CUMULATIVE-ANTICIPATIVE CAR-FOLLOWING MODEL FOR ENHANCED SAFETY IN AUTONOMOUS VEHICLES

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ABSTRACT

As the rapid development of smart cities, autonomous vehicles are considered to be the future ground transportation measure which provides many benefits over traditional human-driving vehicles. However, there will be decades before the autonomous vehicles fully penetrate, during when human-drivers will share the same road systems with the autonomous vehicles, where the majority of accidents associated with autonomous vehicles are induced by the operation inconsistency of human drivers, which can be avoided if there is communication between the autonomous vehicles and the infrastructure (V2I). This study develops cumulative-anticipative car-following (CACF) model for autonomous vehicles based on the Cooperate Adaptive Cruise Control/ Adaptive Cruise Control (CACC/ACC) model by considering cumulative influences from multiple preceding vehicles. The simulation results from 128 simulation runs using the micro-simulator VISSIM showed that the CACF model can improve the safety and traffic congestions compared to the Wiedemann 99, the ACC, and the CACC models.

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LIST OF ABBREVIATIONS

ACC ....Adaptive Cruise Control

ADAS...Advanced Driver Assistance Systems

API ....Application Programmer's Interface

CACF ....Cumulative-Anticipative Car-Following

CACC...Cooperative Adaptive Cruise Control

CC ....Traditional Cruise

C-ITS..Cooperative Intelligent Transport Systems

COM ....Component Object Model

DLL..Dynamic Link Library

DR ....Deceleration Rate

FHWA..Federal Highway Administration

GUI ....Graphical User Interface

GFM...Generalized Force Model

MaxS ....Maximum Speed

OVM ....Optimal Velocity Model

PET ....Post Encroachment Time

SSAM...Surrogate Safety Assessment Model

VBA ....Visual Basic for Applications

VBS..Visual Basic Script

V2I ....Vehicle-to-infrastructure

V2N..Vehicle-to-network

V2P ....Vehicle-to-pedestrian

V2V..Vehicle-to-vehicle

V2X..Vehicle-to-everything

1. INTRODUCTION

1.1. Smart City and Autonomous Vehicles

The operational definition of the city which consider as smart manages the investments in human and social capital and traditional (transport) and modern (Information and Communication Technologies) wisely to achieve sustainable economic growth and high quality of life (Caragliu et al. 2011). Smart city is also known as digital city since it supports digital media (high-tech and creative industries) to share information (Hollands 2008). Incorporating new sensing, communication and social capacities with vehicles is one of the key aspects of a smart city. The fundamental step to make a smart city is to achieve the goal that autonomous vehicles access data through mobile wireless sensing and communication (Maglaras 2016) as shown in Figure 1.

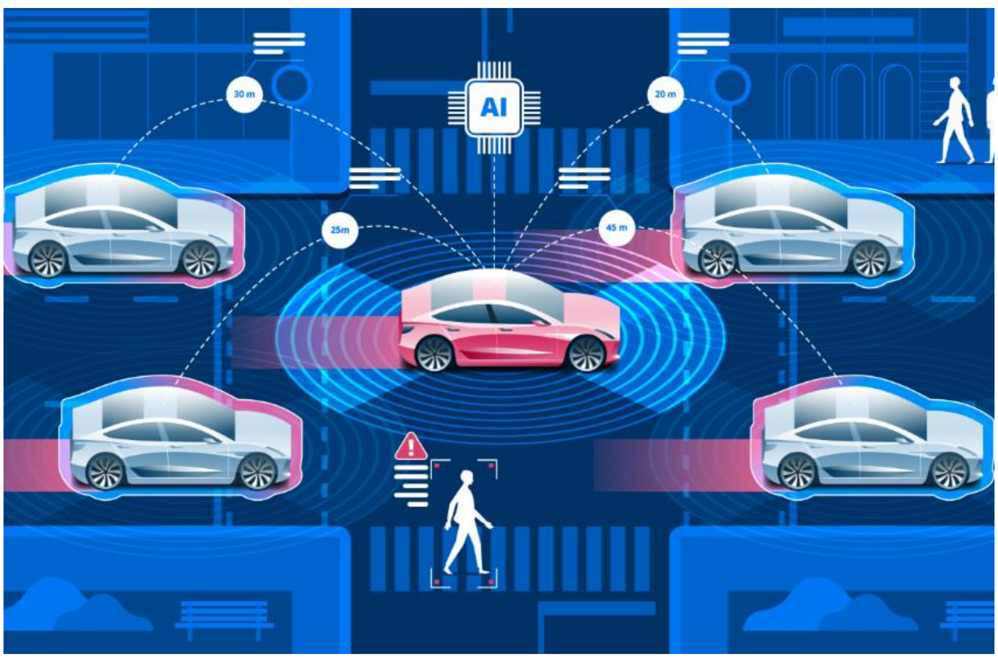

Figure 1. The schematic of a smart city (Beevor 2020)

To drive automatically, an autonomous vehicle relies on sensors on board of the vehicle, such as video cameras, radar sensors, ultrasonic sensors, lidar, global positioning system and the central computer (Younsi 2020, Harlow et al. 2001, Wu et al. 2020, Tang et al. 2020). The cameras, radar sensors and lidar units used to detect the information surrounding such as the distance to the objects (e.g. pedestrians) and traffic conditions (e.g. traffic signs), speed and acceleration of nearby objects. Then, autonomous vehicles will send all of that information to the central computer, and the computer combines and organizes the data collected by the ego autonomous vehicles and communication with other devices to control the behavior of the autonomous vehicle. The schematic diagram of sensing and its working mechanism as shown in Figure 2. Autonomous vehicles either fully automatic or with adaptive cruise control (ACC) and cooperative adaptive cruise control (CACC) provides the possibilities of smart transportation in a smart city.

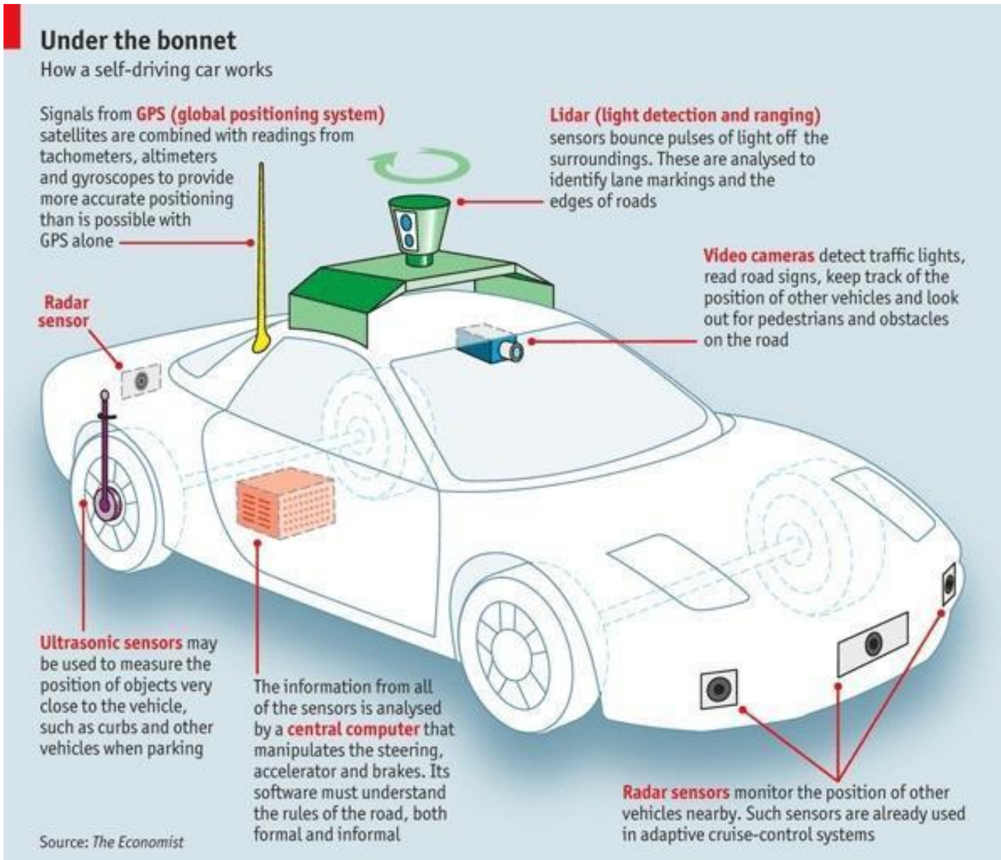

Figure 2. Sensing technologies in an automobile. (Source: The Economist)

Adaptive cruise control (ACC) extends traditional cruise control (CC) system which reaches and keeps the vehicle's pre-set speed (Stanton et al. 2005). As the first driver control assistance system entering the market, ACC has the potential to influence traffic flow characteristics (VanderWerf et al. 2001). ACC system can automatically adjust speed based on the desired spacing or speed from the preceding vehicle (Li et al. 2010). Cooperate Adaptive Cruise Control (CACC) has better performance on collision avoidance and safety than ACC since it not only receives the information from preceding vehicles but also the vehicles before the preceding one (Milanés et al. 2013).

