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Safety and Mobility Evaluation of Cumulative-Anticipative Car-Following Model for Connected Autonomous Vehicles

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Abstract: In the typical landscape of road transportation, about 90% of traffic accidents result from human errors. Vehicle automation enhances road safety by reducing driver fatigue and errors and improves overall mobility efficiency. The advancement of autonomous vehicle technology will significantly impact traffic safety, potentially saving more than 30,000 lives annually in the United States alone. The widespread acceptance of autonomous and connected autonomous vehicles (AVs and CAVs) will be a process spanning multiple decades, requiring their coexistence with traditional vehicles. This study explores the mobility and safety performance of CAVs in mixed-traffic environments using the cumulative-anticipative car-following (CACF) model. This research compares the CACF model with established Wiedemann 99 and cooperative adaptive cruise control (CACC) models using a VISSIM platform. The simulations include single-lane and multi-lane networks, incorporating sensitivity tests for mobility and safety parameters. The study reveals increased throughput, reduced delays, and enhanced travel times with CACF, emphasizing its advantages over CACC. Safety analyses demonstrate CACF's ability to prevent traffic shockwaves and bottlenecks, emphasizing the significance of communication range and acceleration coefficients. The research recommends early investment in vehicle-to-infrastructure (V2I) communication technology, refining CACC logic, and expanding the study to diverse road scenarios.

Keywords: cumulative-anticipative car-following; connected autonomous vehicles; vehicle-everything communication; intelligent transportation system; microsimulation

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1. Introduction

According to the U.S. National Highway Traffic Safety Administration (NHTSA), 38,680 people died in motor vehicle traffic crashes in 2020, even though people drove less because of the COVID-19 pandemic [1]. According to the World Health Organization, road traffic injuries ranked as the eighth-leading cause of global mortality in 2016, accounting for around 1.35 million deaths [2]. Further, an infrastructure report card by the American Society of Civil Engineers (ASCE) stated that in 2017, Americans spent about 8.8 billion hours delayed in traffic, and traffic congestion cost the country around 166 billion US dollars [3]. This suggests that ensuring the safety of road systems, enhancing traffic operations, and ensuring convenient mobility are significant priorities. The future transformations of vehicle automation sectors promise potential benefits for societies by delivering safe and convenient mobility options. Autonomous vehicles (AVs) or connected AVs (CAVs) are expected to soon incorporate several automated driving functions that would allow the car to be driven with or without a need for a human driver [4]. As more than 90% of crashes are caused by human errors [5], it is projected that autonomous driving could save 30,000 lives per year in the United States and prevent about 5 million accidents [6]. Morgan Stanley projected that self-driving cars could contribute annual savings of up to 1.3 trillion

U.S. dollars to the U.S. economy and over 5.6 trillion U.S. dollars globally [7]. Furthermore, KPMG projects potential economic benefits of approximately 51 billion UK pounds from CAVs by 2030 [8]. This shows that AVs or CAVs have the potential to enhance safety and influence transportation costs, traffic patterns, and congestion [9]. Moreover, autonomous cars are anticipated to reduce mobility expenses, mitigate climate change risks, enable enjoyable driving experiences for disabled and elderly individuals, and revolutionize product delivery [10].

While AVs offer positive impacts on travel, they also pose safety concerns and potential negative effects, such as increased congestion from zero-occupancy vehicles. AVs coordinating lane changes and exits may significantly disrupt traffic flow, causing slowdowns or accidents [11]. Factors like fail-safe technology, privacy, security, personal choices, affordability, and infrastructure requirements influence AV fleet entry. Despite technological progress, achieving Level 5 (fully autonomous) self-driving vehicles will require further advancements to prevent potential malfunctions and crashes [12,13]. At this stage, AVs and CAVs are still in the development stage, and until the complete market adoption of autonomous technology, a long transition period of coexistence between conventional and automatic cars will exist. It is important to study and improve the expected driving behaviour of future autonomous cars.

The future challenges also comprise potential interactions of automatic cars with conventional cars, i.e., vehicle-to-vehicle (V2V) communication, and with infrastructure units, i.e., vehicle-to-infrastructure (V2I) communication. V2V communication, a component of vehicle-to-everything (V2X) communication, facilitates information exchange between vehicles and all available devices [14,15]. V2X encompasses vehicle-to-infrastructure (V2I) [16], vehicle-to-pedestrian [17], and vehicle-to-network [18]. The application of other V2X systems in AVs is limited due to insufficient information and a lack of algorithms. Nevertheless, as V2X systems evolve, the information they provide will be valuable for AVs or CAVs to collect data from their surroundings, especially in mixed-driver conditions involving human-driven vehicles or partial AVs [19].

The recent cumulative-anticipative car-following model (CACF) model was published [20], considering V2X, especially V2I communication. However, no-in depth analysis has been conducted on how the CACF model would impact the traffic and safety of road users. This paper is focused on evaluating the safety and mobility impacts of the CACF model for CAVs in a mixed-traffic environment by carrying out various sensitivity tests using the VISSIM microsimulation platform. The results of the CACF model are compared with the results of the VISSIM default driving behaviour (Wiedemann 99) and the cooperative adaptive cruise control (CACC) car-following model that considers V2V communication.

The remainder of this paper is organized into five sections. Section 2 presents a literature review on types of simulation models and existing forward movement and lateral movement models. Section 3 presents the implementation of CAV models in the VISSIM microsimulation platform. Sections 4 and 5 present the study test setup and the evaluation results, respectively. Lastly, Section 6 presents the conclusion of the study and recommendations for future research.

2. Literature Review

2.1. Impact of AVs and CAVs Technology on Traffic Flow

As mentioned previously, the emergence of autonomous and connected vehicles brings potential benefits and unique challenges to traffic engineering. With the continuing market penetration of AVs and CAVs, they will significantly influence traffic engineering parameters, including road capacity, delays, travel times, cost factors, and safety. Initially, AVs/CAVs would maintain larger headways than traditional human-driven cars, leading to reduced road capacity and slower overall traffic speeds. However, increased AV penetration and cooperative driving, such as platooning, will ultimately enhance mobility, safety, and environmental benefits [21–24]. Human driving exhibits stochastic behaviour, characterised by a tendency to be more cautious and hesitant in accepting risks. In contrast, AVs/CAVs driving behaviour is deterministic, displaying predictable driving dynamics. Consequently, the calibration parameters and constants in existing car-following models, such as the Wiedemann psycho-physical car-following models from 1974 or 1999, require revision for autonomous cars [21].

In a study conducted by Atkins for the UK Department for Transport (DfT) on the influence of CAVs on traffic flow in the UK road network, CAVs were modelled with varied longitudinal, lateral, and other driving behaviour parameters. The study analysed the benefits of CAVs in terms of average delay and journey time for different market penetrations, revealing substantial improvements, especially with higher levels of CAV market penetration, as shown in Table 1. In another study, Peter et al. examined the consequences of escalating AV penetration across three distinct desired speeds in a single-lane VISSIM network. Desired speeds ranged linearly from minimum to maximum values—50 km/h (48–52), 100 km/h (99–101), and 130 km/h (125–135). Market penetration increased incrementally from 0–100% at 10% intervals. The findings indicated that higher capacities could be achieved at elevated speeds. Moreover, the rise in capacity exhibited an almost linear pattern up to 60% AV penetration, with a slightly more gradual increase beyond this threshold (>60%) [22].

Table 1. Lane-change to a faster lane and relevant four types [25].

Scenario	**Average Delay**		**Average Journey Time**	
	(s)	**(%)**	**(s)**	**(%)**
Base	35.84	-	539.79	-
25% CAV	36.17	+0.9	538.49	−0.2
50% CAV	33.39	−6.8	533.62	−1.1
75% CAV	29.77	−16.9	527.72	−2.2
100% CAV	23.72	−33.8	517.77	−4.1
Upper bound *	21.38	−40.3	479.29	−11.2

* Upper bound is a fleet consisting of fully automated vehicles.

2.2. Transport Simulation Models

Transport simulation models encompass macroscopic, mesoscopic, and microscopic types, each chosen based on the required detail for network analysis. Macroscopic models aid planners in managing large-scale traffic networks and forecasting travel demands but lack the ability to model individual vehicle interactions like conflict management and gap-acceptance. These interactions are handled by microscopic models [26–28]. Mesoscopic models integrate macroscopic and microscopic simulation features. While offering less precise individual vehicle characteristics than microsimulation, mesoscopic tools exhibit superior performance in typical planning analyses [28]. Microscopic models record individual vehicle attributes through car-following, lane-changing, and gap-acceptance logics, which are crucial for modelling complex roadway scenarios, urban congestion, pedestrian movements, road safety, proposed transportation enhancements, and detour impacts [28].

Microsimulation models encompass various components, enabling users to simulate real traffic flow systems, incorporating road design, signal systems, vehicle types, and driving behaviour. Logics defining driving behaviour emulate human phenomena on highways, covering gap acceptance, speed adaptation, ramp merging, overtaking, lane-changing, and car-following models [29]. Driving involves longitudinal tasks (acceleration, maintaining safe speed, gap) and lateral actions (lane changing, overtaking) [30]. Subsequent sections introduce key elements of driving behaviour. Several commercially available traffic microsimulation packages model real-world network configurations, problems, and solutions. These packages employ distinct car-following behaviour, lane-change, and gap-acceptance models. Prominent tools include AIMSUN, CORSIM, PARAMICS, and VISSIM [29,31,32].

PTV VISSIM, developed by the German company PTV Vision in 1992, is a leading microsimulation tool. Utilising the Wiedemann 99 car-following model, it excels in diverse analyses such as signalised junctions, transit operations, corridor modelling, multimodal systems, active traffic management, emission modelling, connected vehicles, and facility operations like airports and terminals [33]. VISSIM's Wiedemann model determines following vehicle behaviour based on distance and speed differences, incorporating random numbers and statistical variations for diverse behaviours in each time-step. The lane-change algorithm operates on a rule-based model [34,35]. This software distinguishes itself by enabling users to customise parameters for lane-change, gap-acceptance, and car-following models, setting it apart from other commercially available simulation tools. This study concentrates on VISSIM software for several reasons: (1) supports external driver models through APIs, (2) utilises a psychophysical car-following model based on driver assumptions, (3) allows user calibration of model parameters, (4) features a robust graphical user interface with built-in capabilities for connected autonomous vehicles, and (5) provides effective evaluation techniques for capacity and safety.

2.3. Forward Movement Models

The car-following model describes how drivers interact longitudinally with the preceding vehicle in the same lane [36]. Over the years, several researchers have developed various car-following models for human-driven vehicles, considering different acceleration behaviours, safety gaps, and reaction times of the subject-following vehicle. These models include stimulus-based sensitivity framework models [37,38], collision-avoidance models [39], optimal velocity models [40], and psycho-physical models [41]. Considering the impact of the dynamic behaviour of drivers and the driving environment on the performance of the car-following models, detailed reviews and analyses of existing car-following models have been conducted by numerous researchers [19,42]. Sun Lu et al. [43] introduced a novel FVD (full velocity difference) car-following model, incorporating driver memory, and formulated a corresponding macroscopic continuum traffic flow model that mitigates the occurrence of wrong-way travel. Jafaripournimchahi et al. [44] expanded the FVD model by integrating factors related to memory, velocity, and the headway between the object vehicles and the preceding vehicle during the previous time period.

