Cumulatively Anticipative Car-Following Model with Enhanced Safety for Autonomous Vehicles in Mixed Driver Environments

Xinyi Yang 1, Hafiz Usman Ahemd 1, Ying Huang 1,* and Pan Lu 2

1 Department of Civil and Environmental Engineering, North Dakota State University, Fargo, ND 58102, USA; xinyi.yang@ndsu.edu (X.Y.); hafiz.ahmed@ndsu.edu (H.U.A.)
2 Department of Transportation, Logistics and Finance, North Dakota State University, Fargo, ND 58102, USA; pan.lu@ndsu.edu

* Correspondence: ying.huang@ndsu.edu; Tel.: +1-701-231-7651

Abstract: The contribution of autonomous vehicles to traffic is one of the key aspects of future ground transportation in smart cities. Autonomous vehicles are able to provide many benefits, but some benefits can only provide advantages if these vehicles comprise a large percent of on the road/driven vehicles, which may take decades. Until then, the robotic drivers in autonomous vehicles will share the same road system with human divers in a mixed-driver environment where the majority of road accidents for autonomous vehicles are associated with the operational inconsistency of human drivers. In this paper, a cumulatively anticipative car-following model (which considers cumulative influences from multiple preceding vehicles) is developed to potentially improve the safety of autonomous vehicles in mixed-driver environments that benefit from enhanced communication between the autonomous vehicles and other components in the transportation system. Through intensive simulations (200 simulations), this study comprehensively evaluates four models including the cumulative anticipative car-following model, the Wiedemann 99 model, adaptive cruise control, and the cooperative adaptive cruise control model. Across 10 scenarios and five speed limits (24.59–33.53 m/s), the cumulative anticipative car-following model consistently demonstrates superior conflict reduction, with average, maximum, and minimum conflict percentages ranging from 77.69% to 91.97% against the Wiedemann 99 model, 67.00% to 93.94% against the adaptive cruise control model, and 69.17% to 93.25% against the cooperative adaptive cruise control model. Notably, the cooperative adaptive cruise control model exhibits suboptimal performance, especially in mixed-driver settings. The cumulative anticipative car-following model also enhances vehicle mobility, reducing average stops by up to 93.54%, 91.74%, 92.04%, 88.60%, and 91.35% in comparison to the other three models at speeds of 24.59 m/s, 26.82 m/s, 29.06 m/s, 31.29 m/s, and 33.53 m/s. Overall, the cumulative anticipative car-following model holds significant potential for conflict reduction and traffic enhancement.

Keywords: autonomous vehicles; car following model; safety; smart cities; mixed-driver environment

1. Introduction

Based on the automation level defined by SAE International, a conditional, high or fully autonomous vehicle (AV) with Level 3 or up can monitor its own driving environments, access data through wireless sensing and communication, and perform driving with a significantly reduced need for direct human involvement [1]. While the potential of AVs is promising, there are certain flaws and drawbacks inherent in their current state. One of the challenges faced by today's AVs is their occasional misreading of traffic signs or signals, which can lead to incorrect decision-making. Additionally, some AVs tend to overreact to obstacles or sudden changes in their surroundings, potentially causing abrupt stops or maneuvers that could be unsettling to passengers and other road users. Another
limitation lies in lane changing behavior, where AVs might not always make optimal decisions, leading to inefficient lane changes or hesitations.

For an AV to drive safely by itself, it relies heavily on sensors onboard the vehicle, such as cameras, radar sensors, ultrasonic sensors, lidar, and global positioning systems, to detect surrounding information including traffic infrastructures (e.g., traffic signs), distance to other objects (e.g., pedestrians), and speed and acceleration of nearby objects [2–5]. In addition, an AV may also receive information wirelessly shared from other connected vehicles through vehicle-to-vehicle (V2V) communication which is a key feature in a smart city that supports high-tech and creative industries [6,7]. With all the detected and shared data, the central computer of an AV will then combine, analyze, and input this information into a car-following model to make the best decisions concerning its driving behaviors.

There are a number of car-following models developed as the evolution of the AVs, such as stimulus–response models, safe-distance models, desired headway models, psychophysical models, and artificial intelligence models [8–10]. Among these models, the stimulus–response model is the most widely adopted car-following model, which assumes that each driver responds to the stimulus such as the velocity, acceleration, and headway from the other vehicles, independently [11,12]. The most commonly used stimulus–response car-following model is the adaptive cruise control (ACC) car-following model [13]. The ACC system can automatically adjust speed based on the desired spacing from or speed of the preceding vehicle [14,15]. For ACC models, the acceleration range of AVs can be estimated by [13,16,17]:

$$a = \max\{a_{\text{min}}, \min(a_c, a_{\text{max}})\}$$ (1)

where, $a$ is the acceleration range, $a_{\text{min}}$ and $a_{\text{max}}$ are the minimum and maximum allowed acceleration, $a_c$ is the control acceleration that the AVs will use if within the acceleration allowable range as in (1), which can be calculated as:

$$a_c = k_a * a_p + k_v * (v_p - v) + k_d * (r - r_{\text{system}})$$ (2)

where, $a_p$ and $v_p$ are the acceleration and speed of the preceding vehicle, and $v$ is the current speed of the following vehicle (the AV). The constants $k_a$, $k_v$, and $k_d$ appear as coefficients before the acceleration ($a_p$), velocity ($v_p$, $v$), and distance ($r$, $r_{\text{system}}$) variables. These constants are utilized in the formulation to compute the control acceleration, with $k_a$ to be zero for the ACC model, $r$ is the current following distance between the preceding vehicle and the AV, $r_{\text{system}}$ is recommended following distance according to the system time setting, which can be estimated as:

$$r_{\text{system}} = l_{\text{system}} * v$$ (3)

in which, $l_{\text{system}}$ is the minimum desired time gap of the AV, which is estimated to be between 0.5 and 1.4 s for the ACC model [13,17].

To improve the safety of AVs by including data from vehicles around the AV through vehicle-to-vehicle (V2V) communications, based on the ACC model, cooperative adaptive cruise control (CACC) was developed [18,19]. With data from multiple vehicles around the AV considered, a CACC system can follow another vehicle at a much shorter headway with $l_{\text{system}}$ equals to 0.5 s, resulting in smoother traffic flow in addition to enhanced traffic safety [20–22]. However, for the CACC car-following model, it still controls the following behavior of the AV using (2) based only on the speed and acceleration of the preceding vehicle in front of the AV even though it receives information from multiple vehicles equipped with CACC systems around it. The CACC model can work well if AVs or vehicles with CACC systems fully penetrate the market. But in reality, it will take decades to reach full penetration of AVs. During this period, the AVs will share the roads with human drivers and partial AVs which may not be equipped with CACC systems. At a low AV penetration rate, the AVs might be far away from other vehicles equipped with CACC systems resulting in a low effectiveness of the CACC model, especially when there
are multiple vehicles with human drivers or partial AVs between the AV and other vehicles with a CACC system.

In addition, there have been other well-known car-following models using different stimulus for car following, such as the optimal velocity model (OVM). The OVM was developed in 1995 [23] and it used the difference between the optimal velocity and the velocity of the vehicle as a stimulus whereas ACC/CACC model also considers acceleration. This model can explain qualitative characteristics (such as the stop-and-go phenomenon, traffic instability, and the congestion evolution) of real traffic flow successfully in a simple way [24]. However, the OVM only considered the preceding vehicle ahead of the vehicle and the calibration using field data showed that the OVM produces unrealistically high acceleration and deceleration. Crashes might occur even though the deceleration was unrealistically large since the vehicle did not change velocity until close to the standing vehicle [25].