However, the vehicle with CACC system can only communicate with other autonomous vehicles that equipped with the CACC systems. CACC systems can work well if the autonomous vehicles are fully penetrated. Unfortunately, the full penetration of autonomous vehicles will take decades, during when human-drivers will share the same road systems with the autonomous vehicles. In such a mixed driver condition, the majority of accidents associated with autonomous vehicles are induced by the operation inconsistency of human drivers.

1.2. Vehicle-to-everything (V2X)

Vehicle-to-everything (V2X) communication can solve the operation inconsistency between human drivers and autonomous vehicles since it passes information between the vehicles and other devices that may affect the driving to avoid collisions, reduce traffic congestion, and improve the driving environment. It is an integration of several more specific vehicular communication systems (Chen 2017), including vehicle-to-vehicle (V2V) (Gupta et al. 2020), vehicle-to-pedestrian (V2P) (Bagheri et al. 2014), vehicle-to-network (V2N), and vehicle-to-infrastructure (V2I) (Milanes et al. 2012). In this section, we will briefly introduce the V2X systems.

The V2V systems exchange information, such as speed, location, and heading, with surrounding vehicles based on wireless communication technologies (Harding et al. 2014).

Vehicles equipped with V2V devices will exchange their information with each other when they are within a certain distance so that the program built in the system will then decide if there is any risk or threat. If there is a potential collision risk or other threats, the V2V system will then send a warning to drivers with sound, tactile, and visual alerts — usually, a combination of them.

The V2P technologies are those connecting vehicles with the surrounding infrastructure and pedestrians to improve the pedestrian safety. It includes a broad set of road users including pedestrians, passengers boarding or get off buses and trains, handicapped people, and people riding bicycles and other mobility devices. Government and private institutions have developed many V2P technologies or systems, and they can be implemented in the infrastructure, vehicles, or pedestrians to provide warnings to pedestrians, drivers, or both (Craig et al. 2017). Unlike V2V which only requires information between vehicles, V2P usually requires information from vehicles, pedestrians, and infrastructures. As one part of a larger connected vehicle ecosystem, it is an interdisciplinary field that strongly relies on other V2X systems. Therefore, many V2P technologies are still under research and generally less sophisticated when comparing with V2V technologies.

The V2N systems link vehicles to cellular infrastructure and the cloud (application server) to exchange the information such as upcoming road conditions, traffic situations, and vehicle location. V2N communication helps a wide range of road transport activities in different fields, including regulated Cooperative Intelligent Transport Systems (C-ITS) (Kim et al .2016), Advanced Driver Assistance Systems (ADAS) (Sun et al. 2016), fleet management and logistics services, traffic planning, and navigation services.

The V2I allows vehicles to share information with traffic infrastructures which mainly include overhead RFID readers, streetlights, traffic lights, cameras, lane markers, parking meters, and so on. V2I communication is applied in this thesis by transferring the traffic data (includes basic vehicle data (such as location, velocity, and acceleration) and environment-related data (e.g. weather, humidity, temperature, and so on)) from in-pavement sensors to vehicles. The data from the in-pavement vehicle is accurate and quick. It can pass information to the autonomous vehicles to support it make the decision.

For most of the autonomous vehicles, the V2V systems are commonly implemented as connected vehicles. The application of the V2P, V2N, and V2I systems on the autonomous vehicles are still limited, however, these vehicular communication systems not only provide the information of autonomous vehicles but also the data of human-driving vehicles to the autonomous vehicles. The autonomous vehicles can significantly reduce human errors by collecting numerous data and information that can be used in autonomous driving models.

1.3. Car-following Models for Autonomous Vehicles

An autonomous vehicle requires a car-following model to be functional when the robot car is driving by itself on a road. A car-following model, as a basic model used in traffic flow simulation, can simulate the behaviors of vehicles and provides recommendations of reactions of the autonomous vehicle. There are many kinds of car-following models such as stimulus-response models, safe-distance models, desired headway models, psychophysical models, and artificial intelligence models (Chen et al. 2016, Brackstone et al. 1999, Aghabayk et al. 2015). Among those, stimulus-response model is a widely-used car-following model. Its assumption that each driver responses the stimulus from the other vehicles, the stimulus include velocity, acceleration, headway, etc. In this chapter, three most commonly used stimulus-response car-following models were reviewed with the advantages and challenges including the CACC/ACC model, the optimal velocity model (OVM), and the multi-anticipative car-following model.

1.3.1. CACC/ACC Model

The acceleration model was used for the simulation of the Cooperative Adaptive Cruise Control (CACC) and Adaptive Cruise Control (ACC) model as below (Zhao et al. 2013, Van Arem et al. 2006, VanderWerf et al. 2001):

$$a_c = k_a * a_p + k_v * (v_p - v) + k_d * (r - r_{system}) \tag{1}$$

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

$$r_{system} = t_{system} * v \tag{3}$$

where, a_p, v_p are the acceleration and speed of target vehicle; v is the current speed of the ego vehicle; a_c is the control acceleration with the liner function; a is the acceleration in next step of the objective vehicle; a_{min} is the minimum allowed acceleration; a_{max} is the maximum allowed acceleration; r is the current clearance to the target vehicle; r_{system} is following distance according to the system time setting; t_{system} is 0.5 if target vehicle has CACC, and 1.4 otherwise, and k_a, k_v, k_d are constant factors, with $k_a$to be zero for ACC.

The CACC/ACC model presented the behaviors of the vehicles in a good way, however, it controls the behavior of the model only based on the information of the target vehicle, even though ego vehicle can get information from multiple vehicles before it. The need to use multiple vehicles before the ego vehicle, the OVM (only related to preceding vehicle) and multiple-anticipate car-following model (use the information from multiple preceding vehicles) are considered and advanced.

1.3.2. Optimal Velocity Model (OVM)

The optimal velocity model (OVM), first developed by Bando et al. (Bando et al. 1995), is a well-known car-following model and considered as a famous stimulus-response model. The OVM is performed based on four assumptions (Bando et al. 1995), including 1) the motion of each vehicle is based on the responses of the driver to the stimulus from other vehicles; 2) The driver can express the response by acceleration which is direct control by the driver; 3) Each vehicle has a legal velocity which depends on the headway of the preceding vehicle; and 4) There is no time lag of response. Based on these assumptions, the OVM set the stimulus as the difference between the optimal velocity and the velocity of the considered vehicle, and the sensitivity is a constant factor. The detail model can be as shows below:

$$\ddot{x_n}(t) = a\{\mathrm{V}\left(\Delta x_{n,n+1}\right) - \dot{x_n}(t)\} \tag{4}$$

$$\Delta x_{n,n+1} = x_{n+1}(t) - x_n(t) \tag{5}$$

$$\mathrm{V}\left(\Delta x_{n,n+1}\right) = \tanh\left(\Delta x_{n,n+1} - 2\right) + tanh2 \tag{6}$$

For each vehicle number, t is the time, a represents the driver's sensitivity (assumed to be independent of n), the coordinate of the nth vehicle and the vehicle before it represents by x_n and x_{n+1}. The dots above the x_n denote differentiation with respect to time t. The headway of vehicle n and n+1 is Δx which determines the optimal velocity $\mathrm{V}(\Delta x)$.

The OVM explained the dynamic evolution characteristics (such as the stop-and-go phenomenon, traffic instability and the congestion evolution and so on) of the real traffic flow in a simple way successfully. However, the calibration using field data showed that the OV model produces unrealistically high acceleration and deceleration (Helbing et al. 1998).

Based on the optimal parameter values for city traffic in Stuttgart, the parameters of optimal velocity are k = 0.85m^{-1}, V_1 = 6.75 m/s, V_2 = 7.91 m/s, C_1 = 0.13m^{-1} and C_2 =1.57. Then vehicles adapt to a distance-dependent optimal velocity equation (Helbing et al. 1998), which can be described as:

$$V\left(\Delta x_{n,n+1}\right) = V_1 + V_2 \tanh\left(C_1 \Delta x_{n,n+1} - C_2\right) \tag{7}$$

Helbing compared the velocity and netto distance of follow-the-leader data of Bleile (Bleile 1997), generalized force model (GFM), T3 and OVM, which used the parameters in the Stuttgart. All of the models fit the data except the OVM which had extremely high acceleration. The Netto Distance did not fit the data for the OVM model although all other models fit well. Helbing assumed that there was an unobstructed vehicle and the following vehicle which were rest at the beginning, then applied OVM and T3 model to both of the vehicles and compared the acceleration change of them depending on time. It proved that the acceleration of the OVM was too large since empirical accelerations were limited to $4 \, {}^{m}/_{s^2}$ (Helbing et al. 1998). Not only the acceleration had some problems, but also the deceleration showed abnormal from the experiment. Helbing assumed there was a car moving freely at the beginning, then applied the OVM, T3 and GFM to that car and checked if it could stop efficiently when it approached the standing vehicle which were far away from it. The results showed that cars did not change the velocity until close to the standing vehicle, and there was a crash even though the deceleration was unrealistic large (Helbing et al. 1998).