In addition to conventional car-following models, researchers have developed mixed traffic flow car-following models comprising conventional and autonomous vehicles that are based on the intelligent driver model (IDM) algorithm, which considers the potential characteristics of AVs [45,46]. These models consider advanced driver assistance features of AVs such as adaptive cruise control (ACC) and cooperative ACC (CACC), relying on the speed detection sensors onboard the vehicle for V2V communication between the leading and following vehicle in the range of communication. In the CACC model, the leading vehicle sends information about its recommended speed and (sometimes) lane assignment to the following vehicle, which adjusts its speed and desired distance without the involvement of the driver [47,48]. The CACC acceleration mathematical model is expressed as:

$$a_c = k_a * a_p + k_v * \left(v_p - v_f\right) + k_s * (s - v \times t_d) \tag{1}$$

$$a = max[a_{min}, min(a_c, a_{max})] \tag{2}$$

where a_c is the control acceleration with the liner function, a is the acceleration in the next step of the objective vehicle, a_p is the acceleration of the preceding vehicle, t_d is the time gap 0.5 s, v_p is the speed of the preceding vehicle, v_f is the speed of the following vehicle, a_{min} is the maximum allowed acceleration 2 m/s^2, a_{max} is the maximum allowed deceleration -3 m/s^2, and k_a, k_v, k_s are constant factors.

Several researchers have investigated the impact of the CACC model and found that it has the ability to improve the traffic network capacity at higher penetration rates [48–50]. In 2012, Shladover et al. conducted a mixed traffic flow simulation study consisting of conventional, ACC, and CACC vehicles, assuming that the driver holds the capability to follow the vehicles safely with shorter gap settings. The results of the study showed that with the increasing penetration rate of CACC vehicles, the per-lane capacity can increase from 2000 to 4000 vehicles and reach a maximum value of 3389 vehicles at a 90% CACC vehicle penetration rate [51]. However, the reduced gap between the two vehicles is only possible if both vehicles are equipped with the CACC technology. Additionally, at least 40% market penetration is required to acquire some benefits of the CACC technology [48].

Recently, a cumulative anticipative car-following model (CACF) for CAVs was developed [20], which implements V2X communications (e.g., V2I sensors embedded in the roadways in addition to V2V) for real-time traffic data of multiple surrounding vehicles for car-following. The acceleration model of the CACF model can be described as:

$$a_c = k_a * a_p + k_v(v_p - v) + k_d * \left(r - t_{system} * v + (-1)^c * |(X_d - X_r)|\right) \tag{3}$$

$$a_d = max[a_{min}, min(a_c,\ a_{max})] \tag{4}$$

$$X_d = v_d * t_{system} + \frac{1}{2}a_d * t_{system}{}^2 \tag{5}$$

$$X_r = v * t_{system} + \frac{1}{2}a * t_{system}{}^2 \tag{6}$$

where a_c is the control acceleration of the ego vehicle, a_d is the desired acceleration in the next step of the objective vehicle, a_p is the actual acceleration of the preceding vehicle. t_{system} is the time gap, 0.5 s (if the preceding vehicle is an AV), otherwise 1.4 s, v_p is the actual speed of the preceding vehicle, v is the actual speed of the following vehicle, a_{min} is the maximum allowed acceleration = (2 m/s^2), and a_{max} is the maximum allowed deceleration (−3 m/s^2). Additionally, X_d is the predicted clearance (distance) based on the "desired" data of the preceding vehicle, X_r is the predicted clearance (distance) based on the "real (current)" clearance of the preceding vehicle, r is the real end-to-front clearance (or distance) between the preceding and lead vehicle and is given by $r = x_p - x - l_p$, c is equal to 0 if $X_d > X_r$ and $r > X_s$ (safe distance), and 1 otherwise, X_s (safe distance) = standstill distance + gap time × current velocity (v), $k_a = 1.0$,$k_v = 0.58$, $k_d = 0.1$ are constant gains in accordance with the simulation of intelligent cruise control studies [50,52,53] and greater than zero, respectively, x and x_p are current coordinates (position) of following and preceding vehicle, respectively, and l_p is the length of the preceding vehicle.

CACC vehicles rely on the V2V communication channel where each vehicle is expected to have a communication capability for effective implementation of the logic. Hence, until a significant market penetration of connected autonomous cars is achieved, the implementation of CACC will be a challenge. Alternatively, the CACF model considers all available communication means such as V2I, V2V, and others. Although the transition phase of conventional vehicles or semi-automatic cars towards fully operational autonomous cars will require decades, and the effective V2X communication will remain a challenge until a substantial number of automatic vehicles are available in the market, the advantages of introducing V2X communication into car-following models are still very attractive. However, until now, no in-depth analysis has been conducted on the performance of the CACF in the mixed-driver environment.

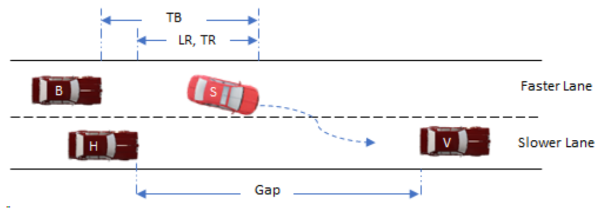
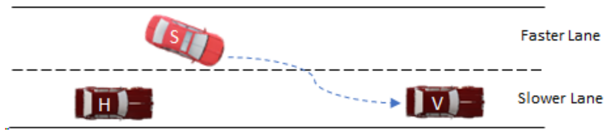
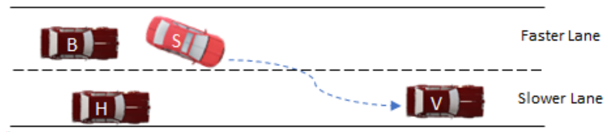
In this study, the CACF model is investigated for its potential wider applications in mixed-driver environments before a full penetration of CAVs. Later sections of this study will examine the implications of implementing the CACC model.

2.4. Lateral Movement Models

Autonomous vehicles utilise a range of systems, including cameras, GPS, radars, lasers, and LiDAR sensors, for lateral maneuvers, such as lane-keeping, lane-changing, and left-turn assist, on multi-lane highways. To aid lane-keeping, vehicles use integrated cameras above the central rearview mirror and positioning systems to track lane markings. If the vehicle deviates, a lane-departure-warning (LDW) system is activated to alert the driver about the potential lane departure. Additionally, the systems can assist the driver in maintaining lane discipline through automated steering and/or braking, functioning as a "lane-keeping assistant" [54]. Similarly, to facilitate lane-changing, the vehicle employs short-range radar sensors [54] to monitor surrounding traffic zones to the sides and rear of the vehicle as the driver contemplates a lane change. This provides a warning to the driver regarding the presence of traffic in the target lane, particularly in the blind spot. If the driver disregards the warning and proceeds with the lane change, an additional robust alert is transmitted to prevent a potential side crash.

The lane-change system uses lane-change models to define the driver's decision as to when it is possible to change lanes or not change lanes in a multi-lane road network system [31]. Most lane-changing models are based on a set of rules [55] that enable the driver to decide when it is necessary to change a lane to reach the desired destination. In 1986, Gipps developed a lane-changing model that explains the structure of lane-changing maneuvers in an urban driving situation and focuses on the risk of possible vehicle-to-vehicle and vehicle-to-obstruction collisions [34]. In 1978, Sparmanns investigated human behaviour towards the lane-changing process on one-way roads and defined that a lane change can be characterized as a move to slower-to-faster and faster-to-slower lanes depending upon the desires and needs of the driver [35]. Prioritizing safety is crucial when initiating the lane-changing process, involving considerations like estimating optimal distances and speed differentials between the lead and trailing vehicles on specific lanes. Sparmanns categorized lane changes into six types, comprising four for faster lane changes and two for slower ones, as outlined in Tables 2 and 3 [35].

Table 2. Slower lane change and its types [35].

Slower lane-change	
Type-1: FREE lane-changes	
Type-2: ACCEL lane-changes	

Notes: S is lane-changing vehicle, M is front vehicle on an actual lane, V is front vehicle on a faster lane, H is following vehicle on a faster lane, GAP, TR, TB are time headways [s], and LR is distance for reaction [m].

Table 3. Faster lane change and its types [35].

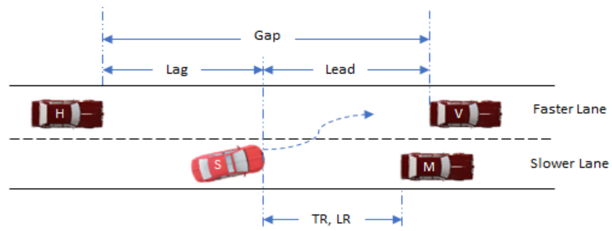
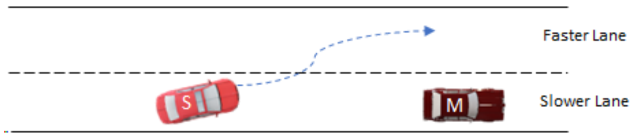
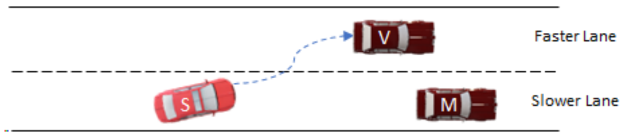
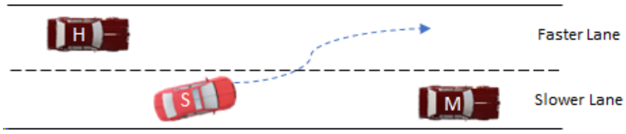
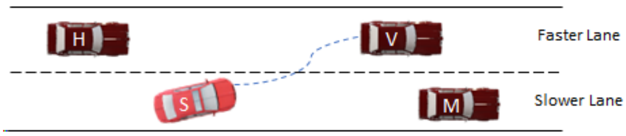
Faster lane-changes	

Table 3. *Cont.*

Type-1: FREE lane-changes	
Type-2: LEAD lane-changes	
Type-3: LAG lane-changes	
Type-4: GAP lane-changes	

Until now, there has been no investigation of how the CACF model would impact the lateral movements of CAVs. Note that the CACC car-following model only controls the longitudinal behaviour of the following cars in the same lane. If a user needs to also perform lateral operations, a desired lane-change logic needs to be added in the CACC model.