To stabilize the dynamic behavior of the OVM by using information collected from multiple vehicles in front of the vehicle, the multi-anticipative car-following (MACF) model was developed. In this model, the velocity of the vehicle is controlled [26]:

\[ V(x) = \frac{e^{x-h} - e^{h-x}}{e^{x-h} + e^{h-x}} + \frac{e^h - e^{-h}}{e^h + e^{-h}} \]  

where \( x \) is the coordinate of the vehicle and \( h \) is a constant. Acceleration, \( \ddot{x}_n \), can be calculated as:

\[ \ddot{x}_n(t) = \sum_{j=1}^{m} s_j \left\{ V \left( \frac{\Delta x_{n,n+j}}{j} \right) - \dot{x}_n \right\} \]

in which, \( j \) is the number of vehicles ahead and \( m \) is the maximum number of vehicles to be considered, \( \dot{x}_n \) is the velocity of the \( n \)th vehicle, \( \Delta x_{n,n+j} \) is the difference between the position of the \( n \)th and the \( n+j \)th velocities, \( s_j \) are sensitivity coefficients of a driver to the difference between the \( n \)th and the \( n+j \)th velocities with the sensitivity ratio of each vehicle in front of the vehicle which is assumed to satisfy the condition that \( s_j/s_1 \leq 1 \) with \( j = 2, 3, \ldots, m \). When \( m \) equals 1, the multi-anticipative model only considers information from one vehicle in front and it is equivalent to the OVM.

By using the MACF model, the stability region of the vehicle’s dynamic car-following behavior increases as information from more vehicles is considered and the weight ratio \( s_j/s_1 \) increases. However, there are two limitations to the MACF model which significantly affect its accuracy. First, based on (5), it can be seen that the acceleration of each vehicle in the model, \( \ddot{x}_n \), depends on the order of the vehicles, which should not be the case when any unnormal velocity or acceleration occurs in the network. Second, from (4), it can be seen that the desired velocity of this model is controlled by the average clearance of preceding vehicles but not actual measurements of traffic data or reaction between vehicles. Thus, if any unusual condition such as a car crash occurs, its influence on the vehicle would be divided for an average, inducing a delay in decision-making of the following AV for increased potential of conflict. To further improve the accuracy of the MACF model, any approaches to collect data from vehicles and partial AVs in addition to V2V may significantly benefit AV performance in terms of safety and mobility.

As is known, V2V communication is one subordinate of the vehicle-to-everything (V2X) communication, which can communicate information between vehicles and all available devices [27,28]. Together with V2V, V2X also includes vehicle-to-infrastructure (V2I) [29], vehicle-to-pedestrian [30], and vehicle-to-network [31]. Although the CACC car-following model considers V2V communication, the application of other V2X systems on the AVs are still limited due to the fact that there is limited information available and no algorithm available to implement this information. However, as the evolution of the V2X systems continues, the information provided by these communication systems will be valuable to the AVs to collect data from their surrounding environments, especially
information from the vehicles such as human-driven vehicles or partial AVs in mixed driver conditions.

Based on the MACF and CACC models, to potentially deploy the data received from various V2X systems for multiple vehicles in front of the AV into the AV’s car following, this paper proposes a new cumulatively anticipative car-following (CACF) model. The new CACF model develops a new approach to estimate the weight factor of each vehicle in front of the AV by considering the relationship between each of the two preceding vehicles and the filtered cumulative influence of multiple preceding vehicles under real traffic conditions with actual measured data from V2X systems. The effectiveness of the new models was evaluated using the VISSIM micro-simulator and showed improved safety and mobility. Accordingly, in this paper, Section 2 explains the new CACF model with consideration of cumulative influence from multiple preceding vehicles and real-time inputs from the V2X system; Section 3 sets up the VISSIM simulation for evaluation of the new model; Section 4 discusses the simulation results obtained from VISSIM to evaluate the effectiveness of the new model; Section 5 concludes this study and discusses potential future work.

2. Methodology

Inspired by the development of the MACF model from the OVM, the new CACF model is built upon the CACC model with considerations of real-time measured traffic data from multiple vehicles in front of the AV and the reactions between these vehicles through V2X communications. Specifically, in each desired time-gap of vehicles \( t_{\text{system}} \) in (3), the predicted and desired driving distances of each vehicle are calculated separately based on the measured traffic data, which can be used to estimate the predicted and desired clearances between each vehicle. The difference between the predicted and desired clearances between two vehicles can be used to guide the AV to a safer decision. There are many parameters, please refer to Appendix A for more information.

Figure 1 shows the schematic of the new CACF model. This diagram presents the current AV implemented with the CACF model, denoted as Vehicle N (yellow in Figure 1), which is the last vehicle in the network. Since the radar equipped in the vehicles is not able to collect the vehicle’s information outside of 50 m [32,33], only the previous vehicle within range will be considered as a reference vehicle (green color as Vehicle 1 through K + 1 in Figure 1) in this study, which does not account for occlusion cases within the desired radius. Notably, this study establishes the autonomous vehicle penetration rate but refrains from specifying the specific timing for determining vehicle types, positions, and quantities before the AV employing the CACF model. Consequently, these attributes preceding the ego vehicles are treated as random variables. The CACF model will pre-analyze with the reference vehicles’ information, as described in the following Equations (6)–(12).

![Figure 1. Schematic of the new CACC model. Note: Vehicle N is the autonomous vehicle, while vehicles 1 through K + 1 are other vehicles that the radar is detecting/considering for the algorithm. Vehicle M (gray color) is outside the range of the radar and is not considered. Note that there are \( k - 2 \) vehicle(s) between Vehicle 1 and Vehicle K.](image-url)

After the reference vehicles are selected, the CACF model will pre-analyze with the reference vehicles’ information from Vehicle K + 1 to Vehicle 1 based their distance to the AV in which the CACC model has been implemented (Vehicle N). The desired velocity \( (v_d) \) of reference vehicle K + 1, in Figure 1 can be calculated as:
\[ v_d = g \cdot [v_p + k_d \cdot (r - t_{\text{system}} \cdot v)] + m \cdot \left\{ v_p + k_d \cdot \left[ r - t_{\text{system}} \cdot v + (-1)^c \cdot \left| X_d - X_r \right| \right] \right\} + k \cdot \left[ v + (a_d \cdot t_{\text{system}}) \right] \]  

(6)

where, \( a_d \) is the desired acceleration of Vehicle \( K + 1 \), and \( g \), \( m \), and \( k \) are parameters defining network uncertainties for the desired acceleration. Specifically, the parameter \( g \) is equal to 1 if the desired acceleration of the Vehicle \( K + 1 \) is unknown and 0 otherwise. For parameter \( m \), it is equal to 1 if the desired acceleration of the Vehicle \( K + 1 \) is known and the control acceleration of Vehicle \( K + 1 \). Additionally, the parameters \( v \) and \( v_p \) are the measured velocities of Vehicle \( K + 1 \) and Vehicle \( K \), \( k_d \) is a constant factor, which is similar to the \( k_d \) for the ACC/CACC model describing how distance between vehicles influences the velocity. The \( k_d \) was set to 0.2 based on trial and error as well as previous works \([16,21,34]\). Sensitivity analysis on the value of the \( k_d \) is able to be applied to the hardcoded values within the dynamic link library (DLL) for each set of simulation runs and obtain the optimal one. \( t_{\text{system}} \) is the desired time gap which was also described in (3) for the ACC/CACC model with a value of 0.5 for ACC/CACC models, otherwise the reference vehicles are assumed to be human drivers or partial AVs with ACC systems, for which \( t_{\text{system}} = 1.4 \) s \([13]\). \( r \) is the following clearance between Vehicles \( K \) and \( K + 1 \), which can be calculated as:

\[ r = x_p - x - l_p \]  

(7)

in which, \( x \) and \( x_p \) are the measured coordinates of Vehicle \( K + 1 \) and Vehicle \( K \) and \( l_p \) is the measured length of Vehicle \( K \). In addition, in (6), \( X_d \) and \( X_r \), are the predicted clearances based on desired and actual measured data for Vehicle \( K \) and \( c \) is related to the relationship of \( X_d \) and \( X_r \) as shown in Figure 2. If \( X_d < X_r \), Vehicle \( K \) drives quicker than it is expected, Vehicle \( K + 1 \) needs to accelerate, and then \( c \) is set as 0. When \( X_d > X_r \), two conditions may exist. In the first condition, Vehicle \( K \) drives slower than it is expected, and Vehicle \( K + 1 \) will need to maintain the same acceleration as Vehicle \( K \), then \( c \) is also set as 0. In the second condition, Vehicle \( K \) deaccelerated because of a traffic event ahead of it, and Vehicle \( K + 1 \) needs to deaccelerate accordingly to stay safe, then \( c \) is set as 1. In order to distinguish which condition Vehicle \( K \) is facing, this study sets \( c \) equals 1 when \( r \) is larger than the safe distance, \( X_s \), in the case of \( X_d > X_r \), otherwise, \( c \) equals 0, in which, \( X_s \) can be calculated as below:

\[ X_s = CC0 + CC1 \cdot v \]  

(8)

where \( CC0 \) is standstill distance and \( CC1 \) is headway time.