1.3.3. Multi-anticipative Car-following

The unrealistically high acceleration and deceleration of OVM can be resolved by using the multi-anticipative car-following model, which was developed by Lenz et al. in 1999(Lenz et al. 1999). The multi-anticipative car following mode solves the issue of instabilization of dynamical behavior of the OVM model by considering the reaction to more than one vehicle ahead the ego vehicle, which can be described as (Lenz et al. 1999):

$$\ddot{x_n}(t) = \sum_{j=1}^{m} a_j \{\mathrm{V}\left(\frac{\Delta x_{n,n+j}}{j}\right) - \dot{x_n}\} \tag{8}$$

$$\mathrm{V}\big(\Delta x_{n,n+j}\big) = \tanh\big(\Delta x_{n,n+j} - h\big) + \tanh(h) \tag{9}$$

where h is a constant number, overall sensitivity $a = \sum_{j=1}^{m} a_j$ (the sensitivity ratios are assumed to satisfy $\frac{a_j}{a_1} \leq 1, j = 2,3, \ldots, m$). Multi-anticipative Car-following will be totally same as the OVM when the number of m equals to 1 where m is the number of vehicles ahead. The region of the stability increase since the number of interacting vehicles and sensitivity ratio $\frac{a_j}{a_1}$ growing.

Although the multi-anticipating model considered the stabilization of dynamical behavior by multiple preceding vehicles, two problems exist in this model that the desired velocity depends on the average clearance of preceding vehicles which will influence the accuracy of the result when the unnormal velocity, acceleration occurs to the vehicles.

1.4. Problem Statements

From the literature reviews, it can be seen that the commonly applied car following models to the vehicles can smoothen traffic flow and enhancing traffic safety. However, these current algorithms control the vehicles through acceleration and deceleration which only depend on ego vehicle and target vehicle, even though the CACC can get the information from multiple preceding vehicles. The multi-anticipate car-following model can solve the problem of OVM by considering more information from more preceding vehicles, however, there are some shortcomings supposed to be dealt with by the considering of cumulative-anticipative which proposed by this article. In addition, none of the car following models currently available considers potentials of using data from V2P, V2N, and V2I systems.

1.5. Objectives and Arrangement of This Thesis

In this study, the objective is to build a new car-following model which considers the importance of the selected cumulative influence of multiple preceding vehicles in the real conditions and prove its improvement of traffic safety and congestion by simulations. To achieve the objectives, there are two specific tasks including:

1) Developing new car-following models considering the filtered cumulative influence of multiple preceding vehicles;
2) Evaluating the effectiveness of the new models with the traffic data obtained from various V2X systems as input using the VISSIM micro-simulator.

Accordingly, this thesis is organized as follows:

Chapter 2 develops the new cumulative-anticipative car-following models with consideration of real-time inputs from V2X;

Chapter 3 sets up the VISSIM simulation for evaluation of the new models;

Chapter 4 discusses the simulation obtained from VISSIM to prove the effectiveness of the new models;

Chapter 5 concludes this study and introduces potential future work.

2. CUMULATIVE-ANTICIPATIVE CAR-FOLLOWING MODEL ECUTE WITH V2X

ACC/CACC model performs well with only consider the information of one target vehicle since the penetration rate of the autonomous vehicle is high which might need decades to achieve. The information of multiple preceding vehicles is necessary for autonomous vehicles since the penetration rate of the autonomous vehicles is low. The development of the ACC/CACC model from considering the information from one vehicle to multiple vehicles learns from the development from OVM to multi-anticipative car-following model. OVM is a well-known car-following model that can demonstrate the dynamic evolution characteristics of the real traffic flow in a simple way successfully, however, the OVM exists unrealistic acceleration and the inevitable crashes while deceleration is abnormally larger than normal (Helbing et al. 1998). Multi-anticipating model solve the problems with the consideration of multiple preceding vehicles' reaction, however, its accuracy influenced when abnormal velocity, acceleration occurs to the vehicle while desired velocity calculated through multi-anticipating model depends on the average clearance of preceding vehicles. This chapter develops the accumulative car-following model which considers multiple vehicles ahead and the reaction between every two vehicles among them to increase the safety of the CACC model with high stabilization and similar speed.

2.1. The Cumulative-anticipative Car-following Model

The traditional multi-anticipative car-following model also considered multiple vehicles to increase the safety following distance of the autonomous vehicles (AVs). However, the desired velocity in traditional multi-anticipative car-following model depends on the average car following clearance of the vehicles in front of the AVs, which might lead to errors, since it ignores the influences of the unusual conditions such as car crashes. For example, if ten cars were assumed ahead one AV and a car crash occurred for the fifth car, the average clearance of vehicles ahead would decrease since some vehicles begin to reduce their speeds. But the influence of the crash would be divided by the ten cars for an average in such a model, which would induce delay of the ego vehicle to make the decision.

Different from the traditional multi-anticipative car-following model, the cumulative-anticipative car-following (CACF) model developed in this study will select the data which can provide the right decision to the AVs for enhanced safety. The new CACF model uses the actual measured information of vehicles from V2X systems to calculate the desired velocity and acceleration of the AVs, then predict the driving distances after every system time period with the actual measured traffic data and the desired data separately and also calculate the difference between them. Instead of just summing all of the difference of predicted desired clearance and predicted clearance of each vehicle together and dividing the sum by the total number of vehicles, the new CACF model considers the influences of every two adjacent vehicles interaction. The new CACF model applies the difference of predicted desired clearance and predicted clearance to provide assistances to the following vehicle one by one and guide the AVs for a safer decision. The new CACF model also considers the crashes and set factors to avoid the influences of the crashes.

In the new CACF model, reference preceding vehicles will need to be selected as shown in Figure 3. Not all of the vehicles ahead of the ego vehicle will be considered as reference vehicles. Based on the headway between each two preceding vehicles, the CACF model will only select the vehicles (in green color) whose headway is less than the maximum range of the vehicles' headway (h) and ignore other vehicles (yellow color). The value of the maximum range of the vehicles' headway (h) depends on the speeds of vehicles and the volumes of the road.

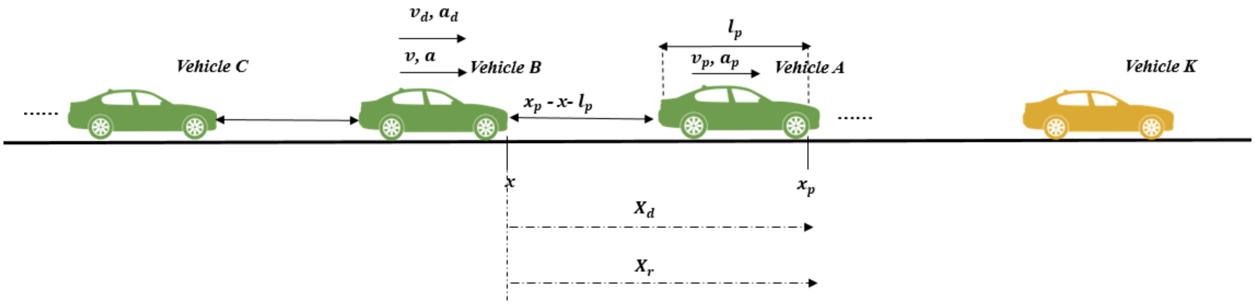

Figure 3. Schematic of the new CACC model

After each reference preceding vehicle selected, the desired velocity of the next vehicle (v_d) will be calculated based on the coordinate of itself and the vehicles before it(x and x_p), the length of preceding vehicle (l_p), actual velocity of itself and the vehicles before it(v and v_p), actual acceleration of the following vehicle (a) and predicted clearance of desired and real data of the preceding vehicle (X_d and X_r), as below:

$$v_d = g * [v_p + k_d * (r - t_{system} * v)] + m * \{v_p + k_d * [r - t_{system} * v + (-1)^c * (X_d - X_r)]\} + k * [v + (a * t_{system})] \tag{10}$$

in which, factors, g, m, and k, determine the working environment of Equation (10). g, m, k works at the condition that the desired acceleration of the target vehicle is unknown, the desired acceleration of target vehicle is known and the control acceleration is not exceeding range of acceleration (not more than maximum acceleration and not less than minimum acceleration), the desired acceleration of target vehicle is known and the control acceleration is exceeding range of acceleration, respectively. Thus, g equals to 1 if the desired acceleration of the target vehicle is unknown and 0 otherwise; m equals to 1 if the desired acceleration of the target vehicle is known and $a_c = a_d$, and 0 otherwise; k is equal to 1 if the desired acceleration of the target vehicle is known and $a_c \neq a_d$, and 0 otherwise; k_d is constant factor; t_{system} is system time period, if the preceding and following vehicles are in the CACC model, the system time period is 0.5s, otherwise, it is 1.4s. c is equal to 1 if $X_d > X_r, r >$ safe distance, and 0 otherwise.

The equation of following vehicle clearance (r) and the safe distance (X_s) is:

$$r = x_p - x - l_p \tag{11}$$

$$X_s = CC0 + CC1 * v \tag{12}$$

where, CC0 is standstill distance and CC1 is headway time.

The control acceleration of the following vehicle can then be computed based on the clearance of the following vehicle(r), actual velocity of itself and the vehicles before it(v and x_p), actual acceleration of the preceding vehicle (a_p) and predicted clearance of desired and real data of the preceding vehicle (X_d and X_r), as below:

$$a_c = k_a * a_p + k_v * \left(v_p - v\right) + k_d * \left(r - t_{system} * v + (-1)^c * (X_d - X_r)\right) \tag{13}$$

where, k_a, k_v is constant factors.