3. CAV Modeling

In this study, the PTV VISSIM 2020 micro-simulation tool was utilised. This tool uses the Wiedemann 99 psychophysical car-following model, since it is the default driving behaviour model where a user can edit parameters that control the driving behaviour of a vehicle, such as car-following, lane change, and lateral behaviour. The Wiedemann 99 psychophysical car-following model was used as a reference model. The details and guidelines for each driving parameter is provided in the VISSIM user manual [33]. Additionally, considering the technical capabilities of CAV, the distribution of desired acceleration and deceleration functions, as well as the distribution of maximum acceleration and deceleration functions, for the CAV have been defined to be linear functions because they are expected to result in smoother driving behaviour compared to conventional vehicles [56].

3.1. Integration of CACC and CACF Driving Models in VISSIM

VISSIM's internal car-following model lacks the ability to directly execute external driver models (EDMs) such as CACC and CACF. The VISSIM EDM dynamic library (DLL) interface was utilised, which enables users to completely replace the internal car-following model and lane-change models with a user-defined algorithm for the selected or all vehicle types. Zhao and Sun (2013) developed an external driver model using the CACC framework through the VISSIM application programming interface (API) i.e., DriverModel-DLL [57]. Yang (2023) developed an external driver model using the CACF framework through the VISSIM API [20]. This study selected the most common EDM model CACC as a comparable model for evaluating the performance of the CACF model.

The DLLs for these custom car-following models were developed using C++ logic code. During a simulation run, VISSIM calls the DLL code for each impacted vehicle employing the EDMs. It then determines the longitudinal and lateral behaviour of the vehicle for each simulation time-step, considering the current state of the affected vehicle and the surrounding vehicles within the communication range, as illustrated in Figure 1.

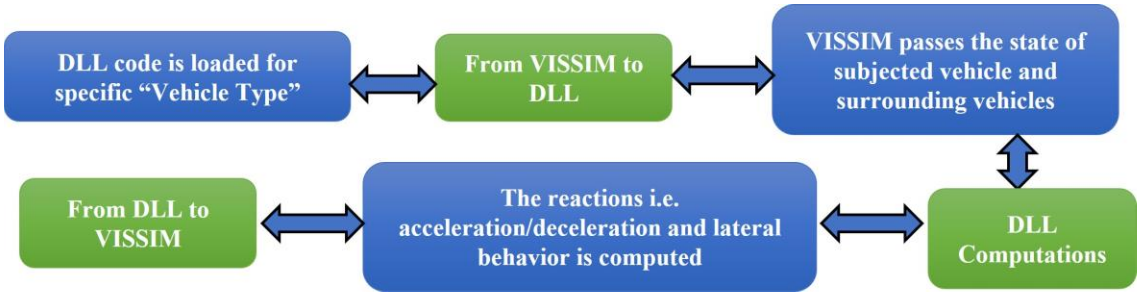


Figure 1. VISSIM and external driver model DLL workflow.

To manage lateral control in CACF vehicles, this study developed a lane-changing algorithm with VISSIM API support. The algorithm operates in two stages. First, the autonomous vehicle monitors the acceleration/deceleration behaviour of preceding stationary or slow-moving vehicles downstream and initiates a lane change if the leading vehicle's acceleration falls below -3 m/s^2. In the second stage, the vehicle checks for a safe gap in the adjacent lane. If one is found, the car changes lanes. If no safe gap is found, the vehicle waits for clearance or remains in its current lane, as shown in Figure 2. Two sets of safe distances (front and rear) are considered based on prior research, reflecting cautious [58] and aggressive [59] behaviours accordingly. This lane-change logic specifically targets a two-lane basic freeway segment and facilitates communication between the ego vehicle with both conventional and connected autonomous cars.

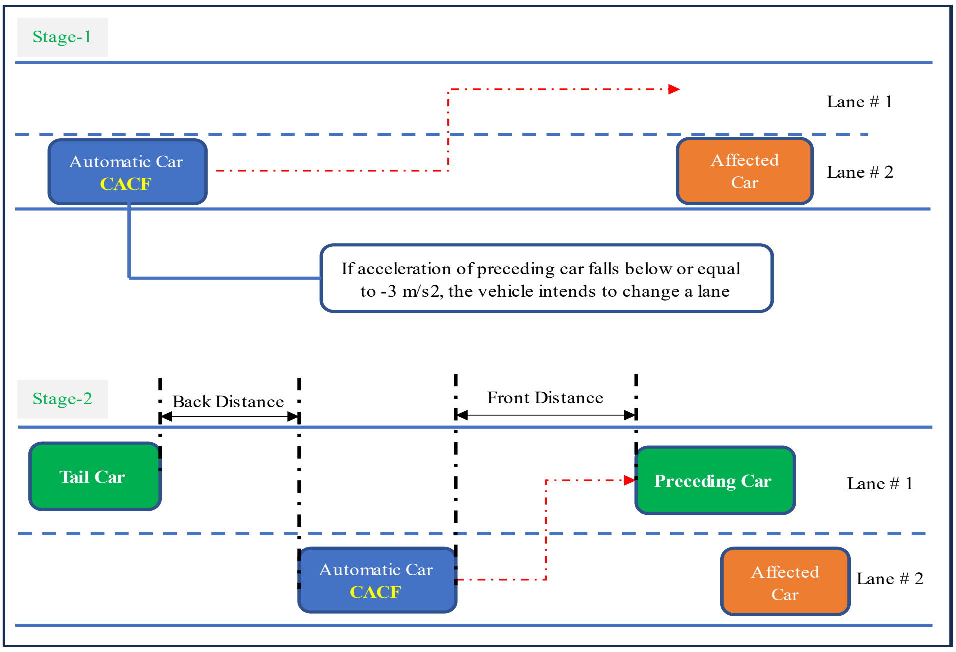


Figure 2. Lane−change logic for the CACF model.

3.2. Safety Performance Analysis Configuration

To analyse the safety performance of selected CAV driving models, the safety surrogate assessment model (SSAM) [60] was utilised in this study. Researchers have used SSAM tool analysis to evaluate traffic safety during the transitional phase between human-driven and autonomous vehicles [61,62]. The VISSIM software generates a vehicle trajectory file after each simulation run, which is imported into SSAM for traffic conflict analysis. The SSAM tool uses two threshold attributes for surrogate measures of safety, such as time-to-collision (TTC) and post-encroachment-time (PET), and outputs several types of V2V interaction conflicts such as rear-end, lane-change, and crossing conflicts. TTC is the most-used surrogate measure of safety, with a default TTC value of 1.5 s, as suggested in previous research [63,64]. However, in this study, different TTC values were utilised to evaluate the sensitivity of traffic simulation. For the PET surrogate safety measure, a default value of 5 s was utilised, as recommended by other researchers [65].

3.3. Simulation Configurations for Evaluation

The settings of VISSIM simulation and evaluation parameters have a major influence on the simulation results. Different sets of values create variation in the output results and hence, generate stochastic distributions. According to the Massachusetts Department of Transportation (MassDOT) [66], the "warm-up" time comes before the simulation settles, when the number of vehicles in the network levels out. The best warm-up time, about twice the estimated longest travel time in normal conditions, depends on the network size. A simple rule is to pick at least double the estimated longest travel time in the network during normal conditions. Because the length of the network is approximately 5 km (3.1 miles), the warming and cooling of 900 s (15 min) was sufficient for this study.

For mobility performance evaluation, a simulation period of 5400 s was selected, in which the initial warm-up period of 900 s and the final cooling-down period of 900 s were excluded from simulation evaluation. However, the safety analysis using the SSAM tool was evaluated for the whole simulation period of 5400 s.

This simulation setting is incorporated by running 10 simulations for each sensitivity test, as the minimum requirement defined by the Oregon Department of Transportation (ODOT) [67] and the Washington State Department of Transportation (WSDOT) [68].

The FHWAs' Traffic Analysis Toolbox defines an equation for calculating the number of simulations runs, as described below [69]:

$$N = (2 * t_{0.025,N-1} * \frac{S}{R})^2 \tag{7}$$

where R is the 95% confidence interval for a true mean, s is the standard deviation for a selected MOE parameter, N is the number of simulation runs required, and $t_{0.025,N-1}$ is the student's t-statistics for a two-sided error of 2.5% (totals 5 percent) with $N-1$ degrees of freedom (for 4 runs, t = 3.2, for 6 runs t = 2.6, and for 10 runs, t = 2.3).

(Note: there is one less degree of freedom than car runs when looking up the appropriate values of t in the statistics table). Simulation runs are determined by an MOE parameter such as average speed. This study employs 10 runs, meeting WSDOT and ODOT minimum requirements.

4. Test Setup

In this study, the sensitivity of the VISSIM default driving behaviour, using the Wiedemann 99 model, was analysed as a reference for comparison and to evaluate the safety and mobility performances of the CACF model. Seven sensitivity tests were performed for the CACF model, in addition to the CACC model, for further comparison and validation. Among the seven sensitivity tests, six of the analysis cases were performed using a single-lane network, and the last test was conducted to investigate the influence of lane changes on the CACF model. The summary of all sensitivity tests is provided in Table 4. There are seven sensitivity tests performed. Test 1 investigates the maximum throughput of the CACF model. Tests 2 and 3 compare the performance of the CACF model with the most popular existing EDM model CACC model in the no-crash and crash environments. Tests 4, 5, and 6 evaluate the impact of changing acceleration coefficient, V2I communication range, and communication lag on the performance of the CACF model. Test 7 investigates the safety performance of the CACF model in a multi-lane environment. Specifically, further test descriptions are provided in the following subsections.

Table 4. Summary of all sensitivity tests.

Type of Test Setup	Type of Analysis	
	Mobility	Safety
Test 1—Maximum Throughput for CACF Model	✓	
Test 2—Performance of CACC and CACF Models (No-Crash)	✓	
Test 3—Performance of CACC and CACF Models (With-Crash)	✓	✓
Test 4—Impact of Acceleration Coefficients on CACF Model (With-Crash)		✓
Test 5—Impact of V2I Communication Range on CACF Model (With-Crash)		✓
Test 6—Impact of Communication Signal Lag on CACF Model (With-Crash)	✓	✓
Test 7—Safety Performance of CACF Multi-lane Logic		✓

4.1. Test 1–Maximum Throughput for CACF Model

This test consists of a single-lane 5 km freeway network, featuring two network objects positioned between 1000 m and 4000 m. These objects include "vehicle travel time measurements" to calculate average travel time and "data collection points" for computing vehicle arrival numbers, acceleration, and distance at the end of each link. To assess the CACF model's maximum expected mobility benefits, the simulation sets the vehicle input at 10,000 passenger cars per hour per lane (pc/h/ln). This configuration ensures that VISSIM generates the highest logical car arrival rate for each run. The simulation spans market penetrations from 0% to 90% of AVs in 10% increments. Conventional cars adhere to VISSIM's default speed distribution of 120 km/h, while the external CACF model maintains a fixed desired speed of 75 mph (120.7 km/h) without stochastic distribution, as discussed in the literature.