Figure 2. Schematic of the vehicles’ driver behavior based on different conditions.

In contrast to Equation (2), which does not account for cumulative car-following dynamics, this study advances the control acceleration model through Equation (9). The desired velocity following clearance and safe distance are calculated using Equations (6) to (8). Following a comprehensive analysis of the absolute distance between the predicted clearance based on desired and actual measured data of Vehicle \( K \), and considering their
relationship that impacts the parameter \( c \), the control acceleration of Vehicle K + 1 using the CACF model can be determined using the following equation:

\[
a_c = k_a * a_p + k_v * (v_p - v) + k_d * \left( r - t_{system} * v + (1 - \frac{1}{c}) * |X_d - X_r| \right)
\]  

(9)

where \( k_a, k_v, \) and \( k_d \) are constant factors. \( k_a \) is equal to 1.0, \( k_v \) and \( k_d \) equal to 0.58 and 0.1 in accordance with simulation of intelligent cruise control studies [16,21,34].

Thus, the desired acceleration of Vehicle K + 1, \( a_d \), can then be obtained by limiting control acceleration to be greater than the minimum acceleration \( (a_{min}) \) and smaller than the maximum acceleration \( (a_{max}) \) as:

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

(10)

where the minimum and maximum acceleration is the constant factor depending on the types of the vehicles.

Based on the desired velocity and acceleration obtained from (6) to (10), the predicted desired clearance, \( X_{d_d} \), of Vehicle K + 1, at the next desired time period, \( t_{system} \), can then be predicted using the kinematic equation as:

\[
X_{d_d} = v_d * t_{system} + \frac{1}{2} a_d * t_{system}^2
\]  

(11)

The predicted actual clearance, \( X_{r} \), of Vehicle K + 1 at next desired time period, \( t_{system} \), can be predicted using the actual measured velocity and acceleration through the kinematic equation as below:

\[
X_{r} = v * t_{system} + \frac{1}{2} a * t_{system}^2
\]  

(12)

When the predicted desired clearance, \( X_{d_d} \), is greater than the predicted actual clearance, \( X_{r} \), \( X_{d} \geq X_{r} \), Vehicle K + 1 is considered to be too close to Vehicle K if Vehicle K + 1 still maintains the same velocity and acceleration at the next desired time period. The vehicles behind Vehicle K + 1 (for instance, Vehicle N, the target AV) are recommended to consider the difference between \( X_{d_d} \) and \( X_{r} \), thus, increase their headway, and deaccelerate to reduce the possibility of a car crash. However, if \( X_{d} < X_{r} \), Vehicle K + 1 is away from Vehicle K when Vehicle K + 1 maintains the same velocity and acceleration at next system time period. Two potential conditions would occur in the case of \( X_{d} < X_{r} \): (1) Vehicle K + 1 drives too slowly due to driving behavior, and (2) there is conflict between Vehicle K + 1 and Vehicle K which slows down Vehicle K + 1 to avoid the conflict leading to less distance between these two vehicles. When the distance between the Vehicle K + 1 and the vehicle after it is greater than their safe distance \( X_{s} \), the first circumstance was met, the difference between \( X_{d} \) and \( X_{r} \) will be input into the CACF model of the following vehicles after Vehicle K + 1 to recommend an increase in acceleration and a decrease in headway for safer and more responsive car-following behavior, thereby enhancing the overall maneuverability of the vehicles on the road. In contrast, if the safe distance between the Vehicle K + 1 and its following vehicle is less than their real distance under the second circumstance, the following vehicles behind Vehicle K + 1 are recommended to slow down instead, and the difference between \( X_{d} \) and \( X_{r} \) will be input into the CACF model of the following vehicles to decrease their acceleration and increase the headway.

Thus, if the coordinates \( (x) \), lengths \( (l) \), speeds \( (v) \), and accelerations \( (a) \) of all the K + 1 vehicles before the AV (Vehicle N) can be detected, monitored, and transmitted between each vehicle in real time through V2X, the desired velocity and acceleration \( (v_d \text{ and } a_d) \), and the predicted desired and actual clearance \( (x_{d_d} \text{ and } x_{r}) \) of each vehicle between Vehicle K + 1 and Vehicle N can then be calculated using (6) to (12), so this is what Vehicle N does. Compared with traditional car following models, the new CACF model can consider all possible inputs of N vehicles ahead of the AV from the V2X including V2V and V2I for instance. In addition, it also evaluates the important interaction between every two vehicles and their overlay of differences between the desired and real velocity and acceleration.
More importantly, to improve the safety of the AV, the change in the acceleration of the
AV takes into account the difference between the predicted desired and actual clearance
to avoid unusual conditions, such as car crashes. These major advances are expected to
enhance the safety and stabilization of the following behavior of the AV compared with
the current ACC or CACC models. The designed C++ code based on the CACF model is
shown in Appendix B.

3. Results Evaluating the CACF Model Using Micro-Simulation

To evaluate the effectiveness of the new CACF model for improving the mobility
of AVs in case of availability of V2X communication, this study conducted a case study
using a micro-simulator, the Verkehr In Städten—SIMulationsmodell (VISSIM, developed
by Planung Transport Verkehr (PTV) in Karlsruhe, Germany). The VISSIM software is
a behavior-based micro-simulation traffic software, which is widely used in urban and
highway simulations. To evaluate the effectiveness of the newly developed model on
its enhanced safety, this study applied the surrogate safety assessment model (SSAM)
in combination with the VISSIM [35,36]. The SSAM can automatically perform conflict
analysis using the data obtained from the simulation results in the VISSIM software.

3.1. Model Setup in VISSIM

In the VISSIM, there are three approaches to modifying the car following models,
including the use of a graphical user interface (GUI), the component object model (COM),
or the dynamic link library (DLL) [37]. The user-friendly GUI has integrated car-following
models using basic default parameters which can easily be changed for different needs.
The current VISSIM [38] has built the Wiedemann 99 (W99) driver behavior model for
human drivers. In this study, W99 driver behavior was also used to model the following
behavior of the human drivers. The two key parameters of the W99 driver behavior model,
the standstill distance (CC0) and headway time (CC1) were set to be the same as the default
values. If users want to define a new car-following model, it is possible to achieve this by
editing the DLL with C++ [38] in the main source file of the DLL file (DriverModel.cpp).
By defining a new car-following model through the DLL, the VISSIM will call up the DLL
code for each affected vehicle in every desired simulation time gap to guide the driving
behavior of the vehicle instead of using the internal driver models. In this case study, to
evaluate the safety and mobility of the newly developed CACF model, the DLL codes for
the new CACF, the existing ACC, and CACC models were programed according to (1) to
(3) and (6) to (12). For the new CACF model, in the case study, the total number of vehicles
in the communication range, N, was set as ten. Thus, the AV with CACF model will be the
10th vehicle for every 10 vehicles whereas all other nine vehicles are either AVs with ACC
or CACC models or regular human drivers. Although any V2X communication can be
applied, in this case study, we assumed the real-time traffic data of the nine vehicles ahead
of the AV can be obtained using the V2I system to demonstrate the effectiveness of the new
model. Different to the V2V system which needs the vehicles to equipped with sensors to
collect data, the V2I system supports the autonomous vehicle in obtaining the information
from all of the vehicles (the sensors are assumed to be installed under the road in this
study). The traffic data obtained by the V2I system include vehicle lengths, coordinates,
velocities, and accelerations. Based on this information, the new CACF model optimizes
the AV’s (the tenth vehicle’s) driving speed, following distance, and other operations for a
safer performance.