The desired acceleration can be obtained by limiting control acceleration greater than minimum acceleration and maximum acceleration as:

$$a_d = max[a_{min,}\min(a_{c,}a_{max})] \tag{14}$$

If the desired acceleration of the third reference preceding vehicle is the minimum/maximum acceleration, the desired velocity of the third reference preceding vehicle can be estimated using kinematic equation. If the desired acceleration is equal to control acceleration, the desired velocity is calculated using the new CACF model.

Based on the desired velocity and acceleration obtained from Equation (10,13), the desired clearance of the following vehicle at next system time period (t_{system}) can be predicted using kinematic equation as:

$$X_d = v_d * t_{system} + \frac{1}{2} a_d * {t_{system}}^2 \tag{15}$$

Then the clearance of the following vehicle at next system time period can be predicted using the actual velocity and acceleration through the kinematic equation as below:

$$X_r = v * t_{system} + \frac{1}{2} a * {t_{system}}^2 \quad (16)$$

If the predicted desired clearance (X_d) is greater than predicted clearance (X_r), it means that the following vehicle keeps more distance from the vehicle before it while it keeps the same velocity and acceleration at the next system time period. Then the difference between the predicted desired clearance and predicted clearance need to be subjected from the CACF model to decrease the acceleration of third reference preceding vehicle to increase its headway. However, if the desired distance is less than predicted clearance, that indicates that the following vehicle does not have enough distance from the vehicle before it while it keeps the same velocity and acceleration at next system time period.

There are potentially two reasons which can lead to such a condition, including 1) although the following vehicle supposes to drive quick but it drives too slow, and 2) there is conflict before the preceding vehicle inducing the slow-down of the preceding vehicle to avoid the conflict which leads to less distance between the preceding and following vehicles. In the first circumstance, the difference between the predicted desired clearance and predicted clearance need to be subjected from the CACF model to increase the acceleration of vehicle next to the following vehicle and decrease the headway. For the second circumstance with a conflict before the ago vehicle, the third reference preceding vehicle is supposed to slow down. Then the difference between the predicted desired clearance and predicted clearance need to add to the CACF model to decrease the acceleration of third reference preceding vehicle and increase the headway.

Thus, if the traffic data from preceding vehicles (speed, clearance, etc.) is updated in real time, the desired velocity, desired acceleration, predicted desired clearance and predicted clearance of ego vehicle can then be calculated using Equations (10-16). The desired velocity and acceleration of the vehicle after ego vehicle can then be estimated for conditions with n vehicles ahead. More details for the derivation of n vehicles are shown in next section.

2.2. CACC Model Setup with Inputs from V2X

Any data transferred through V2X can be used as inputs to the developed new CACC model. However, in this study, we have selected an example of a V2I system to demostrate the setup of the model. In this example, we assume that there is a total of n vehicles and the nth vehicle is an AV. All the traffic information of the (n-1) vehicles ahead of the AV can be obtained using infrastructure or roadside sensors. The traffic data obtained includes the vehicle length, coordinate, velocity and acceleration. These data is expected to be transmitted to the AV through the V2I system. The new CACF model optimizes the AV's (the tenth vehicle's) driving speed, following distance, clearance, and other operation for a safer performance through the information of the preceding vehicles (also known as reference vehicles in the model) from the V2I system. Considering that in this example there are (n-1) vehicles before the AV, the number of reference preceding vehicles will be less than (n-1) vehicles in the model setup the number of the reference vehicle. As shown in Figure 4,l_1, l_2, l_3, ... , l_{n-1}, $l_n$is the length of the 1st, 2nd, 3rd, ... , (n-1)th, and nth vehicle. x_1, x_2, x_3, ... , x_{n-1}, $x_n$is the coordinate of the 1st, 2nd, 3rd, ... , (n-1)th, and nth vehicle. v_1, v_2, v_3, ... , v_{n-1}, v_n is the velocity of the 1st, 2nd, 3rd, ... , (n-1)th, and nth vehicle. a_1, a_2, a_3, ... , a_{n-1}, $a_n$is the acceleration of the 1st, 2nd, 3rd, ... , (n-1)th, and nth vehicle.

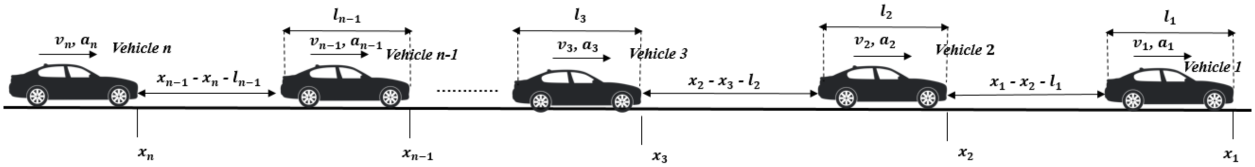

Figure 4. Schematic of the new CACC model with n vehicles

Since the clearance of the first and second vehicle is unknown, the desired acceleration of the first vehicle is also unknown. Thus, for the second vehicle, we have $\mathrm{g} = 1, \mathrm{m} = 0, \mathrm{k} = 1$. Based on Equation (10-15), for the second vehicle, the desired velocity ($v_{d(2)}$), the control acceleration ($a_{c(2)}$), the desired acceleration ($a_{d(2)}$), the predicted desired clearance ($X_{d(2)}$), and the predicted clearance ($X_{r(2)}$) can be given as:

$$v_{d(2)} = v_1 + k_d * \left((x_1 - x_2 - l_1) - t_{system} * v_2\right) \tag{17}$$

$$a_{c(2)} = k_a * a_2 + k_v * (v_1 - v_2) + k_d * \left((x_1 - x_2 - l_1) - t_{system} * v_2\right) \tag{18}$$

$$a_{d(2)} = max[a_{min,} \min(a_{c(2),} a_{max})] \tag{19}$$

$$X_{d(2)} = v_{d(2)} * t_{system} + \frac{1}{2} a_{d(2)} * t_{system}{}^2 \tag{20}$$

$$X_{r(2)} = v_2 * t_{system} + \frac{1}{2} a_2 * t_{system}{}^2 \tag{21}$$

in which, t_{system} is system time period, k_a, k_v, k_d is constant factors.

For the third vehicle, since the desired acceleration of the second vehicle is now known, we have $\mathrm{g} = 0$. The safe distance of the third vehicle can be obtained as:

$$X_s = CC0 + CC1 * v \tag{22}$$

If $a_{c(2)} = a_{d(2)}$, the difference of the predicted desired clearance and the predicted clearance of the second vehicle does not exceeding the range of acceleration. That means the difference of the predicted desired clearance and the predicted clearance can be valid to calculate the desired velocity of the third vehicle, and its meet the condition for factors $\mathrm{m} = 1, \mathrm{k} = 0$. If $X_{d(2)} > X_{r(2)}\ and\ x_2 - x_3 - l_2 > X_{s(3)}$, it means even though the predicted desired clearance is greater than the predicted clearance, there is no unnormal condition such as crash before the second vehicle because its clearance is greater than the safe distance, then, we have $\mathrm{c} = 1$. In this case, the desired velocity of the third vehicle can be written as:

$$v_{d(3)} = v_2 + k_d * \left[(x_2 - x_3 - l_2) - t_{system} * v_3 + (-1) * \left(X_{d(2)} - X_{r(2)}\right)\right] \quad (23)$$

In the condition of $a_{c(2)} = a_{d(2)}$, if $X_{d(2)} \leq X_{r(2)}$ or $x_2 - x_3 - l_2 \leq X_{s(3)}$, the predicted desired clearance is greater than the predicted clearance because there is unusual condition exists before the second vehicle since its clearance is less than safe distance, then, we $c = 0$. Thus, the desired velocity of the third vehicle can be given as:

$$v_{d(3)} = v_2 + k_d * \left[(x_2 - x_3 - l_2) - t_{system} * v_3 + \left(X_{d(2)} - X_{r(2)}\right)\right] \quad (24)$$

If $a_{c(2)} \neq a_{d(2)}$, the difference of predicted desired clearance and the predicted clearance of the second vehicle exceeds the range of acceleration, and the difference of the predicted desired clearance and the predicted clearance cannot be valid to calculate the desired velocity of the third vehicle, which is the reason that it meets the condition for factors we have $m = 1, k = 10$. In this case, the desired velocity of the third vehicle can be calculated as:

$$v_{d(3)} = k * [v_3 + \left(a_3 * t_{system}\right)] \quad (25)$$

If $X_{d(2)} \leq X_{r(2)}$ or $x_2 - x_3 - l_2 \leq X_{s(3)}$, we have $c = 1$, the control acceleration of the third vehicle can be calculated as:

$$a_{c(3)} = k_a * a_2 + k_v * (v_2 - v_3) + k_d * \left((x_2 - x_3 - l_2) - t_{system} * v_3 + (-1) * (X_{d(2)} - X_{r(2)})\right) \quad (26)$$