4.2. Test 2—Performance of CACC and CACF Models (No-Crash)

This test uses the same network configuration as used in Test 1. However, the mobility performance of the CACC and CACF models is analysed for a speed of 65 mph (104.7 kmph), with a vehicle input of 1680 pc/h/ln for varying penetration rates of AVs. This scenario is named "no-crash" because no potential traffic disturbance is created in the simulation through various network objects such as stop signs or reduced speed areas.

4.3. Test 3—Performance of CACC and CACF Models (With-Crash)

Test 3 uses a network configuration similar to that discussed in Test 1, with consistent vehicular input and speed distribution as used in Test 2. Additionally, a vehicle breakdown spot is provided downstream, where a specific vehicle type decelerates aggressively until reaching a speed of zero, causing upstream vehicles to react to the breakdown vehicle and generate traffic congestion or produce rear-end conflicts. A "stop sign" with a dwell time of 0.2 s is located at the 4000 m position of a single-lane network. The input volume of the breakdown vehicle is kept at 1% for all market penetration rates of CAV.

In Figure 3, green cars are externally controlled vehicles, such as the CACC and CACF cars; black and red cars are conventional vehicles, where the red car represents a breakdown vehicle. The conventional vehicles have higher deceleration values compared to the maximum deceleration values of the CACC and CACF models, which are restricted to -3 m/s^2. Because this is a single-lane network, only rear-end conflicts are reported for corresponding TTC values, considering varying market penetration rates of CAV.

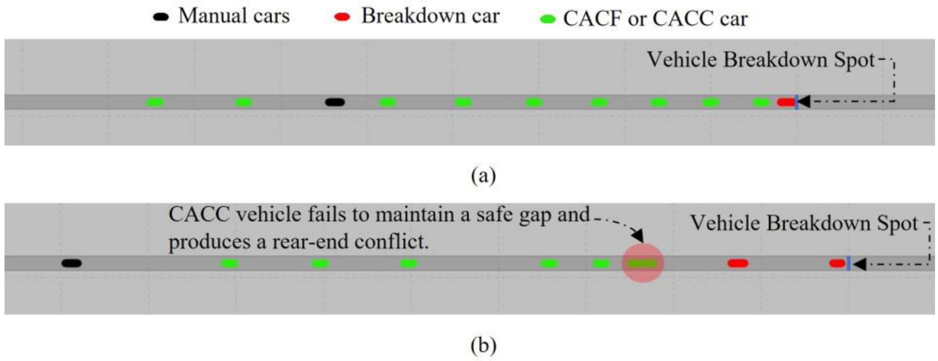


Figure 3. Performance of (**a**) CACF and (**b**) CACC models in "with-crash" scenario.

4.4. Test 4—Impact of Acceleration Coefficients on CACF Model (With-Crash)

Because the CACF model is an extension of the CACC algorithm, it uses the same acceleration coefficients, such as K_a for the acceleration of the preceding vehicle, K_v for velocity difference, and K_d for distance difference, respectively. The base values for acceleration coefficients, such as K_a = 1.0, K_v = 0.58, and K_d = 0.1, describe "strong behavior" [48,52]. Arem et al., (2006) evaluated the performance of the CACC model by varying K_v and K_d values and keeping K_a = 1.0 constant [48]. This test uses the same network configuration as Test 1 and evaluates the performance of the CACF model by applying different sets of acceleration coefficients, which are adopted by Arem et al. (2006) in a CACC traffic-flow characteristics study [48], as listed in Table 5. The CACF model's performance for each acceleration coefficient case is analysed for the "with-crash" scenario explained in Test 3, using the same vehicular input and speed distribution as used in Test 2 for varying TTC values during the gradual introduction of CACF vehicles.

Table 5. Comparison of acceleration coefficients for the CACF model.

Coefficient Comparison Cases	Coefficient Values		
	K_a	K_v	K_d
Base-case	1.0	0.58	0.1
Case-1	1.0	0.58	0.2
Case-2	1.0	3.0	0.2
Case-3	1.0	3.0	0.1

4.5. Test 5—Impact of V2I Communication Range on CACF Model (With-Crash)

As discussed in the literature, AVs and CAVs use different types of communication channels, such as V2V, V2I, and V2X, to communicate with the surrounding environment. Therefore, this test investigates the impact of communication range on the safety and mobility of vehicles. Because the vehicles equipped with V2V technology can communicate with other vehicles in the operational range of 300 m using various advanced driving assistance technologies [70], this study uses a base value of 300 m for the V2I communication range, and four different communication ranges have been implemented in the CACF code, as shown in Table 6. Additionally, the capability of recording data from the "n" number of vehicles ahead is also investigated, with 10 cars as the base case. The simulation is conducted for varying market penetration of CACF vehicles, with a TTC range of 1–3 s at 0.5 s intervals, for the "with-crash" scenario explained in Test 3.

Table 6. V2I communication range and capability comparison.

Cases for Different Communication Ranges	Values (m)	Capability for Communication with "n" Number of Cars [1]	No. of Cars (#)
Base Case	300	Base Case	10
Case-1	150	Case-1	5
Case-2	200	Case-2	15
Case-3	250		
Case-4	400		

[1] The default communication range for each case is 300 m.

4.6. Test 6—Impact of Communication Signal Lag on CACF Model (With-Crash)

Because CACF vehicles communicate with the surrounding environment (i.e., V2I communication) using data transferred from sensors embedded on the roadways [20], it is expected that the network transmission will have lags at some point, as a result of poor internet signals, low 4G/5G coverage, equipment malfunction, etc. Thus, it is important to investigate the impact of communication signal response lag on the safety and mobility of vehicles. The response lag is considered by increasing the time-gap, i.e., the t_{system} value, and the default time-gap value is 0.5 s, where the response lag is 0 s. This test uses a similar network configuration as Test 1, with a varying penetration rate of CACF vehicles against different TTC values, except in this test, three signal response lag cases are considered, as mentioned below:

- Case-1 for 0.1 s lag = t_{system} = 0.6 s.
- Case-2 for 0.2 s lag = t_{system} = 0.7 s.
- Case-3 for 0.3 s lag = t_{system} = 0.8 s.

4.7. Test 7—Safety Perfromane of CACF Multi-Lane Logic

For the multi-lane behaviour analysis of the CACF model, the VISSIM simulation network consists of a two-lane basic freeway segment with a vehicle input of 3360 pc/h and a 65 mph (104.7 km/h) traffic speed, performing at "LOS C" Highway Capacity Manual (HCM) [71]. A "stop sign" with a dwell time of 0.2 s is located near the 3870 m position, which only activates for a "breakdown-vehicle". The percentage of "breakdown-vehicle" is kept at 1% for all market penetrations to introduce an accident location to evaluate the safety implications of multi-lane CACF logic. Various penetration rates of CAVs are evaluated, considering all discussed lane-change conflict cases for TTC values ranging from 1 s to 3 s. The test is conducted for three different cases, as listed below:

- Base Case: Using a single lane CACF model where the lateral behaviour is controlled through VISSIM default driving logic.
- Case-1 (Cautious Behaviour): Front gap = 60 m and rear gap = 60 m [58].
- Case-2 (Aggressive Behaviour): Front gap = 10.32 m and rear gap = 15.32 m [59].

5. Results and Discussion

5.1. Test 1—Maximum Throughput for CACF Model

This test provides the results for the maximum mobility benefits expected from the CACF model, as shown in Figure 4. The maximum throughput for a single-lane network at a 0% market penetration rate is about 2350 pc/h/ln, which is close to the maximum capacity at "LOS E" of the basic freeway segment, as per HCM [71]. The CACF model increases the overall road capacity by 35% for a 90% market penetration, with a maximum throughput of approximately 3350 pc/h/ln, which is close to the CACC model's performance [51], as discussed in the literature. Additionally, the average travel time and average speed performance also marginally improved at high rates of CACF vehicles.

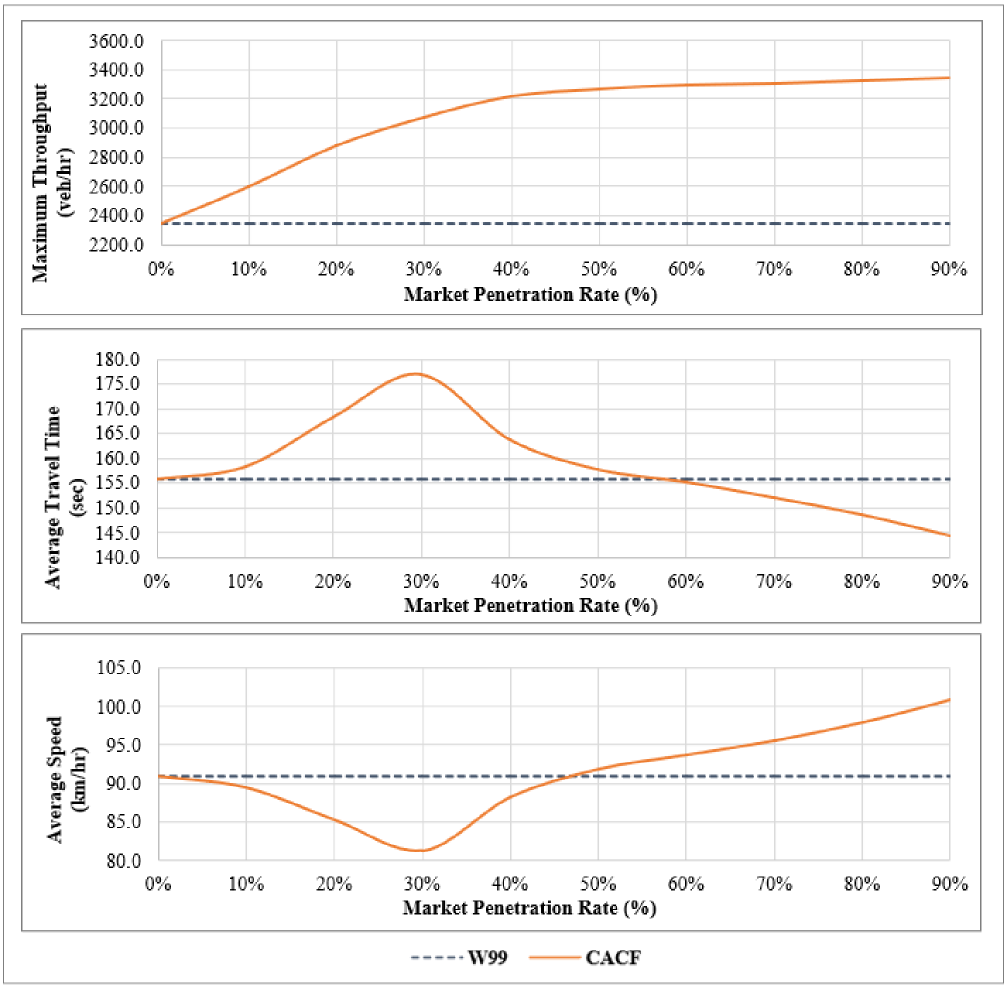


Figure 4. Maximum throughput results—CACF model.