In this case study, to simplify the simulation, the analysis was performed on a single-
lane freeway road segment of 5 km. To simulate the mixed-driver environment, the human
driver and AVs were considered to co-exist. The W99 model was used for the human driver,
whereas three different external car-following models were applied to the AVs including
the ACC model, the CACC model, and the new CACF model. Thus, on the simulated road
segment, there are three types of cars accordingly as shown in Figure 3. All of the AVs
were set as Type A, for the human drivers, two types of vehicles were considered based on
their characteristics including Type B which would stop in front of a stop sign to induce a conflict to occur, whereas Type C would not stop in front of a stop sign. Since the analysis is targeted at mixed traffic environments with human drivers dominating the traffic, the penetration rate of AVs was assumed to be 10% of the traffic flow, which is a very low penetration rate. Thus, for every 100 vehicles, there will be 10 AVs (Type A), one Type B human driver, and 89 Type C human drivers. The occurrence order of the types of vehicles is random. For Type A vehicles (AVs), the $k_0$ and $k_d$ values in (2) for the ACC and CACC models, and in (9) for the CACF model, were set to be 0.58 and 0.1 in the DriverModel.cpp file of the DLL, respectively, as recommended by Zhao and Sun [17].

![Diagram of vehicle information when simulated in the VISSIM (Source: VISSIM).](image_url)

The simulation considered five speed limits, including 24.59 m/s (55 mph), 26.82 m/s (60 mph), 29.06 m/s (65 mph), 31.29 m/s (70 mph), and 33.53 m/s (75 mph). The freeway capacity was set to be 2250, 2300, 2350, 2400, and 2450 passenger cars per hour per lane (pc/h/ln), with speed limits of 24.59 m/s, 26.82 m/s, 29.06 m/s, 31.29 m/s, and 33.53 m/s, respectively [39]. For each simulation run, the total simulation time was set to be 4500 s and it was divided into five travel intervals. Thus, each travel interval was 900 s and the initial 900 s was allocated for simulation warmup, which was not be included in the traffic simulation results. The simulation parameters are shown in Table 1.

### Table 1. Parameters of the simulations.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Length of Freeway Road</td>
<td>5000 m</td>
</tr>
<tr>
<td>Number of Vehicles</td>
<td>2250 pc/h/ln</td>
</tr>
<tr>
<td>(freeway capacity)</td>
<td>2300 pc/h/ln</td>
</tr>
<tr>
<td></td>
<td>2350 pc/h/ln</td>
</tr>
<tr>
<td></td>
<td>2400 pc/h/ln</td>
</tr>
<tr>
<td></td>
<td>2450 pc/h/ln</td>
</tr>
<tr>
<td>Types</td>
<td>autonomous vehicle</td>
</tr>
<tr>
<td>(Type A, 10% of freeway capacity)</td>
<td>human driver vehicle</td>
</tr>
<tr>
<td>(Type B, 1% of freeway capacity, stop in front of a stop sign)</td>
<td>human driver vehicle</td>
</tr>
<tr>
<td>(Type C, 89% of freeway capacity, no stopping in front of a stop sign)</td>
<td>human driver vehicle</td>
</tr>
<tr>
<td>Time Interval</td>
<td>0–900 (warmup time, not included)</td>
</tr>
<tr>
<td></td>
<td>900–1800</td>
</tr>
<tr>
<td></td>
<td>1800–2700</td>
</tr>
<tr>
<td></td>
<td>2700–3600</td>
</tr>
<tr>
<td></td>
<td>3600–4500</td>
</tr>
</tbody>
</table>

With the road segment modeled, this case study also considered the stochastic variations in vehicle arrivals to reflect traffic variations as in the real world using the random seeds under the simulation parameter settings in VISSIM. For the same DLL file, if the seed value is different, the stochastic functions are assigned a different value sequence, leading to changes in traffic flow. Therefore, each seed value provides a different scenario of traffic...
conditions. In this study, authors simulated ten different seed values from 1 to 46 with an increment of 5 to represent ten different traffic conditions, the initial random seed was set to 1 with an increment of 5 for each simulation. In addition, this case study used a simulation resolution of 10 to ensure a realistic demonstration of traffic simulation, which means in each simulation second there are ten time-steps. Given that the nature of traffic varies with respect to time, multiple simulations are performed to compare the results for each run. A total of 10 simulation runs were performed \[39,40\]. Therefore, a total of 200 simulations were performed in this case study with the conditions as shown in Table 2.

**Table 2.** Conditions of the simulations.

<table>
<thead>
<tr>
<th>Model</th>
<th>Speed</th>
<th>Seed</th>
<th>Case</th>
</tr>
</thead>
<tbody>
<tr>
<td>W99</td>
<td>24.59 m/s</td>
<td>1, 6, 11, 16, 21, 26, 31, 36, 41, 46</td>
<td>1–10</td>
</tr>
<tr>
<td></td>
<td>26.82 m/s</td>
<td>1, 6, 11, 16, 21, 26, 31, 36, 41, 46</td>
<td>11–20</td>
</tr>
<tr>
<td></td>
<td>29.06 m/s</td>
<td>1, 6, 11, 16, 21, 26, 31, 36, 41, 46</td>
<td>21–30</td>
</tr>
<tr>
<td></td>
<td>31.29 m/s</td>
<td>1, 6, 11, 16, 21, 26, 31, 36, 41, 46</td>
<td>31–40</td>
</tr>
<tr>
<td></td>
<td>33.53 m/s</td>
<td>1, 6, 11, 16, 21, 26, 31, 36, 41, 46</td>
<td>41–50</td>
</tr>
<tr>
<td>ACC</td>
<td>24.59 m/s</td>
<td>1, 6, 11, 16, 21, 26, 31, 36, 41, 46</td>
<td>51–60</td>
</tr>
<tr>
<td></td>
<td>26.82 m/s</td>
<td>1, 6, 11, 16, 21, 26, 31, 36, 41, 46</td>
<td>61–70</td>
</tr>
<tr>
<td></td>
<td>29.06 m/s</td>
<td>1, 6, 11, 16, 21, 26, 31, 36, 41, 46</td>
<td>71–80</td>
</tr>
<tr>
<td></td>
<td>31.29 m/s</td>
<td>1, 6, 11, 16, 21, 26, 31, 36, 41, 46</td>
<td>81–90</td>
</tr>
<tr>
<td></td>
<td>33.53 m/s</td>
<td>1, 6, 11, 16, 21, 26, 31, 36, 41, 46</td>
<td>91–100</td>
</tr>
<tr>
<td>CACC</td>
<td>24.59 m/s</td>
<td>1, 6, 11, 16, 21, 26, 31, 36, 41, 46</td>
<td>101–110</td>
</tr>
<tr>
<td></td>
<td>26.82 m/s</td>
<td>1, 6, 11, 16, 21, 26, 31, 36, 41, 46</td>
<td>111–120</td>
</tr>
<tr>
<td></td>
<td>29.06 m/s</td>
<td>1, 6, 11, 16, 21, 26, 31, 36, 41, 46</td>
<td>121–130</td>
</tr>
<tr>
<td></td>
<td>31.29 m/s</td>
<td>1, 6, 11, 16, 21, 26, 31, 36, 41, 46</td>
<td>131–140</td>
</tr>
<tr>
<td></td>
<td>33.53 m/s</td>
<td>1, 6, 11, 16, 21, 26, 31, 36, 41, 46</td>
<td>141–150</td>
</tr>
<tr>
<td>CACF</td>
<td>24.59 m/s</td>
<td>1, 6, 11, 16, 21, 26, 31, 36, 41, 46</td>
<td>151–160</td>
</tr>
<tr>
<td></td>
<td>26.82 m/s</td>
<td>1, 6, 11, 16, 21, 26, 31, 36, 41, 46</td>
<td>161–170</td>
</tr>
<tr>
<td></td>
<td>29.06 m/s</td>
<td>1, 6, 11, 16, 21, 26, 31, 36, 41, 46</td>
<td>171–180</td>
</tr>
<tr>
<td></td>
<td>31.29 m/s</td>
<td>1, 6, 11, 16, 21, 26, 31, 36, 41, 46</td>
<td>181–190</td>
</tr>
<tr>
<td></td>
<td>33.53 m/s</td>
<td>1, 6, 11, 16, 21, 26, 31, 36, 41, 46</td>
<td>191–200</td>
</tr>
</tbody>
</table>

### 3.2. Integration of SSAM into VISSIM

In the SSAM, a traffic event could be considered to be a traffic conflict when the drivers need to make evasive maneuvers, such as slowing down quickly or changing lanes suddenly to avoid collision \[41\], which could be applied to evaluate unsafe driving maneuvers before a collision occurs \[42\]. Instead of evaluating safety based on the collision data, which requires long collection periods since collisions do not occur frequently enough to produce a sufficient dataset in a short time, traffic conflicts reduced collection time with less cost and provide enough data to conduct analysis of safety \[41\]. Based on the angle of a conflict, there are three types of conflicts \[43\], including the rear-end with a collision angle less than 30°, lane changes with a collision angle larger than 30° and less than 85°, and the crossover with a collision angle larger than 85°. In this case study, since the simulation was conducted on a one-lane freeway, only the rear-end conflict was counted for safety evaluation.