Otherwise, the control acceleration of the third vehicle can be calculated as:

$$a_{c(3)} = k_a * a_2 + k_v * (v_2 - v_3) + k_d * \left((x_2 - x_3 - l_2) - t_{system} * v_3 + \left(X_{d(2)} - X_{r(2)}\right)\right) \quad (27)$$

Therefore, the desired acceleration ($a_{d(3)}$), the predicted desired clearance ($X_{d(3)}$), and the predicted clearance ($X_{r(3)}$) of the third vehicle can be computed as:

$$a_{d(3)} = max[a_{min,} \min(a_{c(3),} a_{max})] \quad (28)$$

$$X_{d(3)} = v_{d(2)} * t_{system} + \frac{1}{2} a_{d(2)} * t_{system}{}^2 \quad (29)$$

$$X_{r(3)} = v_3 * t_{system} + \frac{1}{2} a_3 * t_{system}{}^2 \quad (30)$$

Similarly, for the n^th^ vehicle, since the desired acceleration of the previous vehicle is known, then we have $g = 0$, the safe distance of the n^th^ vehicle can be obtained as:

$$X_{s(n)} = CC0 + CC1 * v_n \quad (31)$$

If $a_{c(n-1)} = a_{d(n-1)}, X_{d(n-1)} > X_{r(n-1)}\ and\ x_{n-1} - x_n - l_{n-1} > X_{s(n)}$, we have $m = 1, k = 0, c = 1$. Then, the desired velocity of the n^th^ vehicle can be obtained as:

$$v_{d(n)} = v_{n-1} + k_d * \left[(x_{n-1} - x_n - l_{n-1}) - t_{system} * v_n + (-1) * \left(X_{d(n-1)} - X_{r(n-1)}\right)\right] \quad (32)$$

If $a_{c(n-1)} = a_{d(n-1)}, X_{d(n-1)} \leq X_{r(n-1)}\ or\ x_{n-1} - x_n - l_{n-1} \leq X_{s(n)}$, we have $m = 1, k = 0, c = 0$. The desired velocity of the n^th^ vehicle can be calculated as:

$$v_{d(n)} = v_{n-1} + k_d * \left[(x_{n-1} - x_n - l_{n-1}) - t_{system} * v_n + \left(X_{d(n-1)} - X_{r(n-1)}\right)\right] \quad (33)$$

If $a_{c(n-1)} \neq a_{d(n-1)}$, then $m = 0, k = 1$. The desired velocity of the n^th^ vehicle can be obtained as:

$$v_{d(n)} = k * \left[v_n + \left(a_n * t_{system}\right)\right] \quad (34)$$

If $X_{d(n-1)} \leq X_{r(n-1)}\ or\ x_{n-1} - x_n - l_{n-1} \leq X_{s(n)}$, then $c = 1$, the control acceleration of the n^th^ vehicle can be shown as:

$$a_{c(n)} = k_a * a_{n-1} + k_v * (v_{n-1} - v_n) +$$

$$k_d * \left((x_{n-1} - x_n - l_{n-1}) - t_{system} * v_n + (-1) * (X_{d(n-1)} - X_{r(n-1)})\right) \quad (35)$$

Otherwise, the control acceleration of the n^th^ vehicle can be obtained as:

$$a_{c(n)} = k_a * a_{n-1} + k_v * (v_{n-1} - v_n) +$$

$$k_d * \left((x_{n-1} - x_n - l_{n-1}) - t_{system} * v_n + \left(X_{d(n-1)} - X_{r(n-1)}\right)\right) \quad (36)$$

Thus, the desired acceleration ($a_{d(n)}$), the predicted desired clearance ($X_{d(n)}$), and the predicted clearance ($X_{r(n)}$) of the nth vehicle can be calculated as:

$$a_{d(n)} = max[a_{min,} \min(a_{c(n),} a_{max})] \tag{37}$$

$$X_{d(n)} = v_{d(n-1)} * t_{system} + \frac{1}{2} a_{d(n-1)} * t_{system}{}^{2} \tag{38}$$

$$X_{r(n)} = v_n * t_{system} + \frac{1}{2} a_n * t_{system}{}^{2} \tag{39}$$

where k_a equal to 1 only for the nth vehicle which is autonomous vehicle, and equal to zero for other vehicles.

2.3. Summary

All in all, this chapter derives the mathematical model of the new CACF model and how it applied to the multiple vehicles by communicating with the V2X system. Compared with traditional car following models, the contributions of the new CACF includes:1) the use of the real-time traffic data from the V2X systems, especially from V2I systems, 2) the consideration of the importance of every two vehicles' interaction and the overlay of differences between the predicted desired and velocity to predict the actual velocity of every vehicle one by one, and 3) the change of the acceleration relatively based on the difference between the predicted desired clearance and the predicted clearance to avoid the unusual conditions such as car crashes and to smoother the traffic flow, respectively.

3. EVALUATION OF CACF MODEL USING SIMULATION

To evaluate the effectiveness of the newly developed CACF model for and enhanced safety operation of AVs with considerations of inputs from V2X, in this study, we used the micro-simulator “Verkehr In Städten – SIMulationsmodell” (VISSIM), which is developed by PTV Planung Transport Verkehr AG in Karlsruhe, Germany, to provide a case study. T The case study considers integrating the traffic data from nine cars in front of an AV, which means that the tenth car is the autonomous vehicle. The traffic data of the nice cars in front of the AV is assumed to be obtained through the V2I system from infrastructure or roadside sensors, which does not have independence of V2V systems. In this case, the nine cars in front of the AV can be a regular human driving vehicle, which is the most common traffic condition in current traffic and will maintain in such a condition for quite a while before the penetration rate of the AVs arise. The obtained traffic data from the V2I system includes vehicle velocity, acceleration, and coordinate from the nine vehicles before the AV. Based on these assumptions, a simulation model is built using the micro-simulator VISSIM with the new CACF model. Based on these model setups, comparisons will be performed in Chapter 4 between the new CACF model and traditional human-driver model, the ACC model, and the CACC model. This chapter introduces the VISSIM software and the parameters determination for this case study to run the simulation on the VISSIM.

3.1. VISSIM Interfaces and Safety Evaluation Model SSAM

The VISSIM software is a behavior-based micro-simulation traffic software that widely used in the urban and highway simulation. The technical features of pedestrians, bicyclists, motorcycles, cars, trucks, buses, trams, light (LRT), and heavy rail are included in the VISSIM to analyze and optimize traffic flow under variety of traffic conditions, such as lane setting, traffic composition, traffic signals, and bus stops (Fellendorf et al. 2010). Users can control the simulations of transportation flow based on the Graphical User Interface (GUI), the Component Object Model (COM) and the Dynamic Link Library (DLL) (Tettamanti et al. 2012). Surrogate Safety Assessment Model (SSAM) could be applied to evaluate the number of conflicts between vehicles to test the suitability of the transportation model. The result of simulations could be used to improve the traffic state to reduce congestions and emissions.

3.1.1. Graphical User Interface (GUI)

In order to provide support to more users, the VISSIM offers a user-friendly graphical interface (GUI) which controls most of the factors of simulation (PTV Group, 2019a) as shown in Figure 5. The GUI includes various user-friendly operational functions such as title bar (file, program name), menu bar (call program functions), toolbars (call program functions), network editors (show the currently open network), network objects toolbar (select visibility and selectability, edit graphic parameter, show and hide label for network objects; select insert mode of network objects types; context menu for additional functions), levels toolbar (select visibility and editing option of levels), background toolbar (select visibility of background), project explorer (display projects), lists (show and edit different data), quick view (show and change attribute value), smart map (shows a small-scale overview of the network), and status bar (show current state). Even though the VISSIM GUI can control the internal VISSIM parameters conveniently, the external software packages still need other interfaces to operate.

Figure 5. VISSIM GUI with a network file opened (PTV Group, 2019a)

3.1.2. Component Object Model (COM)

The VISSIM software has a COM interface which can access the data and functions though many programming languages and scripting languages, such as Visual Basic for Applications (VBA), Visual Basic Script (VBS), Python, C, C++, C#, Delphi, JAVA and MATLAB (PTV Group, 2019b). There are four general steps to perform adaptive control logic through the COM interface in the VISSIM software (Tettamanti et al. 2015) as below:

1) creating an overall traffic network through the VISSIM GUI;
2) selecting a programming or scripting language which allows the COM interface to access the data and functions of simulation;
3) programing the simulations using the COM interface with specific commands including multiple and automated runs, vehicle behavior, evaluation during simulation run (online), and traffic-responsive signal control logic;
4) simulation running using the programed COM interface.

3.1.3. Dynamic Link Library (DLL)

In addition to the COM interface, the VISSIM also provides variety of Application Programmer's Interface (API) packages including Signal Control, Signal GUI, Emission Model, and Driver Model DLL files (PTV Group, 2019a). The use-defined attributes can also be conducted through the VISSIM DLL. Compared with the COM interface, users can control the vehicles with user defined car-following model by editing the DLL with C++. To perform the case study in this study, we selected the DLL for simulation. The Driver Model DLL files includes three parts (PTV Group, 2019c), which are:

1) the header file, DriverModel.h, which contains the definitions of all "type" and "number" constants used by VISSIM;

2) the main source file, DriverModel.cpp, which contains calculations and calls of functions of driving behavior model algorithm;
3) the resource file: DriverModel.vcproj, which can be used if the DLL is to be created with Microsoft Visual C++.

