higher fluctuation in this variable results in higher conflicts. Meanwhile, the increased traffic flow (throughput) in the network implies higher conflicts in the network.

5 | DISCUSSION

The findings of the literature review revealed that most simulation-based AV studies conduct the impact assessment on traffic efficiency [18, 21, 22, 30, 34, 35, 66], safety [17, 22, 28, 32, 55], and some also focus on environmental effects [24, 25, 75]. Regarding the mobility impacts, researchers reported that higher PRs of AVs and CAVs reduce travel time and increase capacity and throughput [17, 18, 21, 22, 33]. However, other studies claimed that in a mixed driving environment where AVs interact with HDVs, the capacity degrades [19, 34], and travel time increases [66]. In addition, it is reported that in higher speed limits, the impact of AVs on Freeway capacity is significant. In contrast, in lower speed limits, the change is not considerable [35]. Meanwhile, most studies reported that CAVs outperform AVs in many aspects due to their communication capabilities. For instance, [22] reported that at least 20% PR of CAVs is required to significantly reduce travel time, whereas, for AVs, at least 40% PR is required. On the other hand, the results of our research show that a mixed environment of AVs and HDVs increases the network travel time, vehicle time loss, and average flow. Second, regarding safety impacts, most studies suggested that by increasing the PR of AVs, the total number of conflicts in the network reduces significantly [17, 22, 32, 55]. Some also highlighted the negative impacts of AVs on roundabout safety [64]. However, our research revealed that a comparable mix of AVs and HDVs might result in an increased number of conflicts. Since different driving behaviours of AVs and CAVs may lead to the frequent adjustment of driving actions, the number of conflicts increases. However, with higher PRs of AVs (e.g. more than 80%), the total number of conflicts significantly reduces in comparison to a fully HDV environment. With 100% AV PR, the total number of conflicts decreases by around 25%. The inconsistent conclusion on the impacts of AV PRs could be associated with two main influencing factors: the assumption on the potential CF parameters of AVs driving behaviour and the scope of the study.

The driving behaviour of AVs might significantly differ from HDVs. In MTMs, the driving behaviour of AVs is distinguished from HDVs by modifying the parameters of the CF model. However, the magnitude of these changes depends on the researchers' own assumptions (due to the lack of large real-world data for AVs). Most studies, for instance, assume that AVs might drive closer to the leading vehicles and could react relatively faster. However, AVs may have more cautious behaviour and strictly follow the traffic rules, especially the speed limits, compared to HDVs. Therefore, in this research, we utilize AVs' optimized and safe driving behaviour instead of assuming the CF model parameters.

Another important aspect is the scope of the study. Most studies conduct the impact assessment on freeways and highways, where the fluctuation of traffic flow elements is not huge. Thus, AV driving behaviour brings a significant change in efficiency and safety. In contrast, in an urban network, many other influencing factors such as the type of roads, number of lanes, type and number of intersections, curvatures, control devices, speed limits, and more could have direct impacts on the driving performance and impress the potential effects of driving behaviour itself. In other words, these influential factors could diminish the effects of AV driving behaviour on traffic efficiency. Therefore, in this research, the findings differ for efficiency evaluation. A similar result is also reported by [66], where the investigation is conducted at the network level. On the other hand, regarding safety, driving behaviour significantly affects the number of conflicts. Since a conflict occurs between two vehicles (following and leading) in a short period and is unrelated to the entire vehicle's trip, the driving behaviour is responsible for any possible conflict.

6 | CONCLUSION

It is expected that AVs have a different driving behaviour than HDVs. This behavioural difference might bring a significant change in mobility, safety, and emissions. Identification of the potential driving behaviour of AVs is a crucial aspect of impact assessment studies. Since AVs might have safe and efficient driving behaviour, a simulation-based impact assessment with optimal driving behaviour of AVs might report more realistic results on the potential impacts of AVs. Hence, in this research, we conduct a comprehensive simulation-based impact assessment under varying scenarios to evaluate the effects of AVs on efficiency and safety in an urban network. An experimental setup is conducted to run the simulations in the Munich city network. We utilize Krauss and IDM models to mimic the CF behaviour of AVs and HDVs, respectively. The parameter of the HDV CF model is calibrated using PSO algorithm, whereas for the Krauss model, the optimized parameters are used from another study.