5.2. Test 2—Performance of CACC and CACF Models (No-Crash)

Table 7 shows the mobility performance results by comparing the average travel time, delay, and speed obtained from the W99, CACC, and CACF models with no crash considered, while the W99 model is used as the control in this test. As the simulation performs smooth operations due to moderate traffic input values, the mobility results for the CACC and CACF models showed less significant results for average travel time and speed. However, the average delay is drastically reduced to 0 s for the CACF and 0.6 s for CACC at a 90% market penetration rate, respectively. The average travel time begins to improve from a 30% market penetration and is improved by 6.6% for CACC and 9.1% for the CACF model at a 90% market penetration rate. This test shows that the efficiency of mobility parameters is enhanced for both CACC and CACF car-following logics. Additionally, the safety analysis using the SSAM tool for the "no-crash" scenario generates no significant potential conflicts for the CACC and CACF models.

5.3. Test 3—Performance of CACC and CACF Models (With-Crash)

Similar to Test 2, Table 8 shows the mobility performance of the W99, CACC, and CACF models with a crash considered, where the W99 is used as the control. Figure 5 further compares the safety results between the CACC model and the CACF model to better demonstrate the performance difference among these two models, with the CACC model used as the control model. For mobility, compared with the W99 control model, the CACF model shows slight mobility improvements over the CACC model for increasing market penetration rates. However, for safety (Figure 5), it can be seen that the safety performance is improved considerably for the CACF model as the penetration rate increases, compared with the CACC model, where the safety analysis has resulted in poor performance, producing higher rear-end conflicts for 30% or greater market penetration rates. The primary reason for this behaviour in the CACC model is because CACC-equipped vehicles tend to follow other CACC vehicles with smaller gaps, creating congestion behaviour in the event of a breakdown. On the other hand, vehicles equipped with the CACF model communicate with the "n" number of vehicles ahead within the base communication range of 300 m and are prepared to react in advance to avoid conflicts.

Table 7. Mobility performance results—W99, CACF, and CACC models (no-crash) scenario.

Market Penetration (%)	Average Travel Time (s)			Average Delay (s)			Average Speed (km/h)		
	W99	CACF	CACC	W99	CACF	CACC	W99	CACF	CACC
0	148.9	-	-	13.9	-	-	97.6	-	-
30	-	146.7	147.2	-	10.2	8.8	-	99.2	98.6
50	-	145	145.3	-	7.3	5.6	-	100.6	99.8
70	-	142.4	142.5	-	3.3	2.7	-	102.9	101.7
90	-	135.9	139.4	-	−5.3 [1]	0.6	-	108.9	103.9

[1] The negative delay is when the desired speed is lower than the actual speed of the vehicles. A negative value is considered as "zero delays" in the analysis.

Table 8. Mobility performance results—W99, CACF, and CACC models (with-crash) scenario.

Market Penetration (%)	Average Travel Time (s)			Average Delay (s)			Average Speed (km/h)		
	W99	CACF	CACC	W99	CACF	CACC	W99	CACF	CACC
0	150.2	-	-	14.9	-	-	96.9	-	-
30	-	147.6	148.8	-	10.9	8.0	-	98.7	97.7
50	-	146.2	147.5	-	8.3	5.7	-	100	98.6
70	-	143.7	144.7	-	4.4	3.5	-	102.2	100.5
90	-	138.4	141.3	-	−3.2 [1]	1.1	-	107.2	102.8

[1] The negative delay is when the desired speed is lower than the actual speed of the vehicles. A negative value is considered as "zero delays" in the analysis.

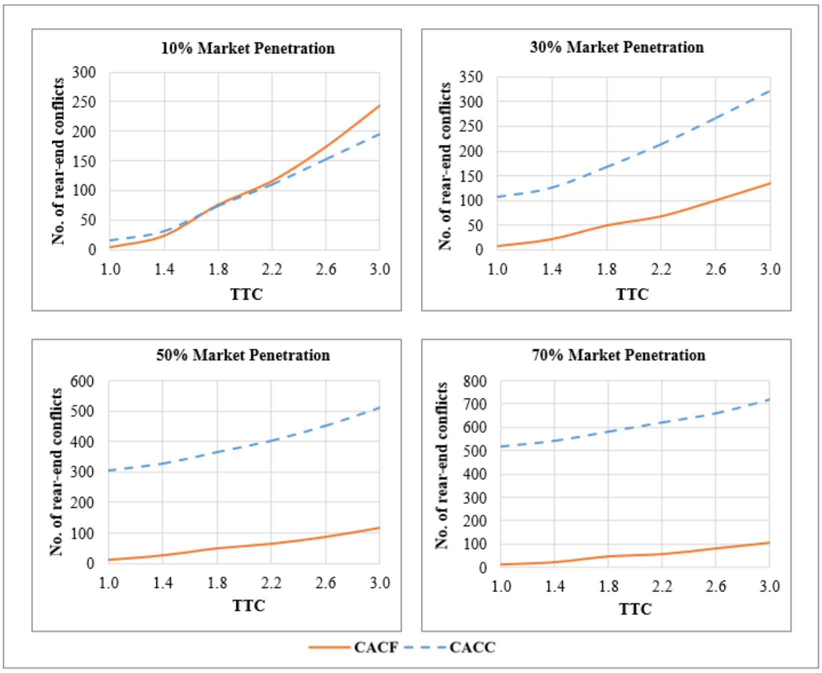


Figure 5. Safety results—CACC and CACF models (with-crash) scenario.

5.4. Test 4—Impact of Acceleration Coefficients on CACF Model (With-Crash)

The safety results from Test 4 are illustrated in Figure 6, following the test setup explained in Table 5 for various penetration rates of 20%, 50%, and 70%. The base case was used as the control for this test to evaluate the influences of different acceleration coefficients, K_a, K_v, and K_d. Figure 6 shows that the most significant parameter is K_d, where a high value of K_d resulted in the greatest number of conflicts, especially in Case-1. The results of Case-3 show that an increase in the value of K_v also produced an increase in the number of conflicts compared to the base case scenario. The mobility performance is insignificant and is hence not reported here.

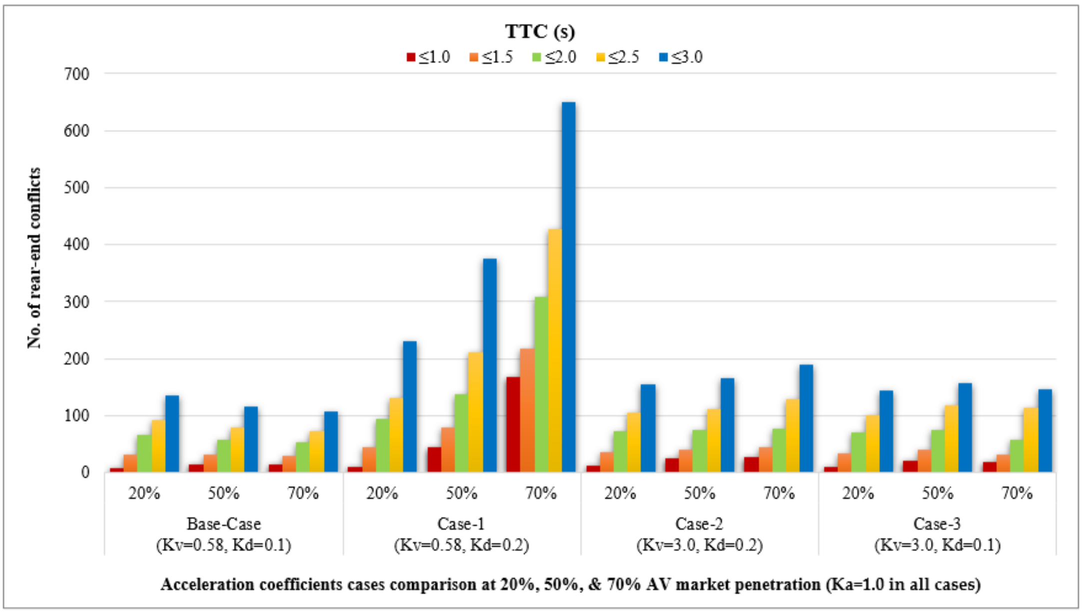


Figure 6. Safety results for acceleration coefficients on the CACF model (with-crash) scenario.

5.5. Test 5—Impact of V2I Communication Range on CACF Model (With-Crash)

Figure 7 shows the average rear-end conflicts for each case as safety results obtained from Test 5, comparing various communication ranges with various penetration rates of 10%, 30%, 50%, and 70%, following Table 6. The base case was used as the control for this test to evaluate the influences of different V2I communication ranges. It can be seen from Figure 7 that the 200–250 m communication range of V2I generates minimal average rear-end conflicts for lower and higher market penetration rates of AVs. A higher communication range of 400 m produces results relatively equal to the base case of 300 m. The results indicate that the CACF model has low significance for an operational range greater than 300 m. Thus, a communication range between 200 m to 250 m is suitable for the CACF model for a single-lane network. Furthermore, the test for the capability of communicating with the "n" number of cars ahead shows no significance for safety and mobility results. Even if the CACF car communicates with five vehicles ahead, it will maintain a safe behaviour because of the nature of the proposed model implementation. Hence, this indicates that the CACF model is more sensitive to the range of communication rather than the number of cars ahead.

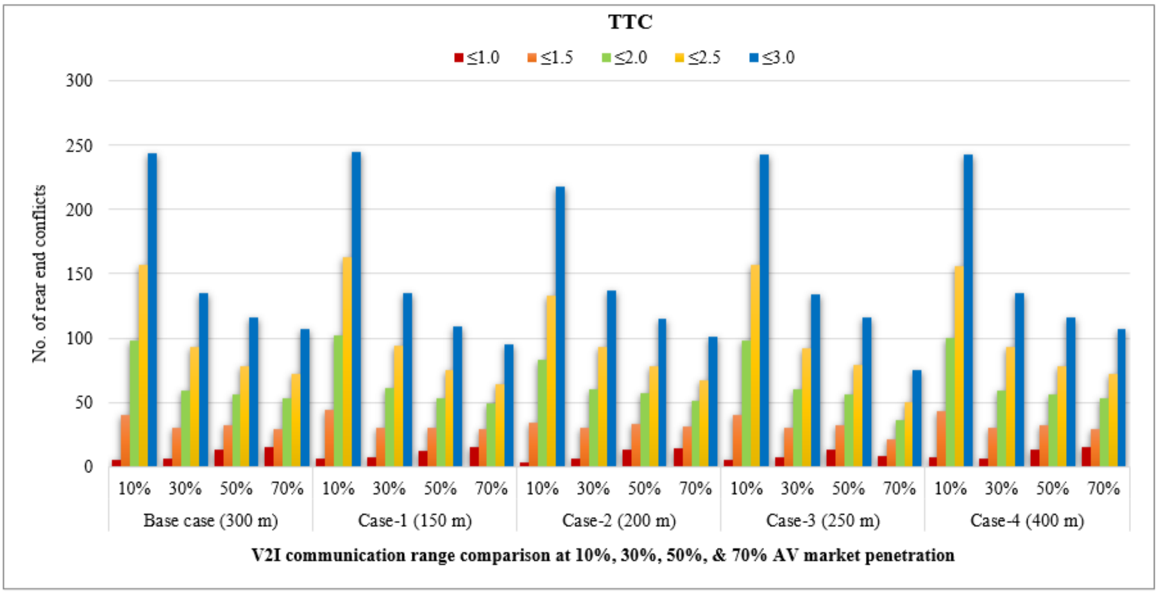


Figure 7. Safety results for V2I communication range on the CACF model (with-crash) scenario.