The SSAM can not only count the number of conflicts (rear-end conflict in this case study), but also distinguish the type, severity, and location of conflicts based on traffic conflict indicators. There are two commonly used traffic conflict indicators, including time-to-collision (TTC) and the post-encroachment time (PET) \[44\]. The TTC was defined as the time required for two vehicles to collide if they maintain current speeds on the same path \[45\], which was determined by dividing the gap distance between a subject vehicle and the conflicting vehicle or pedestrian by their velocity difference \[46\]. The PET is the time between the first vehicle occupied at a position and the next vehicle arriving at the same position. In this case study, a conflict was defined to occur when the TTC and PET reduced to three and five seconds or less, respectively. The SSAM would count the

---

**Smart Cities 2023, 6**

---
conditions as conflicts when the two traffic indicators were out of this defined range. For a safer and less congested traffic environment, fewer conflicts are desired.

To evaluate the safety of the newly developed CACF model by integrating the SSAM into the VISSIM, a hypothetical breakdown using the stop sign was created at a position of 4000 m on the simulated road segment. The stop sign was used to represent the emergency event of a car crash on the simulated freeway. Type B vehicles with human drivers would stop at the stop sign within a dwell time of two seconds and Type C vehicles with human drivers would not stop at the stop sign as described in Figure 3. Part of the simulated road segment after the stop sign of 500 m was used to count the number of cars which would stop to avoid the stopped Type B vehicle. Accordingly, the number of conflicts and stops can be obtained and used to analyze the safety and mobility of the traffic environment. The VISSIM also generates a trajectory file (*.trj) at the end of successive simulation runs. The vehicle trajectories describe the course of vehicle positions through the network. The *.trj file was imported to the SSAM tool to evaluate safety in terms of conflicts. In addition to counting conflicts, all other traffic information, including the type of vehicles, speed, acceleration, and headway, were also used as outputs to analyze the performance of the newly developed model. Figure 4 illustrates the workflow for using external driver models DLL, VISSIM, and SSAM.

**Figure 4.** The workflow diagram of the external driver models DLL, VISSIM, and SSAM.

### 4. Results and Discussion

To evaluate the effectiveness of the new CACF model, the simulation results from the four different models including the W99, the ACC, the CACC, and the newly developed CACF, were compared using safety and mobility measures, including the number of conflicts for all the ten different traffic conditions (seed number), the number of conflicts (total, average, minimum, and maximum), the total number of stops at different time intervals, and the average velocity of all the vehicles.

#### 4.1. Evaluating the Safety of the Models in the Case Study

Figure 5a–e compares the simulation results of the average number of conflicts from the four different models with ten different traffic conditions (seed numbers) at speed limits of 24.59 m/s, 26.82 m/s, 29.06 m/s, 31.29 m/s, and 33.53 m/s, respectively. Despite the variations in the performance of these four models, a consistent observation emerges: across a range of traffic conditions and speed limits, the innovative CACF model exhibits notably fewer conflicts compared to the W99, ACC, and CACC models. Particularly noteworthy is the suboptimal performance of the CACC model, prominently observed in scenario 10. This finding highlights the potential for autonomous vehicles to demonstrate diminished performance when operating alongside human drivers, especially with low autonomous vehicle penetration rates.

In most cases, the CACC model produced the most conflicts with the same traffic condition followed by the ACC model, because its behavior was highly related to the type of preceding vehicle, $f_{system}$ was set to be 1.4 s when it was equipped with the ACC model or human drivers, and 0.5 s if it was equipped with the CACC model. It was too short of
$t_{system} = 0.5 \text{ s}$ to produce conflicts when the penetration rate of AVs with the CACC model was low.

The developed CACF model resulted in the least conflicts because it did not require to know whether the vehicles before it was equipped with any ACC or CACC or CACF models for considering multiple vehicles in the car following. The percentage of reduction ($R_p$) was used to evaluate the effectiveness of the developed new model, which can be calculated as:

$$R_p = \frac{N_c - N_{CACF}}{N_c} \times 100 \tag{13}$$

where $N_c$ and $N_{CACF}$ is the total number of conflicts of the comparison model and CACF model.

Table 3 shows the percentage of reduction ($R_p$) in the total number of conflicts comparing the CACF model with the W99, the ACC, and CACC models at the five different speed limits, respectively. It can be seen that an average of 80% reduction in conflicts was noticed for all five speed limits tested.

![Graphs showing percentage of reduction in conflicts for different scenarios](image_url)
Figure 5. Average number of conflicts from the four different models with different seed numbers at five different speed limits (a) 24.59 m/s; (b) 26.82 m/s; (c) 29.06 m/s; (d) 31.29 m/s; (e) 33.53 m/s.

Table 3. Percentage of reduction in conflicts comparing the new CACF model with the other three models at five different speed limits.

<table>
<thead>
<tr>
<th>Speed Limit</th>
<th>W99</th>
<th>ACC</th>
<th>CACC</th>
<th>CACF</th>
</tr>
</thead>
<tbody>
<tr>
<td>24.59 m/s</td>
<td>77.69%</td>
<td>79.31%</td>
<td>83.31%</td>
<td></td>
</tr>
<tr>
<td>26.82 m/s</td>
<td>80.20%</td>
<td>84.07%</td>
<td>82.16%</td>
<td></td>
</tr>
<tr>
<td>29.06 m/s</td>
<td>83.99%</td>
<td>86.85%</td>
<td>89.60%</td>
<td></td>
</tr>
<tr>
<td>31.29 m/s</td>
<td>80.37%</td>
<td>83.33%</td>
<td>83.84%</td>
<td></td>
</tr>
<tr>
<td>33.53 m/s</td>
<td>80.93%</td>
<td>87.03%</td>
<td>89.20%</td>
<td></td>
</tr>
</tbody>
</table>

Figure 6 further compares the average, maximum, and minimum number of conflicts of the four models at five speed limits of 24.59 m/s, 26.82 m/s, 29.06 m/s, 31.29 m/s, and 33.53 m/s. In general, the new CACF model significantly reduced all the maximum, minimum, and average number of conflicts when compared with all the other three models at all speed limits. Table 4 compares the percentage of average, maximum, and minimum number of conflicts comparing the CACF model with the other three models at speed limits of 24.59 m/s, 26.82 m/s, 29.06 m/s, 31.29 m/s, and 33.53 m/s, respectively. The percentage reduction in the average, maximum and minimum conflicts for the CACF model varies from 77.69% to 91.97% compared with the W99 model, varies from 67.00% to 93.94% compared with the ACC model, and varies from 69.17% to 93.25% compared with CACC model at speeds from 24.59 m/s to 33.53 m/s. The safety performance of the new CACF model was consistently enhanced at all speed limits compared with the other three models. Furthermore, as the speed limit increases from 24.59 m/s to 33.53 m/s, a discernible upward trend emerges in the percentage reduction across the average, maximum, and minimum numbers of conflicts when comparing the W99, ACC, and CACC models to the developed CACF model.
The newly developed CACF model can not only reduce the number of conflicts, but also has the potential to improve mobility by reducing the number of stops for vehicles. The highway capacity manual [47] recommends the 900-s flow rate as a peak hour factor for most of the capacity analyses. The 900-s interval provides a better statistical representation of traffic output in terms of travel time, delays, queues, and other parameters as compared with the 3600-s time interval. As described in Section 3.1, in this case study, for each simulation run, the simulation length of 4500 s was divided into five travel intervals, with the first 900 s used as warmup and not included in the analysis.