During each simulation run, the VISSIM will call the DLL code for each affected vehicle in every simulation time step to determine the behavior of the vehicle. Fully user-defined behavior can be simulated by the VISSIM though replacing the internal driver model algorithm with the user-defined driver model algorithm and functions in the DriverModel.cpp file through C/C++. To integrate the ACC, CACC and new CACF model in the VISSIM DLL, three steps are performed (PTV Group, 2019c) including:

1) setting value through asking the VISSIM to send the current state and surroundings to the DriverModel.cpp file,
2) getting value through the DriverModel.cpp file to calculate the vehicle information (such as desired velocity, desired acceleration, desired lane changes and so on) of the vehicle based on the user-defined model algorithms and passing them to the VISSIM simulation,
3) and executing command in the current time step based on the calculated vehicle data from the values using the user-defined models.

For the sensitivity analysis, the values of the parameter in the ACC, CACC and CACF models, k_v and k_d set to be 0.58 and 0.1 within the base simulation as Zhao and Sun (2013). These values were set down at the DriverModel.cpp file in the DLL.

3.1.4. Surrogate Safety Assessment Model (SSAM)

To evaluate the effectiveness of a new model, Federal Highway Administration (FHWA) suggests the Surrogate Safety Assessment Model (SSAM), which can analyze vehicle safety in the microscopic traffic simulation model (Huang et al. 2013, Abou-Senna et al. 2015). The Gettman and Head surrogate safety from the SSAM model can be integrated with commonly available microscopic traffic simulation models such as the CORSIM, VISSIM, SIMTRAFFIC, PARAMICS, HUTSIM, TEXAS, WATSIM, INTEGRATION, and AIMSUN (Gettman et al. 2003) software. Nowadays, the SSAM can automatically perform conflict analysis by the data from the VISSIM software.

The traffic events could be considered as traffic conflicts when the drivers need evasive maneuvers such as slow down quickly, changes lanes sudden to avoid collision (Fyfe 2016). The traffic conflict first proposed by Perkins and Harris (1968) to identify the traffic events which have higher occurrence frequency than collision. The technique used to record the frequency and severity of conflicts called traffic conflicts technique which could apply to evaluate the unsafe driving maneuvers before the collisions occur (Chin, 1997). Instead of evaluate the safety based on the collision data which required long collection periods since collisions do not occur frequently enough to produce a sufficient data set in a short period, traffic conflicts reduced collection time with less cost and provide enough data to make the data analysis (Fyfe 2016).

Based on the angle of the conflict, there are three types of conflicts (Pu et al. 2008) including the rear end with collision angle less than 30 °, the lane change with collision angle larger than 30 ° and less than 85 °, and the crossover with collision angle larger than 85 °, as shown in Figure 6. In this study, we only concern the rear-end conflict since the simulation execute at the one lane road.

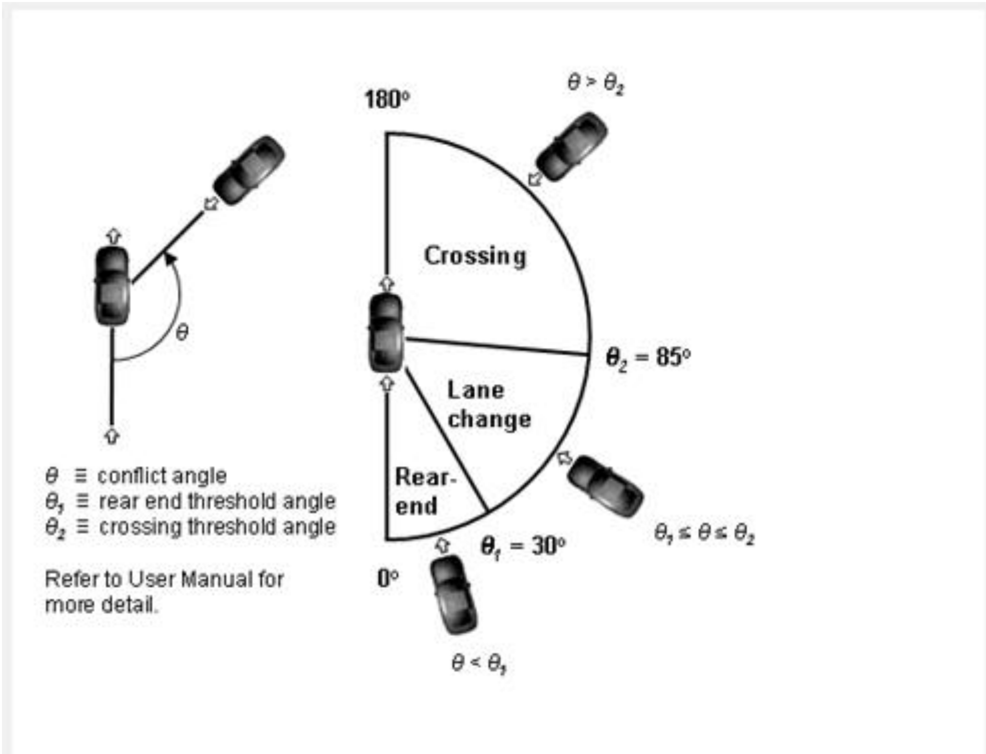

Figure 6. Conflict angle diagram used by SSAM (Source: SSAM Software)

SSAM can count the number of conflicts, types of conflicts, severity, and location of conflicts based on the traffic conflict indicators. There are five common traffic conflict indicators (Das 2018), including: 1) time-to-collision (TTC) which defined by Hayward (1972) as the time required for two vehicles to collide if they keep current speeds on the same path, the gap distance between a subject vehicle and the conflicting vehicle or pedestrian divided by their velocity difference (Lee 1976), 2) the post encroachment time (PET) which is the time between the first vehicle occupied at a position and next vehicle arrived at the same position, 3)the initial deceleration rate (DR) of the second vehicle, 4)the maximum speed (MaxS) of vehicles throughout the conflict, 4) the differences (DeltaS) in vehicle speeds observed at the minimum time to collision. In this simulation, we define there exists a conflict when the TTC and PET is 3 and 5 seconds as shown in Figure 7, the less the conflicts, the safer the situation is.

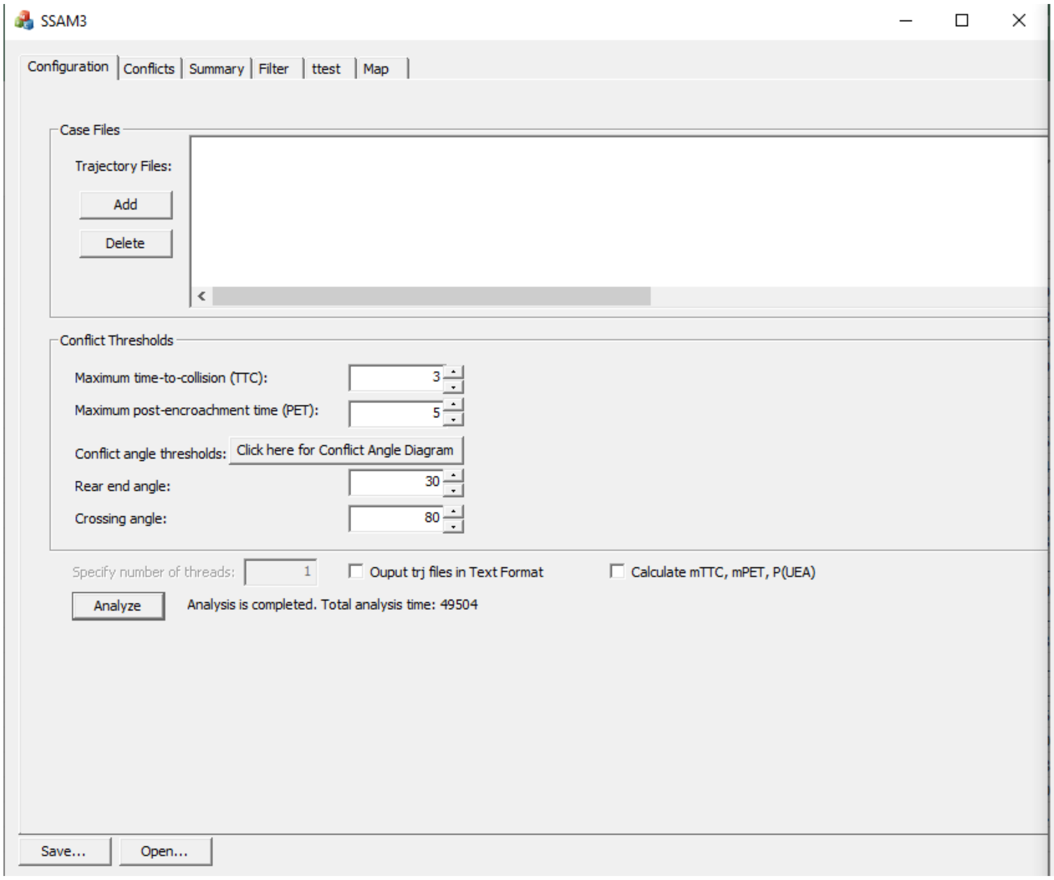

Figure 7. SSAM parameters (source: VISSIM)

3.2. VISSIM Driver Behavior Wiedemann 99

The VISSIM has its own in-build driver behavior models for human drivers including the Wiedemann 74 and 99. In this study, the Wiedemann 99 driver behavior model is used. The driver behavior of the human drivers in the Wiedemann 99 model depends on nine factors as shown in Table 1. To ensure the consistency of the parameters, the values of CC0 and CC1 which used in the CACF model are set to be the same as the default values in Wiedemann99 model during the simulation.