5.6. Test 6—Impact of Communication Signal Lag on CACF Model (With-Crash)

The inclusion of signal response lag negatively impacted the acceleration of AVs, because when the vehicles receive a signal response with a lag, the acceleration of the vehicle is reduced, and the vehicles maintain a "careful" behaviour. Figure 8 shows safety results, indicating the number of conflicts with different signal response lags at various penetration rates of 10%, 30%, 50%, and 70%, following Section 4.6. The number of conflicts is shown to be reduced when the response lag is increased. For TTC $\leq$ 3.0 at a 50% market penetration rate, the average conflicts are reduced by approximately 11% for Case-1, 20% for Case-2, and 21% for Case-3, respectively. Table 9 illustrates the influences of response lags with different market penetration rates. The market penetration shows a positive trend for safety performance, but mobility performance is impacted to some extent, as shown in Table 9. Because the vehicle begins to move at a slower acceleration rate, the average delay begins to increase. The maximum average delay difference is recorded as 0.9 s for Case-3 with lag against the base case scenario at a 70% market penetration rate.

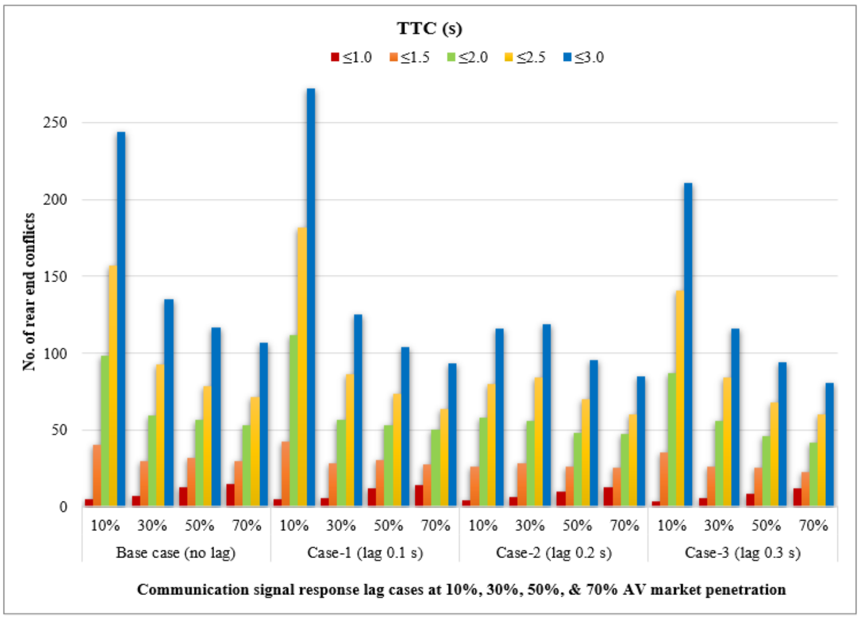


Figure 8. Safety results for communication signal response lag on the CACF model (with-crash) scenario.

Table 9. Mobility results for communication signal response lag on the CACF model (with-crash) scenario.

Market Penetration (%)	Average Delay (s)			
	Base Case	Case 1 0.1 s lag	Case 2 0.2 s lag	Case 3 0.3 s lag
10	13.5	13.6	13.6	13.7
30	10.9	11.1	11.1	11.3
50	8.3	8.4	8.6	8.9
70	4.4	4.7	5	5.3

5.7. Test 7—Safety Performance of CACF Multi-Lane Logic

Figure 9 shows safety performance using the number of conflicts, comparing the base case with cautious or aggressive driving, following Section 4.7, at different penetration rates of 10%, 30%, 50%, and 70%. The base case was used as the control case to investigate the impacts of lane changes. Cautious behaviour produces fewer lane-change conflicts compared to aggressive behaviour. Because the safe distance for aggressive behaviour is between 10 m and 15 m, the ego vehicle is unable to secure enough space for a safe maneuver, resulting in more lane-change conflicts for higher TTC values. Mobility benefits, such as reduced average travel time and average delay, have less significance for different "back" and "front" distance values. Hence, cautious behaviour is suitable for the multi-lane CACF model. However, additional sensitivity tests are required to inspect the behaviour of multilane scenarios.

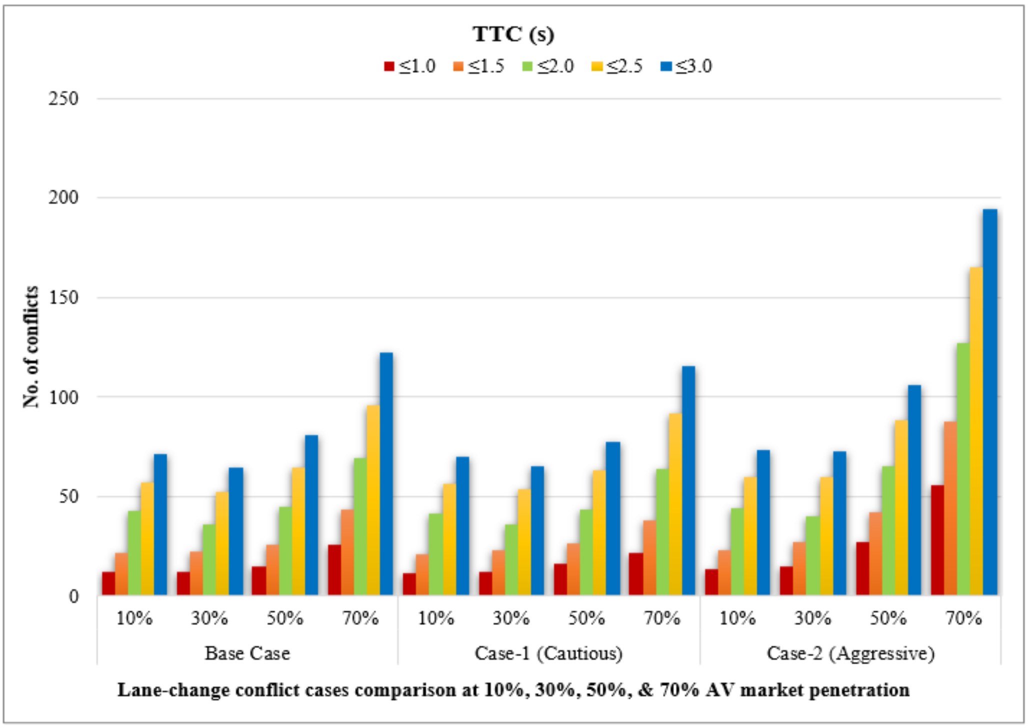


Figure 9. Safety results for CACF multilane logic.

5.8. Discussion

Table 10 summarises the key safety and mobility findings from all simulation sensitivity tests. The results indicate that the CACF model performs similarly in terms of mobility compared to the CACC model but drastically improves network safety for increasing market penetration rates of CAVs in mixed-driver traffic. Notably, the safety improvements of the CACF model become significant even at lower CAV market penetration rates.

Table 10. Summary of all results.

Tests	Mobility [1]	Safety [1]
Test 1—Maximum throughput for CACF model	The road capacity for the CACF model increases by 35% for a 90% market penetration compared to the VISSIM default Wiedemann 99 car-following model.	-
Test 2—Performance of CACC and CACF models (no-crash)	The average delay of the Wiedemann 99 model is 13.9 s. However, the delay is drastically reduced to 0.0 s and 0.6 s for CACF and CACC models, respectively, at a 90% market penetration rate.	
Test 3—Performance of CACC and CACF models (with-crash)	The mobility performance of both models has low significance.	The CACC model only performs better at a 10% market penetration rate. The CACF model drastically improves network safety for increasing market penetration rates.
Test 4—Impact of acceleration coefficients on CACF model (with-crash)	-	The acceleration coefficient of distance "K_d" is most influential to network safety. The number of conflicts increases for higher "K_d" values.
Test 5—Impact of V2I communication range on CACF model (with-crash)		A communication range between 200 to 250 m is suitable for the CACF model.
Test 6—Impact of communication signal lag on CACF model (with-crash)	Because the vehicle begins to move with slower acceleration, average delay starts to increase. The increase in average delay is recorded to be only 0.9 s between base case and Case 3, at a 70% market penetration rate.	The inclusion of signal response lag negatively impacts the acceleration of automatic vehicles, and the vehicle maintains a "careful" behaviour. For TTC $\leq$ 3.0 at a 50% market penetration rate, average conflicts are reduced by approximately 11% for 0.1 s lag, 20% for 0.2 s lag, and 21% for 0.3 s lag.
Test 7—Safety performance of CACF multi-lane logic	-	The CACF cautious lane-change and VISSIM default lane-change performs safer compared to the CACF aggressive model.

[1] The blank fields show insignificance either for mobility or safety analysis. Hence, no analyses are performed accordingly.

6. Conclusions and Recommendations

This research investigated the influencing factors and effectiveness of a recently developed CACF car-following model in enhancing both traffic mobility and safety. The CACF model utilises ITS technologies, specifically leveraging data collected from sensors embedded in roadways and roadside and connected vehicles for V2X communication. There has been a lack of comprehensive analysis regarding the model's performance in mixed-driver environments. This study's contribution is a demonstration of encouraging enhancements in network capacity and roadway safety through the application of the CACF model across single-lane and multi-lane roadway segments. The PTV VISSIM microscopic traffic simulation platform was utilised to compare the impact of the CACF model with the already established CACC car-following model that primarily relies on V2V communication. The simulation involved two network configurations, including single-lane and multi-lane, each with a 5 km freeway segment. Sensitivity tests for "maximum throughput" utilised an ideal maximum vehicle input. For other tests, a vehicle input of 1680 veh/h/lane at 65 mph was assigned. Some tests include a "with-crash" scenario, introducing a slow-moving "breakdown vehicle" stopping midway, creating a hypothetical incident or shockwave at a 4000 m position with a designated stop sign.

To account for the randomness in traffic behaviour, 10 simulation runs with different speeds were employed for each set of sensitivity parameters. The simulation spanned 5400 s (1.5 h), dedicating 900–4500 s (1 h) for mobility evaluation and the full duration for safety assessment. AV market penetration, ranging from 0% to 90%, was modelled in VISSIM. Safety evaluation involved a spectrum of TTC values (1.0 to 3.0 s) using the SSAM tool.