Figure 7 and Table 5 compare the average and percentage of the reduction in the number of stops of each simulation time interval for all four models at speed limits of 24.59 m/s, 26.82 m/s, 29.06 m/s, 31.29 m/s, and 33.53 m/s, respectively. It can be found that the developed model reduced the average number of stops for almost every time interval when compared with the other three models. The number of stops exhibits a slight decrease at average speeds of 24.59 m/s, 26.82 m/s, and 29.06 m/s, while the values increase as the speed reaches 31.29 m/s and 33.53 m/s. The subtlety of the differences can be attributed to the averaging of the ten distinct scenarios. It is important to note that despite maintaining ten different scenarios at each speed limit, any alteration in vehicle
conditions brings about corresponding changes in the real-world scenario. In other words, while the fundamental scenarios remain consistent, variations in speed limits introduce numerous minor adjustments, thereby showcasing the diversity of real-world conditions and offering insight into a wider spectrum of possible scenarios. However, regardless of the specific conditions, the new CACF model consistently shows significant improvements. The new CACF model reduced the numbers of stops occurring up to 93.54%, 91.74%, 92.04%, 88.60%, and 91.35% at speeds of 24.59 m/s, 26.82 m/s, 29.06 m/s, 31.29 m/s, and 33.53 m/s compared with the W99, ACC, and CACC models, respectively. It indicated that if the new CACF model was applied to AVs with a low penetration rate, it has the potential to reduce traffic congestion and improve mobility by reducing the number of vehicle stops.

In addition, Table 6 also compares the average speeds in each time interval for each seed for all four different models with speed limits of 24.59 m/s, 26.82 m/s, 29.06 m/s, 31.29 m/s, and 33.53 m/s, respectively. Compared with the other three models, the new CACF model yielded the highest average speeds between 22.25 m/s to 26.73 m/s. The velocity of the AVs varied from 20.72 m/s to 24.27 m/s, 19.08 m/s to 25.31 m/s, 18.00 m/s to 27.43 m/s, 16.59 m/s to 24.05, and 16.55 m/s to 26.12 m/s at the five different speed limits. In addition, the CACF showed a lowest range and sample variance than the other three models, indicating that the new CACF model can maintain a more stable driving speed and provide better mobility for AVs.
Figure 7. Comparison of the number of stops at five different speed limits (a) 24.59 m/s; (b) 26.82 m/s; (c) 29.06 m/s; (d) 31.29 m/s; (e) 33.53 m/s.

Table 5. Percentage of reduction in number of stops for different time intervals comparing the new CACF model with the other three models at five different speed limits.

<table>
<thead>
<tr>
<th>Speed Limit</th>
<th>Time Interval</th>
<th>W99</th>
<th>ACC</th>
<th>CACC</th>
<th>CACF</th>
</tr>
</thead>
<tbody>
<tr>
<td>24.59 m/s</td>
<td>900–1800</td>
<td>89.96%</td>
<td>79.84%</td>
<td>91.66%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1800–2700</td>
<td>83.09%</td>
<td>70.46%</td>
<td>53.48%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2700–3600</td>
<td>91.32%</td>
<td>84.70%</td>
<td>93.54%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3600–4500</td>
<td>64.34%</td>
<td>89.84%</td>
<td>89.44%</td>
<td></td>
</tr>
<tr>
<td>26.82 m/s</td>
<td>900–1800</td>
<td>88.10%</td>
<td>91.74%</td>
<td>87.32%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1800–2700</td>
<td>88.49%</td>
<td>88.25%</td>
<td>87.89%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2700–3600</td>
<td>80.86%</td>
<td>78.81%</td>
<td>68.67%</td>
<td></td>
</tr>
</tbody>
</table>
Table 5. Percentage of reduction in number of stops for different time intervals comparing the new CACF model with the other three models at five different speed limits.

<table>
<thead>
<tr>
<th>Speed Limit</th>
<th>Time Interval</th>
<th>W99</th>
<th>ACC</th>
<th>CACC</th>
</tr>
</thead>
<tbody>
<tr>
<td>24.59 m/s</td>
<td>900–1800</td>
<td>89.96%</td>
<td>79.84%</td>
<td>91.66%</td>
</tr>
<tr>
<td></td>
<td>1800–2700</td>
<td>83.09%</td>
<td>70.46%</td>
<td>53.48%</td>
</tr>
<tr>
<td></td>
<td>2700–3600</td>
<td>91.32%</td>
<td>84.70%</td>
<td>93.54%</td>
</tr>
<tr>
<td></td>
<td>3600–4500</td>
<td>64.34%</td>
<td>89.84%</td>
<td>89.44%</td>
</tr>
<tr>
<td>26.82 m/s</td>
<td>900–1800</td>
<td>88.10%</td>
<td>91.74%</td>
<td>87.32%</td>
</tr>
<tr>
<td></td>
<td>1800–2700</td>
<td>88.49%</td>
<td>88.25%</td>
<td>87.89%</td>
</tr>
<tr>
<td></td>
<td>2700–3600</td>
<td>80.86%</td>
<td>78.81%</td>
<td>68.67%</td>
</tr>
<tr>
<td></td>
<td>3600–4500</td>
<td>65.07%</td>
<td>72.19%</td>
<td>70.91%</td>
</tr>
<tr>
<td>29.06 m/s</td>
<td>900–1800</td>
<td>87.63%</td>
<td>88.58%</td>
<td>91.02%</td>
</tr>
<tr>
<td></td>
<td>1800–2700</td>
<td>84.93%</td>
<td>87.06%</td>
<td>88.60%</td>
</tr>
<tr>
<td></td>
<td>2700–3600</td>
<td>89.76%</td>
<td>83.63%</td>
<td>92.04%</td>
</tr>
<tr>
<td></td>
<td>3600–4500</td>
<td>71.73%</td>
<td>78.18%</td>
<td>83.52%</td>
</tr>
<tr>
<td>31.29 m/s</td>
<td>900–1800</td>
<td>80.51%</td>
<td>86.40%</td>
<td>88.60%</td>
</tr>
<tr>
<td></td>
<td>1800–2700</td>
<td>84.81%</td>
<td>85.36%</td>
<td>84.44%</td>
</tr>
<tr>
<td></td>
<td>2700–3600</td>
<td>75.34%</td>
<td>66.69%</td>
<td>81.59%</td>
</tr>
<tr>
<td></td>
<td>3600–4500</td>
<td>50.32%</td>
<td>60.69%</td>
<td>64.60%</td>
</tr>
<tr>
<td>33.53 m/s</td>
<td>900–1800</td>
<td>82.49%</td>
<td>87.60%</td>
<td>85.92%</td>
</tr>
<tr>
<td></td>
<td>1800–2700</td>
<td>84.93%</td>
<td>87.06%</td>
<td>88.60%</td>
</tr>
<tr>
<td></td>
<td>2700–3600</td>
<td>75.34%</td>
<td>66.69%</td>
<td>81.59%</td>
</tr>
<tr>
<td></td>
<td>3600–4500</td>
<td>50.32%</td>
<td>60.69%</td>
<td>64.60%</td>
</tr>
</tbody>
</table>

Table 6. Comparison of the mean, maximum, and minimum speeds, and standard deviation of the AVs using the four different models at five different speed limits.