Table 1. Parameters and default values of Wiedemann 99 (Source: VISSIM)

VISSIM Code	Parameter	Default Value
CC0	Standstill Distance	1.50 m
CC1	Headway Time	0.90 s
CC2	Following Variation	4.00 m
CC3	Threshold for Entering 'Following' State	-8.00
CC4	Negative 'Following' Threshold	-0.35
CC5	Positive 'Following' Threshold	0.35
CC6	Speed Dependency of Oscillation	11.44
CC7	Oscillation Acceleration	$0.25\ m/s^2$
CC8	Standstill Acceleration	$3.5\ m/s^2$
CC9	Acceleration at 80 km/h	$1.5\ m/s^2$

3.3. Simulation Framework Setup for The Case Study

To perform the designed case study of ten vehicles, in the VISSM software, the simulation is executed at the 5-kilometer link using a single lane traffic. The freeway behavior type is used with the number of interaction objects of two. In this case study, there are only two types of vehicles considered, the human driving normal vehicle and the autonomous vehicle. The normal vehicle applied default car-following model Wiedemann 99 whereas the autonomous vehicles used the ACC model, CACC model, and new external CACF driver model introduced at the Chapter 2. The type number of all of AVs is set as 110 (which is shown in red color) as shown in Figure 6. For the human driving vehicles, two type numbers are considered which are set as 100 and 101 based on their characteristics (Figure 8). The Type 100 vehicles (green color) will stop before the stop signs whereas The Type 101 (black color) will not stop. The penetration rate of AVs is assumed to be 10% of the traffic flow. The occupation ratio of normal cars Type 100, normal cars Type 101 and AVs are set as 1:89:10, while the appearance order is random. This means that within every 100 cars, there is one human driving Type 100 vehicle will stop and induce a conflict, 89 regular human driving Type 101 cars will tends to behave normal, and 10 AVs will use the newly developed CACC model to operate. The design posted speed of the single lane traffic is set to be 45 mph, 50 mph, 55 mph, and 60 mph whereas the maximum acceleration/deceleration, desired acceleration/deceleration, and desired speed are kept as default.

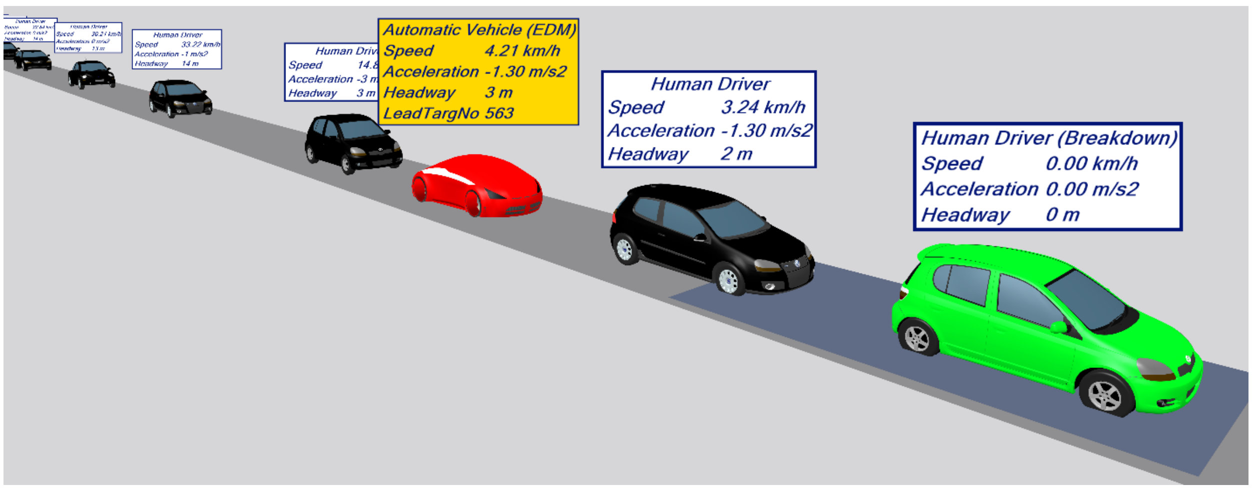

Figure 8. Diagram of vehicle information when simulate in the VISSIM (Source: VISSIM)

The freeway capacity is set to be 1900, 2000, 2100 and 2200 passenger cars per hour per lane (pc/h/ln) with speeds of 45 mph, 50 mph, 55 mph and 60 mph (TRB 2010), respectively. For each simulation run, the total simulation time is 4500 sec which are divided into five travel intervals (each travel interval is 900 sec), and the initial 900 sec is allocated for network warm-up which is not be evaluated as part of the results of traffic simulation.

The random seeds under simulation parameter settings generate stochastic variations between each successive simulation run. The initial random seed is set to be one with an increment of five for each simulation. The simulation will have the same vehicle input when the seed is same. The simulation resolution is a number of time steps per simulation second that specifies how often a vehicle is moving during a simulation second. This study used a simulation resolution of 10 to ensure a realistic demonstration of traffic simulation. Given the nature of traffic varies with respect to time, multiple simulations are performed to compare the results for each run. The number of simulation runs is set to 8 and the results are discussed in the Chapter 4. Figure 9 shows the detailed simulation parameters.

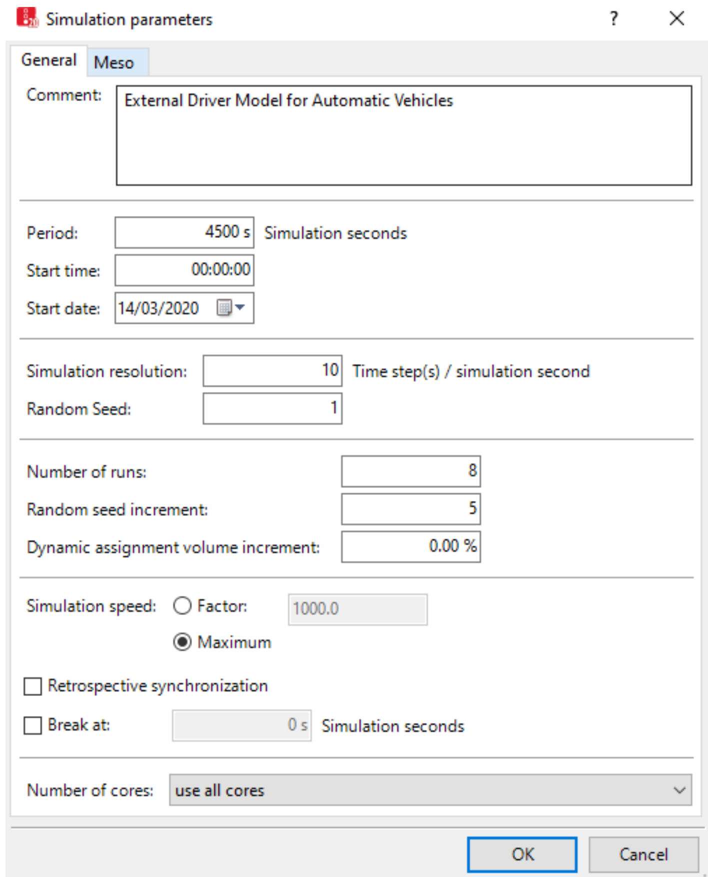

Figure 9. Simulation parameters (Source: VISSIM)

3.4. Safety Feature Evaluation Technique

In the VISSIM, the distance between every two vehicles which generate with the internal model are set to kept safe and standstill distance from preceding vehicles at the normal condition and the emergency condition, respectively. Therefore, there are no vehicles which can be considered as conflicts for most conditions. However, this study wants to evaluate the safety and efficiency of the newly developed models based on the conflicts' numbers and behaviors when the vehicles facing the conflicts. So, a hypothetical breakdown using the stop signs network object is created at a position of 4,000 meters on the link. That stop sign can only stop the normal vehicles with Type 101 and only stop the normal vehicles with Type 101 for 2 seconds. There is a five hundred meters road after the stop sign are set to demonstrated how many cars will stop to avoid the Type 101 vehicles which stop at stop sign and the number of the cars which stop are counted. The SSAM will count the conditions that traffic indicators (such as time-to-collision) out of range as conflicts as shown in Figure 7. The traffic congestion can be proved to be improved if the number of stops is smaller.

The stop sign will only stop the Type 101 vehicle which occupies 1% of the volume of traffic flow. The Type 101 vehicle will stop only two seconds which is set as conflicts in this study. The reflection of the vehicles after the Type 101 vehicle can be used to analyze the safety and smoothness of the traffic. The traffic congestion can be proved to be decrease if the number of stops is smaller. The stop sign acts as a vehicle crash for normal cars with a dwell time of 2 seconds. Inside the vehicle composition, a duplicate for the normal car with the Type 101 vehicle (green color) is created. The stop sign is only active for Type 101 vehicle so that the breakdown is not so frequent.