The two car-following logics (CACC and CACF) were implemented using the VISSIM External Driver Model-DLL, and several sensitivity tests were conducted at varying market penetration of CAVs for traffic safety and mobility analysis. Multiple sensitivity tests analysed the proposed logic's performance in terms of mobility (average travel time, throughput, speed, delay) and safety (rear-end and lane-change conflicts). VISSIM generated detailed mobility reports, while the SSAM tool, developed by the FHWA, computed safety parameters using the vehicle trajectory file extracted from VISSIM after each simulation run. Based on the findings of the analysis, the following conclusions can be drawn:

(1) For the maximum throughput test, it is observed that, with the increase in penetration rates, the CACF can significantly improve traffic capacity up to 42%. The test results for mobility performance for CACC and CACF have shown a drastic reduction in traffic delays at the progressive implementation of the driving logic. However, the CACF mobility benefits are further enhanced, as evident compared to CACC. Additionally, the CACF model avoids aggressive braking and traffic shockwaves, which are created by a breakdown vehicle due to cumulative-anticipative communication with the preceding vehicle. However, the inclusion of signal response delay negatively impacted the acceleration of AVs, and the vehicle maintains a "careful" behaviour.

(2) For the safety analysis of the single-lane segment, the CACC model only performs better at a 10% market penetration rate. In contrast, the CACF model drastically improves network safety by reducing the number of rear-end conflicts with the increasing market penetration rates of CAVs. It is observed that the acceleration coefficient of distance K_d exerts the most influence on the network safety, as the number of conflicts increases for higher K_d values. The communication range of 200–250 m is found suitable for the CACF model, and the inclusion of signal response delay also resulted in the reduction of traffic conflicts. Furthermore, the results for CACF multi-lane logic show significant improvement in traffic safety because it considers both lateral and longitudinal communication for connected vehicles. However, it is only possible when an adequate distance is available in the adjacent lane.

(3) This study recommends adopting the CACF car-following technique for future research, particularly in the context of V2I technology integration. This approach holds the potential to address prevalent challenges related to road safety, traffic delays, and travel costs. While the advantages of V2V technology become feasible with higher market penetration of AVs and CAVs, it is crucial to acknowledge that not all vehicles will be equipped with connected vehicle technology in the near future. Gathering characteristics and data for each vehicle within the communication range could be a challenging task. Therefore, early investments in V2I technology would pave the way for safe and convenient mobility solutions.

(4) Improving the safety of CACC logic during accidents involves enhancing the ego car's communication capabilities, employing a multi-anticipative technique. Effective communication with the environment allows the car to make informed decisions. Forming platoons is expected to positively impact road safety. Establishing criteria for "emergency braking", with an aggressive deceleration value like $-9.9\ \mathrm{m/s^2}$, can further mitigate rear-end conflicts.

However, this study has applied the CACF logic to a basic freeway segment. Further research is needed to explore its applicability to various control scenarios, including multi-lane highways, arterials, and other segments. Similarly, the multi-lane logic should be extended to minimise lane-change conflicts and accommodate freeway networks with more than two lanes. Moreover, the traffic exclusively consists of private cars, excluding heavy vehicles. Introducing trucks and other heavy goods vehicles to the freeway network could affect the safety and mobility performance of the proposed logic. Conducting an additional sensitivity study is necessary to examine the role of various vehicle types. More statistical analysis with these different simulation cases will significantly benefit the confidence of the CACF models in various application environments. In addition, future work can also compare the CACF model's capability with other car-following models such as Gipps' flow model, etc., using other safety measures such as SSMs' measures to better evaluate the safety potential of the CACF model.

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Abbreviations

ACC	Adaptive Cruise Control
API	Application Programming Interface
ASCE	American Society of Civil Engineers
AV	Autonomous Vehicle
CACC	Cooperative Adaptive Cruise Control
CACF	Cumulative-Anticipative Car-Following
CAV	Connected Autonomous Vehicle
DLL	Dynamic Library
EDM	External Driver Model
FHWA	Federal Highway Authority
FVD	Full Velocity Difference
HCM	Highway Capacity Manual
IDM	Intelligent Driver Model
ITS	Intelligent Transportation System
LDW	Lane Departure Warning
LOS	Level of Service
MassDOT	Massachusetts Department of Transportation
MOE	Measures of Effectiveness
NHTSA	National Highway Traffic Safety Administration
ODOT	Oregon Department of Transportation
PET	Post-encroachment-time
SSAM	Safety Surrogate Assessment Model
TTC	Time-to-collision
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-vehicle
V2X	Vehicle-to-everything
W99	Wiedemann 99
WSDOT	Washington State Department of Transportation

References

1. NHTSA. *Early Estimate of Motor Vehicle Traffic Fatalities in 2020*; United States Department of Transportation: Washington, DC, USA, 2022.
2. WHO. *Global Status Report on Road Safety 2015*; World Health Organization: Geneva, Switzerland, 2015.
3. American Society of Civil Engineers (ASCE). *2021 Infrastructure Report Card*; American Society of Civil Engineers: Reston, VA, USA, 2021.
4. Litman, T. *Autonomous Vehicle Implementation Predictions*; Victoria Transport Policy Institute: Victoria, BC, Canada, 2017.
5. NHTSA. *National Motor Vehicle Crash Causation Survey: Report to Congres*; National Highway Traffic Safety Administration Technical Report DOT HS; NHTSA: Washington DC, USA, 2008; Volume 811, p. 59.
6. Greenblatt, N.A. Self-driving cars and the law. *IEEE Spectr.* **2016**, *53*, 46–51. [CrossRef]
7. Shanker, R. *Autonomous Cars: Self-Driving the New Auto Industry Paradigm*; Morgan Stanley Blue Paper; Morgan Stanley: New York, NY, USA, 2013; pp. 1–109.
8. Leech, J.; Whelan, G.; Bhaiji, M.; Hawes, M.; Scharring, K. Connected and Autonomous Vehicles—The UK Economic Opportunity. KPMG. 2015, Volume 80. Available online: https://www.smmt.co.uk/wp-content/uploads/sites/2/CRT036586F-Connected-and-Autonomous-Vehicles-%E2 (accessed on 1 February 2021).
9. Dennis, E.P.; Spulber, A.; Sathe Brugerman, V.; Kuntzsch, R.; Neuner, R. *Planning for Connected and Automated Vehicles. Technology Research*; Center for Automotive Research: Ann Arbor, MI, USA, 2017; Available online: https://www.cargroup.org/publication/planning-for-connected-and-automated-vehicles/ (accessed on 1 February 2021).
10. Hars, A. Autonomous cars: The next revolution looms. *Inven. Innov. Briefs* **2010**, *1*, 2010.
11. Talebpour, A.; Mahmassani, H.S. Influence of connected and autonomous vehicles on traffic flow stability and throughput. *Transp. Res. Part C Emerg. Technol.* **2016**, *71*, 143–163. [CrossRef]
12. Mervis, J. Are We Going Too Fast on Driverless Cars. *Science*. 12 December 2017. Available online: https://www.science.org/content/article/are-we-going-too-fast-driverless-cars (accessed on 1 February 2021).
13. Simonite, T. Prepare to be underwhelmed by 2021's autonomous cars. *MIT Technol. Rev.* **2016**. Available online: https://www.technologyreview.com/2016/08/23/157929/prepare-to-be-underwhelmed-by-2021s-autonomous-cars/ (accessed on 1 February 2021).
14. Chen, S.; Hu, J.; Shi, Y.; Peng, Y.; Fang, J.; Zhao, R.; Zhao, L. Vehicle-to-everything (V2X) services supported by LTE-based systems and 5G. *IEEE Commun. Stand. Mag.* **2017**, *1*, 70–76. [CrossRef]
15. Gupta, M.; Benson, J.; Patwa, F.; Sandhu, R. Secure V2V and V2I communication in intelligent transportation using cloudlets. *IEEE Transp. Serv. Comput.* **2020**, *15*, 1912–1925. [CrossRef]
16. Milanés, V.; Villagrá, J.; Godoy, J.; Simó, J.; Pérez, J.; Onieva, E. An intelligent V2I-based traffic management system. *IEEE Trans. Intell. Transp. Syst.* **2012**, *13*, 49–58. [CrossRef]
17. Bagheri, M.; Siekkinen, M.; Nurminen, J.K. Cellular-based vehicle to pedestrian (V2P) adaptive communication for collision avoidance. In Proceedings of the 2014 International Conference on Connected Vehicles and Expo (ICCVE), Vienna, Austria, 3–7 November 2014; IEEE: Washington, DC, USA, 2014; pp. 450–456.
18. Saeed, U.; Hämäläinen, J.; Mutafungwa, E.; Wichman, R.; González, D.; Garcia-Lozano, M. Route-based radio coverage analysis of cellular network deployments for V2N communication. In Proceedings of the 2019 International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob), Barcelona, Spain, 21–23 October 2019; IEEE: Washington, DC, USA, 2019; pp. 1–6.
19. Ahmed, H.U.; Huang, Y.; Lu, P. A review of car-following models and modeling tools for human and autonomous-ready driving behaviors in micro-simulation. *Smart Cities* **2021**, *4*, 314–335. [CrossRef]
20. Yang, X.; Ahemd, H.U.; Huang, Y.; Lu, P. Cumulatively Anticipative Car-Following Model with Enhanced Safety for Autonomous Vehicles in Mixed Driver Environments. *Smart Cities* **2023**, *6*, 2260–2281. [CrossRef]
21. Tettamanti, T.; Varga, I.; Szalay, Z. Impacts of autonomous cars from a traffic engineering perspective. *Period. Polytech. Transp. Eng.* **2016**, *44*, 244–250. [CrossRef]
22. Sukennik, P.; Lohmiller, J.; Schlaich, J. Simulation-based forecasting the impacts of autonomous driving. In Proceedings of the International Symposium of Transport Simulation (ISTS'18) and the International Workshop on Traffic Data Collection and its Standardization (IWTDCS'18), Matsuyama, Japan, 4–6 August 2018; pp. 6–8.
23. Songchitruksa, P.; Bibeka, A.; Lin, L.I.; Zhang, Y. *Incorporating Driver Behaviors into Connected and Automated Vehicle Simulation*; Center for Advancing Transportation Leadership and Safety (ATLAS Center): New York, NY, USA, 2016.
24. Seraj, M.; Li, J.; Qiu, Z. Modeling microscopic car-following strategy of mixed traffic to identify optimal platoon configurations for multiobjective decision-making. *J. Adv. Transp.* **2018**, *2018*, 7835010. [CrossRef]
25. ATKINS. *Research on the Impacts of Connected and Autonomous Vehicles (CAVs) on Traffic Flow, Stage 2: Traffic Modelling and Analysis*; Technical Report; Department for Transport, ATKINS: London, UK, 2016.
26. Kotsialos, A.; Papageorgiou, M.; Diakaki, C.; Pavlis, Y.; Middelham, F. Traffic flow modeling of large-scale motorway networks using the macroscopic modeling tool METANET. *IEEE Trans. Intell. Transp. Syst.* **2002**, *3*, 282–292. [CrossRef]
27. Lu, X.-Y.; Qiu, T.Z.; Varaiya, P.; Horowitz, R.; Shladover, S.E. Combining variable speed limits with ramp metering for freeway traffic control. In Proceedings of the 2010 american control conference, Baltimore, MD, USA, 30 June–2 July 2010; IEEE: Washington, DC, USA, 2010; pp. 2266–2271.