<table>
<thead>
<tr>
<th>Speed</th>
<th>W99</th>
<th>ACC</th>
<th>CACC</th>
<th>CACF</th>
</tr>
</thead>
<tbody>
<tr>
<td>24.59 m/s</td>
<td>Mean</td>
<td>22.60 m/s</td>
<td>22.41 m/s</td>
<td>22.12 m/s</td>
</tr>
<tr>
<td></td>
<td>Minimum</td>
<td>22.18 m/s</td>
<td>21.18 m/s</td>
<td>20.72 m/s</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>23.17 m/s</td>
<td>23.68 m/s</td>
<td>23.67 m/s</td>
</tr>
<tr>
<td></td>
<td>Standard Deviation</td>
<td>0.51</td>
<td>1.16</td>
<td>1.35</td>
</tr>
<tr>
<td>26.82 m/s</td>
<td>Mean</td>
<td>23.04 m/s</td>
<td>22.33 m/s</td>
<td>22.72 m/s</td>
</tr>
<tr>
<td></td>
<td>Minimum</td>
<td>21.74 m/s</td>
<td>19.08 m/s</td>
<td>20.91 m/s</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>24.50 m/s</td>
<td>24.62 m/s</td>
<td>24.61 m/s</td>
</tr>
<tr>
<td></td>
<td>Standard Deviation</td>
<td>1.39</td>
<td>2.52</td>
<td>1.68</td>
</tr>
<tr>
<td>29.06 m/s</td>
<td>Mean</td>
<td>23.76 m/s</td>
<td>22.58 m/s</td>
<td>22.46 m/s</td>
</tr>
<tr>
<td></td>
<td>Minimum</td>
<td>21.24 m/s</td>
<td>18.00 m/s</td>
<td>18.44 m/s</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>25.50 m/s</td>
<td>26.01 m/s</td>
<td>25.91 m/s</td>
</tr>
<tr>
<td></td>
<td>Standard Deviation</td>
<td>2.17</td>
<td>3.65</td>
<td>3.85</td>
</tr>
<tr>
<td>31.29 m/s</td>
<td>Mean</td>
<td>19.89 m/s</td>
<td>19.08 m/s</td>
<td>19.47 m/s</td>
</tr>
<tr>
<td></td>
<td>Minimum</td>
<td>17.83 m/s</td>
<td>16.89 m/s</td>
<td>16.59 m/s</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>22.00 m/s</td>
<td>22.10 m/s</td>
<td>21.92 m/s</td>
</tr>
<tr>
<td></td>
<td>Standard Deviation</td>
<td>2.41</td>
<td>2.80</td>
<td>3.05</td>
</tr>
<tr>
<td>33.53 m/s</td>
<td>Mean</td>
<td>21.96 m/s</td>
<td>19.91 m/s</td>
<td>19.80 m/s</td>
</tr>
<tr>
<td></td>
<td>Minimum</td>
<td>20.39 m/s</td>
<td>17.0 m/s</td>
<td>16.55 m/s</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>23.35 m/s</td>
<td>21.90 m/s</td>
<td>22.74 m/s</td>
</tr>
<tr>
<td></td>
<td>Standard Deviation</td>
<td>1.71</td>
<td>2.86</td>
<td>3.53</td>
</tr>
</tbody>
</table>

5. Conclusions and Future Work

This paper developed a new CACF model for AVs, which introduces the dynamic effects of multiple preceding vehicles under the assumption that real-time traffic information can be communicated to the AVs through V2X systems and cumulates these influences into the car following to improve the safety, convenience, and economy of AVs in mixed-driver traffic conditions. Simulations were performed using VISSIM on multiple case studies with ten different traffic conditions (seed numbers) and five different limited speeds to evaluate the effectiveness of the new model. The comparison between the new CACF model with the other three different models, the W99 (the in-build models of the VISSIM), ACC, and
CACC, from 200 simulations runs demonstrated that the new model has the potential to significantly outperform these in terms of safety and mobility.

This study conducted an extensive analysis encompassing 10 unique scenarios and five distinct speed limits (24.59 m/s, 26.82 m/s, 29.06 m/s, 31.29 m/s, and 33.53 m/s) to comprehensively assess the performance of four models: CACF, W99, ACC, and CACC. Impressively, the CACF model consistently showcases remarkable reductions in conflicts when compared to the other models. Notably, the percentage reduction in average, maximum, and minimum conflicts for the CACF model varies from 77.69% to 91.97% compared with the W99 model, from 67.00% to 93.94% compared with the ACC model, and from 69.17% to 93.25% compared with the CACC model, across the speed range of 24.59 to 33.53 m/s.

Moreover, the CACF model demonstrates substantial potential in enhancing vehicle mobility, effectively reducing the average number of stops by up to 93.54%, 91.74%, 92.04%, 88.60%, and 91.35% at speeds of 24.59 m/s, 26.82 m/s, 29.06 m/s, 31.29 m/s, and 33.53 m/s, respectively, when compared to the W99, ACC, and CACC models. This reduction signifies a significant improvement in traffic flow and underscores the model's efficacy in alleviating congestion.

In summary, the CACF model consistently surpasses the other models in terms of conflict reduction and improved traffic mobility across diverse scenarios and speed limits. These findings underscore its practical relevance and potential for alleviating congestion while enhancing overall traffic efficiency in mixed-driver environments.

While the time required for data collection and processing by a human driver might exceed that of an autonomous vehicle, there are scenarios where human drivers can outperform autonomous systems. A human driver can, for example, effectively identify a car’s left blinker from a distance and predict deceleration among intermediate vehicles. This eliminates the need to collect data from all these vehicles, shifting focus to determining whether the turning vehicle will promptly complete the maneuver or stop due to opposing traffic, thus streamlining decision-making and potentially enhancing traffic flow. In future work, this specialized function will be incorporated into autonomous vehicle simulations to enhance their capabilities.

In addition, the simulation was only executed in a single traffic environment (a freeway with one lane) and a selected penetration rate of AVs. In the future, the sensitivity of this new model should be tested on AV penetration rates, communication ranges, numbers of cars to be considered in modeling, multiple-lane behaviors, and enhancing the method's robustness in scenarios where manually driven vehicles can overtake others. This comprehensive evaluation aims to further validate the model’s effectiveness before its potential practical applications.


**Funding:** This research was funded by the U.S. Department of Transportation under a university transportation center grant number No. 69A3551747108 through MPC projects No. 547 and No. 685.

**Data Availability Statement:** The data presented in this study are available on request from the corresponding author.

**Conflicts of Interest:** The authors declare no conflict of interest.
## Abbreviations

Abbreviations and their full corresponding names

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Full Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>AV</td>
<td>autonomous vehicle</td>
</tr>
<tr>
<td>ACC</td>
<td>adaptive cruise control</td>
</tr>
<tr>
<td>CACC</td>
<td>cooperative adaptive cruise control</td>
</tr>
<tr>
<td>CACF</td>
<td>cumulatively anticipative car-following</td>
</tr>
<tr>
<td>MACF</td>
<td>multi-anticipative car following</td>
</tr>
<tr>
<td>OVM</td>
<td>optimal velocity model</td>
</tr>
<tr>
<td>W99</td>
<td>Wiedemann 99</td>
</tr>
<tr>
<td>V2V</td>
<td>vehicle-to-vehicle</td>
</tr>
<tr>
<td>V2I</td>
<td>vehicle-to-infrastructure</td>
</tr>
<tr>
<td>V2X</td>
<td>vehicle-to-everything</td>
</tr>
<tr>
<td>VISSIM</td>
<td>Verkehr In Städten—SIMulationsmodell</td>
</tr>
<tr>
<td>PTV</td>
<td>Planung Transport Verkehr</td>
</tr>
<tr>
<td>SSAM</td>
<td>surrogate safety assessment model</td>
</tr>
<tr>
<td>COM</td>
<td>component object model</td>
</tr>
<tr>
<td>DLL</td>
<td>dynamic link library</td>
</tr>
<tr>
<td>GUI</td>
<td>graphical user interface</td>
</tr>
<tr>
<td>PET</td>
<td>post encroachment time</td>
</tr>
<tr>
<td>TTC</td>
<td>time-to-collision</td>
</tr>
</tbody>
</table>

## Appendix A

Definition of variables and parameters ($n$, $i$, and $j$ are integers, $1 \leq i < j \leq 9$)

<table>
<thead>
<tr>
<th>Length</th>
</tr>
</thead>
</table>
| $l_{p,j}$ | length of previous vehicle ($j$)  
|  
| Coordinate |  
| $x$ | coordinate of the ego vehicle  
| $x_p$ | coordinate of the previous vehicle  
|  
| Headway |  
| $h_{p,j}$ | headway of previous vehicle ($i$ and $j$)  
| $h_{ego,p}$ | headway of ego vehicle and previous vehicle  
| $h_{ego,p,j}$ | headway of ego vehicle and previous vehicle ($j$)  
| $CC_{ego}$ | headway time of ego vehicle, equal to $CC_1$, because ego vehicle is AV  
| $CC_{p,j}$ | headway time of previous vehicle ($j$)  
|  
| Distance |  
| $dd_{p,j}$ | predicted desired distance between previous vehicle ($i$ and $j$)  
| $rd_{p,j}$ | predicted real distance between previous vehicle ($i$ and $j$)  
| $sd_{ego}$ | safe distance of ego vehicle  
| $sd_{p,j}$ | safe distance between previous vehicle ($i$ and $j$)  
| $d_{ego,p,r}$ | distance between ego vehicle and its previous vehicle (9th vehicle),  
| $d_{p,j}$ | distance between previous vehicle $i$ and $j$  
| $t_{system}$ | desired distance between ego vehicle and its previous vehicle  
|  
| Velocity |  
| $vd_{ego,p}$ | velocity difference between ego vehicle and previous vehicle ($j$)  
| $v_{ego}$ | velocity of ego vehicle  
| $v_{p,j}$ | velocity of previous vehicle ($j$)  
| $dv_{ego}$ | desired velocity of ego vehicle  
| $dv_{p,j}$ | desired velocity of vehicle ($j$)  
| $dv_{d}$ |  