The evaluation of impacts on traffic efficiency reveals that any PR of AVs might increase the network travel time under various demand scenarios. This increase is mainly due to the behavioural changes of vehicles in mixed environments. With 20–40% PRs, the results show around 10% increase in travel time, where this figure reduces gradually for PRs ranging from 40% to 100%. In a fully AV scenario, the network travel time is almost the same as in the base scenario (0% PR). The same findings are found for other KPIs, including the average number of stops per vehicle, average time loss per vehicle, and average time loss per vehicle per intersection. Hence, behavioural differences in AV driving configurations could not bring huge changes on traffic efficiency in urban networks. On the other hand, the analysis of traffic safety depicts that by increasing the PRs of AVs to 40%, the total number of conflicts (with TTC $<$1.5 s) increases significantly; however, with higher PRs, the number of conflicts reduces significantly. In addition, it is found that the total number of conflicts is around 25% less in a fully AV environment in comparison to the base scenario. Meanwhile, if we consider the sensing capabilities of AVs for their fast reaction in case of a conflict situation, the total number of conflicts in the network reduces significantly by increasing the PRs of AVs. Depending on the TTC value for AV-related conflicts (AV to AV or AV to HDV), the total number of conflicts reduces around 60 to 80% in higher PRs ($>$80%).

The investigation of the potential impacts of AVs showed that AVs might bring safety improvement not only by eliminating the drivers' errors but also by their behavioural changes; however, their impacts on efficiency in a city network scale, where additional infrastructure-related factors (e.g. speed limit, type of roads, number of lanes, type of intersections, traffic control devices, and more) play a vital role is not huge. This research also has limitations that could raise new lines of work for further studies. First, for any PR of AVs, we fixed the driving behaviour of HDVs; however, the mass deployment of AVs might also change the behaviour of HDVs and their interaction with AVs. Thus, a research using a driving simulator experiment of the field test is required to evaluate the potential change in human drivers' behaviour when interacting with AVs and utilize these changes when conducting impact assessment. This will lead to more accurate and reliable findings on AVs impact assessment. Second, in an urban network, among other influential factors, speed limit could have a major contribution in diminishing the real impacts caused by behavioural changes in driving. Hence, a sensitivity analysis of different speed limit policies could be valuable research work to investigate the relationship between speed limits and the potential impacts of AVs on efficiency and safety. Third, in simulation-based studies, the effects of AVs are influenced by factors such as the selection of CF models and the scope of the study. Therefore, it is important to perform a sensitivity analysis using varying modelling techniques to find the interactions among a CF model and the potential impacts and to analyse the relationship between the scope of a study and the impacts of AVs deployment scenarios. Fourth, in this research, we utilized the optimized driving behaviour of AVs (extracted in a city network) to conduct an impact assessment. However, it is interesting to study the impacts of AVs on a freeway or highway by utilizing the AVs' optimal driving behaviour. The aim would be to evaluate the effects of optimal driving behaviour of AVs under high speed and traffic flow. Finally, there is a potential to integrate a data-driven model into a microscopic traffic simulator to replicate the driving behaviour of AVs under varying traffic conditions and conduct impact assessment. This will generate plausible findings on the potential impacts of AVs in mixed traffic.

AUTHOR CONTRIBUTIONS

Hashmatullah Sadid: Conceptualization; formal analysis; methodology; validation; visualization; writing—original draft. **Constantinos Antoniou**: Conceptualization; funding acquisition; supervision; writing—review & editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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