28. FHWA. Types of Traffic Analysis Tools. 2023. Available online: https://ops.fhwa.dot.gov/trafficanalysistools/type_tools.htm (accessed on 1 February 2021).
29. Olstam, J.J.; Tapani, A. *Comparison of Car-Following Models*; Swedish National Road and Transport Research Institute: Linköping, Sweden, 2004; Volume 960.
30. Hoogendoorn, S.P.; Hoogendoorn, R. Generic calibration framework for joint estimation of car-following models by using microscopic data. *Transp. Res. Rec.* **2010**, *2188*, 37–45. [CrossRef]
31. Lochrane, T. A New Multidimensional Psycho-Physical Framework for Modeling Car-Following in a Freeway Work Zone. Ph.D. Thesis, University of Central Florida, Orlando, FL, USA, 2014.
32. Jones, S.L.; Sullivan, A.J.; Cheekoti, N.; Anderson, M.D.; Malave, D. Traffic simulation software comparison study. *UTCA Rep.* **2004**, *2217*, 58.
33. PTV, A.G. *VISSIM 2020.00 User Manual*; PTV Karlsruhe: Karlsruhe, Germany, 2020.
34. Gipps, P.G. A model for the structure of lane-changing decisions. *Transp. Res. Part B Methodol.* **1986**, *20*, 403–414. [CrossRef]
35. Sparmann, U. *Spurwechselvorgänge auf zweispurigen BAB-Richtungsfahrbahnen*; Forsch Strassenbau u Strassenverkehrstech 263; No. 263; Forschungsgesellschaft für Straßen- und Verkehrswesen (FGSV): Berling, Germany, 1978.
36. Pipes, L.A. An operational analysis of traffic dynamics. *J. Appl. Phys.* **1953**, *24*, 274–281. [CrossRef]
37. Gazis, D.C.; Herman, R.; Rothery, R.W. Nonlinear follow-the-leader models of traffic flow. *Oper. Res.* **1961**, *9*, 545–567. [CrossRef]
38. Toledo, T.; Koutsopoulos, H.N.; Ben-Akiva, M. Integrated driving behavior modeling. *Transp. Res. Part C Emerg. Technol.* **2007**, *15*, 96–112. [CrossRef]
39. Gipps, P.G. A behavioural car-following model for computer simulation. *Transp. Res. Part B Methodol.* **1981**, *15*, 105–111. [CrossRef]
40. Bando, M.; Hasebe, K.; Nakayama, A.; Shibata, A.; Sugiyama, Y. Dynamical model of traffic congestion and numerical simulation. *Phys. Rev. E* **1995**, *51*, 1035. [CrossRef]
41. Wiedemann, R.; Reiter, U. *Microscopic Traffic Simulation: The Simulation System MISSION, Background and Actual State*; Project ICARUS (V1052) Final Report; CEC: Brussels, Belgium, 1992; Volume 2, pp. 1–53.
42. Saifuzzaman, M.; Zheng, Z. Incorporating human-factors in car-following models: A review of recent developments and research needs. *Transp. Res. Part C Emerg. Technol.* **2014**, *48*, 379–403. [CrossRef]
43. Sun, L.; Jafaripournimchahi, A.; Kornhauser, A.; Hu, W. A new higher-order viscous continuum traffic flow model considering driver memory in the era of autonomous and connected vehicles. *Phys. A Stat. Mech. Its Appl.* **2020**, *547*, 123829. [CrossRef]
44. Jafaripournimchahi, A.; Sun, L.; Hu, W. Driver's anticipation and memory driving car-following model. *J. Adv. Transp.* **2020**, *2020*, 4343658. [CrossRef]
45. Milanés, V.; Shladover, S.E. Modeling cooperative and autonomous adaptive cruise control dynamic responses using experimental data. *Transp. Res. Part C Emerg. Technol.* **2014**, *48*, 285–300. [CrossRef]
46. Treiber, M.; Hennecke, A.; Helbing, D. Congested traffic states in empirical observations and microscopic simulations. *Phys. Rev. E* **2000**, *62*, 1805. [CrossRef]
47. Kockelman, K.M.; Avery, P.; Bansal, P.; Boyles, S.D.; Bujanovic, P.; Choudhary, T.; Clements, L.; Domnenko, G.; Fagnant, D.; Helsel, J.; et al. *Implications of Connected and Automated Vehicles on the Safety and Operations of Roadway Networks: A Final Report*; The University of Texas: Austin, TX, USA, 2016.
48. Van Arem, B.; Van Driel, C.J.G.; Visser, R. The impact of cooperative adaptive cruise control on traffic-flow characteristics. *IEEE Trans. Intell. Transp. Syst.* **2006**, *7*, 429–436. [CrossRef]
49. Dey, K.C.; Yan, L.; Wang, X.; Wang, Y.; Shen, H.; Chowdhury, M.; Yu, L.; Qiu, C.; Soundararaj, V. A review of communication, driver characteristics, and controls aspects of cooperative adaptive cruise control (CACC). *IEEE Trans. Intell. Transp. Syst.* **2015**, *17*, 491–509. [CrossRef]
50. Werf, J.V.; Shladover, S.E.; Miller, M.A.; Kourjanskaia, N. Effects of adaptive cruise control systems on highway traffic flow capacity. *Transp. Res. Rec.* **2002**, *1800*, 78–84. [CrossRef]
51. Shladover, S.E.; Su, D.; Lu, X.-Y. Impacts of cooperative adaptive cruise control on freeway traffic flow. *Transp. Res. Rec.* **2012**, *2324*, 63–70. [CrossRef]
52. Schermers, G.; Malone, K.M.; van Arem, B. Dutch evaluation of chauffeur assistant traffic flow effects on implementation in the heavy goods vehicle sector. In Proceedings of the 11th World Congress on Intelligent Transport Systems, ITS 2004: ITS for Livable Society (World Congress on Intelligent Transport Systems), Nagoya, Japan, 18–24 October 2004.
53. Van Arem, B.; De Vos, A.P.; Vanderschuren, M.J.W.A. The Microscopic Traffic Simulation Model MIXIC 1.3. 1997. Available online: https://trid.trb.org/view/634929 (accessed on 1 February 2021).
54. Hunter, M.P.; Guin, A.; Rodgers, M.O.; Huang, Z.; Greenwood, A.T. *Cooperative Vehicle–Highway Automation (CVHA) Technology: Simulation of Benefits and Operational Issues*; Federal Highway Administration: Washington, DC, USA, 2017.
55. Hidas, P. Modelling lane changing and merging in microscopic traffic simulation. *Transp. Res. Part C Emerg. Technol.* **2002**, *10*, 351–371. [CrossRef]
56. Liu, J.; Kockelman, K.; Nichols, A. Anticipating the emissions impacts of smoother driving by connected and autonomous vehicles, using the MOVES model. In Proceedings of the Transportation Research Board 96th Annual Meeting, Washington, DC, USA, 8–12 January 2017.

57. Zhao, L.; Sun, J. Simulation framework for vehicle platooning and car-following behaviors under connected-vehicle environment. *Procedia-Soc. Behav. Sci.* **2013**, *96*, 914–924. [CrossRef]
58. Xiaorui, W.; Hongxu, Y. A lane change model with the consideration of car following behavior. *Procedia-Soc. Behav. Sci.* **2013**, *96*, 2354–2361. [CrossRef]
59. Vechione, M.; Balal, E.; Cheu, R.L. Comparisons of mandatory and discretionary lane changing behavior on freeways. *Int. J. Transp. Sci. Technol.* **2018**, *7*, 124–136. [CrossRef]
60. Gettman, D.; Pu, L.; Sayed, T.; Shelby, S.G.; Energy, S. *Surrogate Safety Assessment Model and Validation*; Turner-Fairbank Highway Research Center: McLean, VA, USA, 2008.
61. Miqdady, T.; de Oña, R.; Casas, J.; de Oña, J. Studying traffic safety during the transition period between manual driving and autonomous driving: A simulation-based approach. *IEEE Trans. Intell. Transp. Syst.* **2023**, *24*, 6690–6710. [CrossRef]
62. Miqdady, T.; de Oña, R.; de Oña, J. Traffic Safety Sensitivity Analysis of Parameters Used for Connected and Autonomous Vehicle Calibration. *Sustainability* **2023**, *15*, 9990. [CrossRef]
63. Hayward, J.C. Near Miss Determination through Use of a Scale of Danger. 1972. Available online: https://onlinepubs.trb.org/Onlinepubs/hrr/1972/384/384-004.pdf (accessed on 1 February 2021).
64. Sayed, T.; Brown, G.; Navin, F. Simulation of traffic conflicts at unsignalized intersections with TSC-Sim. *Accid. Anal. Prev.* **1994**, *26*, 593–607. [CrossRef]
65. Hydén, C.; Linderholm, L. The Swedish Traffic-Conflicts Technique. In *International Calibration Study of Traffic Conflict Techniques*; Springer: Berlin/Heidelberg, Germany, 1984; pp. 133–139.
66. MassDOT. MassDOT Guidelines for Calibrating Roundabouts in VISSIM Simulation Models. 2020. Available online: https://www.mass.gov/doc/massdot-roundabout-vissim-microsimulation-guidance/download (accessed on 1 January 2024).
67. Oregon DOT. Protocol for VISSIM Simulation. Available online: www.oregon.gov/odot/td/tp/apm/addc.pdf (accessed on 1 February 2021).
68. Schilperoort, L.; McClanahan, D.; Shank, R.; Bjordahl, M. *Protocol for VISSIM Simulation*; Washington State Department of Transportation: Washington, DC, USA, 2014.
69. Dowling, R.; Skabardonis, A.; Alexiadis, V. *Traffic Analysis Toolbox, Volume III: Guidelines for Applying Traffic Microsimulation Modeling Software*; United States Federal Highway Administration, Office of Operations: Washington, DC, USA, 2004.
70. Harding, J.; Powell, G.; Yoon, R.; Fikentscher, J.; Doyle, C.; Sade, D.; Lukuc, M.; Simons, J.; Wang, J. *Vehicle-to-Vehicle Communications: Readiness of V2V Technology for Application*; National Highway Traffic Safety Administration: Washington, DC, USA, 2014.
71. Manual, H.C. *Highway Capacity Manual*; Transportation Research Board: Washington, DC, USA, 2000; Volume 2.