Acceleration
\[ a_{\text{ego}} \] acceleration of ego vehicle
\[ a_{p_j}, a_{\text{d}} \] desired acceleration of ego vehicle, this value only works when there is no preceding reference vehicle
\[ d a_{\text{ego}}, a_{\text{d}} \] desired acceleration of previous vehicle \( j \)
\[ c a_{p_j} \] emergency acceleration of previous vehicle \( j \), calculate value for the emergency condition where distance between two vehicles is less than \( C C_0 \)
\[ o a_{\text{ego}}, a_{c}, x_{\text{u}} \] optimal acceleration of ego vehicle, the final result

Type
\[ t_{p_j} \] type of previous vehicle \( j \)

Parameter
\( C C_0 \) standstill distance, set as 1.5
\( C C_1 \) headway time, set as 0.5
\( a_{\text{min}} \) minimum acceleration, set as \(-3 \text{ m/s}^2\)
\( a_{\text{max}} \) maximum acceleration, set as \(2 \text{ m/s}^2\)
\( k_a, k_v, k_d \) constant factor set as 1.0, 0.58, 0.1
\( h \) Constant factor
\( s_j \) sensitivity coefficients of a driver to the difference between the \( n \)th and the \( n+1 \)th velocities
\( c, g, m, k \) Constant factors defining the network uncertainties for predicted distance and desired acceleration, equal to 0 or 1

Appendix B
The pseudo code of the CACF model

Input: the information come from PTV VISSIM external driver model DLL and the constant factor of the model \( l_{p_j}, h_{p_i,p_j}, h_{\text{ego},p_{10}}, \sigma d_{\text{ego}}, p_i, v_{\text{ego}}, p_j, d v_{\text{ego}}, a_{p_j}, d a_{\text{ego}}, t_{p_j}, C C_0, C C_1, a_{\text{min}}, a_{\text{max}}, k_a, k_v, k_d \)

Output: optimal acceleration of ego vehicle \( (o a_{\text{ego}}) \)

1: \( s d_{\text{ego}} \leftarrow C C_0, C C_{1,\text{ego}}, v_{\text{ego}} \)
2: \( h_{\text{ego},p_j} \leftarrow h_{\text{ego},p_j}, h_{p_i,p_j} \)
3: \( v_{p_j} \leftarrow v_{\text{ego}}, v d_{\text{ego}, p_j} \)
4: \( s d_{p_i,p_j} \leftarrow C C_0, C C_{1, p_j}, v_{p_j} \)
5: \( d_{\text{ego}, p_j} \leftarrow h_{\text{ego},p_j}, l_{p_j} \)
6: \( d_{p_i,p_j} \leftarrow h_{p_i,p_j}, l_{p_j} \)
7: if \( t_{p_j} = 110 \) then // 110 is the type number for the autonomous vehicle
8: \( C C_{1, p_j} = 0.5 \)
9: else
10: \( C C_{1, p_j} = 1.4 \)
11: \( i = 8 \)
12: while \( i > 0 \) do
13: \( j = i + 1 \)
14: if \( h_{p_i,p_j} \leq 50 \) then
15: \( i = i - 1 \)
16: else:
17: \( \text{break} \)
18: end if
19: end while
20: \( i = i + 1 \)
21: \( j = i + 1 \)
22: if \( d_{\text{ego}, p_j} \leq C C_0 \) then
23: \( c a_{p_j} \leftarrow v_{\text{ego}}, d a_{\text{ego}, p_j} \)
24: \( o a_{\text{ego}} \leftarrow c a_{p_j}, a_{\text{min}} \)
25: else if \( d_{\text{ego}, p_j} > 50 \) then
\[ o a_{ego} \leftarrow d a_{ego} \]

else

28: if \( i = 8 \) then

29: \[ a_{ego} \leftarrow C C 1_{ego}, k_a, k_v, k_s, a_{p_y}, v_{p_y}, v_{ego}, d_{ego, p_y} \]

30: \[ o a_{ego} \leftarrow a_{ego}, a_{max}, a_{min} \]

else

32: \[ a_{p_{j+1}} \leftarrow C C 1_{p_{j+1}}, k_a, k_v, k_s, a_{p_{j+1}}, v_{p_{j+1}}, v_{p_{i+1}}, d_{p_{i+1}}, p_{j+1} \]

while \( i \leq 7 \) do

34: \[ d a_{p_{j+1}} \leftarrow a_{p_{j+1}}, a_{max}, a_{min} \]

if \( d a_{p_{j+1}} = a_{p_{j+1}} \) then

36: \[ d v_{p_{j+1}} \leftarrow C C 1_{p_{j+1}}, k_v, k_s, v_{p_{j+1}}, d_{p_{i+1}}, p_{j+1} \]

else

37: \[ d v_{p_{j+1}} \leftarrow C C 1_{p_{j+1}}, d a_{p_{j+1}}, v_{p_{j+1}} \]

end if

39: \[ d d_{p_{i+1}} \leftarrow C C 1_{p_{i+1}}, d a_{p_{i+1}}, d v_{p_{j+1}} \]

41: \[ r d_{p_{i+1}} \leftarrow C C 1_{p_{i+1}}, a_{p_{j+1}}, v_{p_{j+1}} \]

if \( r d_{p_{i+1}} \geq d d_{p_{i+1}}, p_{j+1} \) and \( j \leq 7 \) then

43: \[ a_{p_{j+2}} \leftarrow C C 1_{p_{j+2}}, k_a, k_v, k_s, a_{p_{j+2}}, v_{p_{j+2}}, v_{p_{j+2}}, d_{p_{j+2}}, p_{j+2} \]

44: \[ + \left( r d_{p_{i+1}}, p_{j+1} - d d_{p_{i+1}}, p_{j+1} \right) \]

50: \[ a_{p_{j+2}} \leftarrow C C 1_{p_{j+2}}, k_a, k_v, k_s, a_{p_{j+2}}, v_{p_{j+2}}, v_{p_{j+2}}, d_{p_{j+2}}, p_{j+2} \]

51: \[ + \left( r d_{p_{i+1}}, p_{j+1} - d d_{p_{i+1}}, p_{j+1} \right) \]

end if

53: end if

54: \[ o a_{ego} \leftarrow a_{ego}, a_{max}, a_{min} \]

55: \( i = i + 1 \)

56: \( j = j + 1 \)

71: end while

58: if \( r d_{p_{A}, p_{B}} \geq d d_{p_{A}, p_{B}} \) then

59: \( a_{ego} \leftarrow C C 1_{ego}, k_a, k_v, k_s, a_{p_y}, v_{p_y}, v_{ego}, d_{ego, p_y} \)

\[ - ( r d_{p_{A}, p_{B}} - d d_{p_{A}, p_{B}} ) \]

63: \[ a_{ego} \leftarrow C C 1_{ego}, k_a, k_v, k_s, a_{p_y}, v_{p_y}, v_{ego}, d_{ego, p_y} \]

64: \[ a_{ego} \leftarrow C C 1_{ego}, k_a, k_v, k_s, a_{p_y}, v_{p_y}, v_{ego}, d_{ego, p_y} \]

65: end if

67: end if

References

1. Sae International Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles. SAE Int. 2018, 4970, 1–5. [CrossRef]


6. Hollands, R.G. Will the Real Smart City Please Stand up? *City* 2008, 12, 303–320. [CrossRef]  


Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.