The external driver model (DLL file) developed using the new CACF model can be uploaded for a specific vehicle type as shown in Figure 10. The user is required to check the options for an external driver in the case where external car following is needed to be used. The recent version of the VISSIM API allows users to utilize multiple cores unlike single core in older versions that ensures faster processing of simulation. The required driver model developed based on the new CACF model is loaded to the VISSIM before the simulation run.

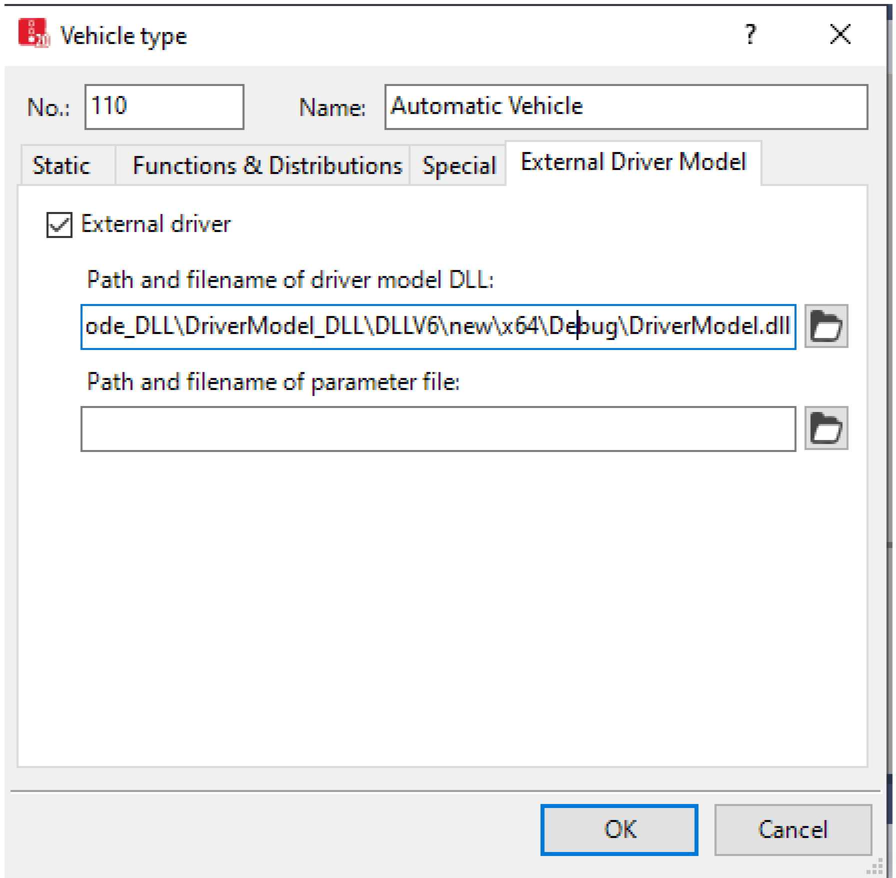

Figure 10. Vehicle type (Source: VISSIM)

All of the traffic information including the type of vehicles, speed, acceleration, and headway as illustrated in Figure 6 will be output to analyze the performance of the newly developed model. For each simulation run for different scenarios, network performance is evaluated using available evaluation parameters including average velocity, delays, stops, travel time, acceleration, and queue length. The VISSIM also generates a trajectory file (.trj) at the end of successive simulation run. The vehicle trajectories describe the course of vehicle position through the network. The *.trj file is imported to the SSAM tool to evaluate the safety in terms of conflicts. Since this study focus on single lane algorithm, only rear end is considered as conflicts. In addition to the new CACF model, traditional models are also simulated to compare the effectiveness of each model. These models include the all human driver model based on

Wiedemann 99, the ACC model, and the CACC model. The detailed comparisons of the results are shown in Chapter 4.

3.5. Summary

In one word, this chapter introduces the VISSIM micro-simulator and the approach to perform simulation using the GUI, COM and DLL. Instead of only using the in-build model Wiedemann 99 to control the vehicles, which is human driving behavior, this study also applied the ACC, the CACC, and the new CACF models to control the AVs at the simulation framework setup for the case study demonstrated in the section 3.3. In order to compare with the performance of the models, the SSAM is applied to evaluate the safety features and the results which is shown in the next chapter.

4. SIMULATION RESULTS AND DISCUSSIONS

After the model setup in VISSM software, this chapter demonstrates the safety features from the SSAM of the case study, such as the number of conflicts and stops and the velocity of the vehicles. Four different vehicle car-following models are compared, including the human-driving vehicle model Wiedemann 99, the ACC model, the CACC model and the newly developed CACF model in this study. In order to avoid the coincidence, eight simulations with different seed values are performed for each model. The simulation results are compared in between the four different models using safety parameters such as the number of conflicts for the eight different seeds, the total/average/minimum/maximum number of conflicts, the total number of stops at different time interval, and the average velocity of all the vehicles. The simulation activities of the vehicles control by the four different models as shown in Fig. 11.

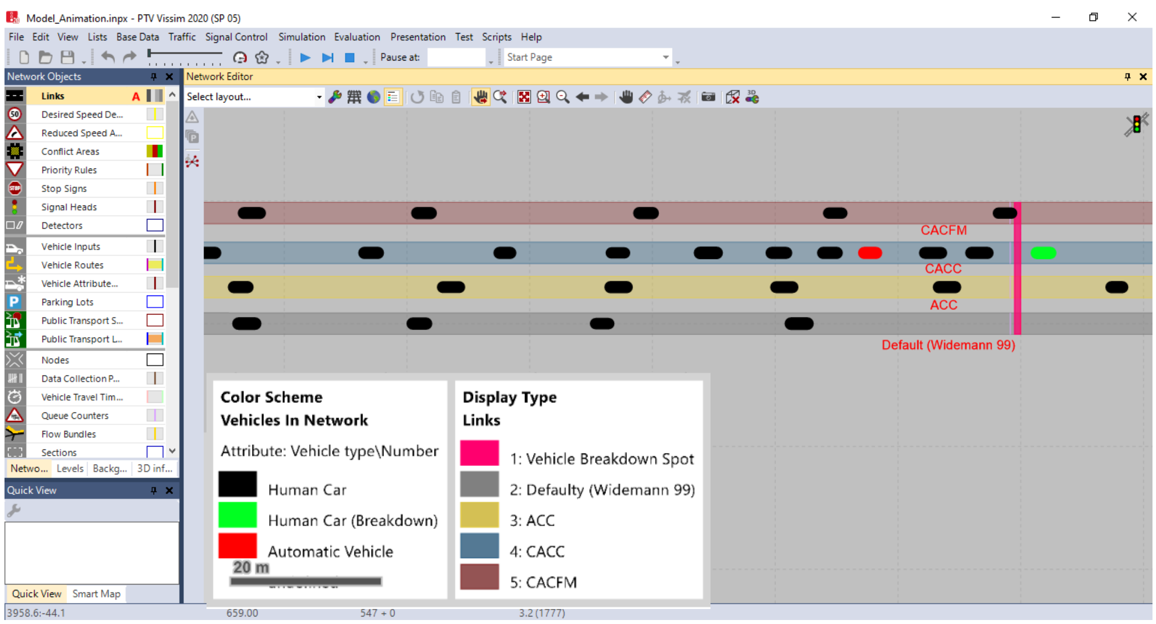

Figure 11. Simulation screen of the vehicles in network

4.1. Number of Conflicts with Different Seeds

To ensure the effectiveness of the comparison between different models, eight different seed numbers are used for the case study, including seed numbers of 1, 6, 11, 16, 21, 26, 31, and

36. The seed number, which can be input in the Random Seed parameter of the VISSIM, allows consideration of the stochastic variations of vehicle arrivals within the VISSIM network that is corresponding to the variations in real-world traffic conditions. Simulation runs with identical DLL files and random seeds generate the same result, however, the stochastic functions are assigned a different value sequence and change the traffic flow if the Ransom Seed is varied while the DLL file is identical. Therefore, these different seed values provide eight different scenarios of traffic conditions. Table 2 and Figure 12 compare the simulation results with a speed limit of 45 mph from the four different models with these eight different seed numbers. For each run of the simulations, the new CACF from this study has minimal conflicts when compared with the Wiedemann 99 and the ACC model, especially in the run with the seed value of 21, where the conflict number of the new CACF model reduced 56.% and 47.09% compared with the Wiedemann 99 and the ACC model, respectively. The CACC model has 6 and 16 fewer conflicts than the new CACF model at the runs with seed number is 16 and 21, however, the CACC model has more conflicts at the other six runs.

Table 2. Number of conflicts from the four different models at 45 mph

Seed Value	Wiedemann 99	ACC	CACC	The new CACF from this study
1	334	305	288	268
6	538	532	561	492
11	571	558	435	416
16	383	406	352	358
21	356	382	317	333
26	600	499	346	264
31	224	195	208	176
36	418	386	276	225

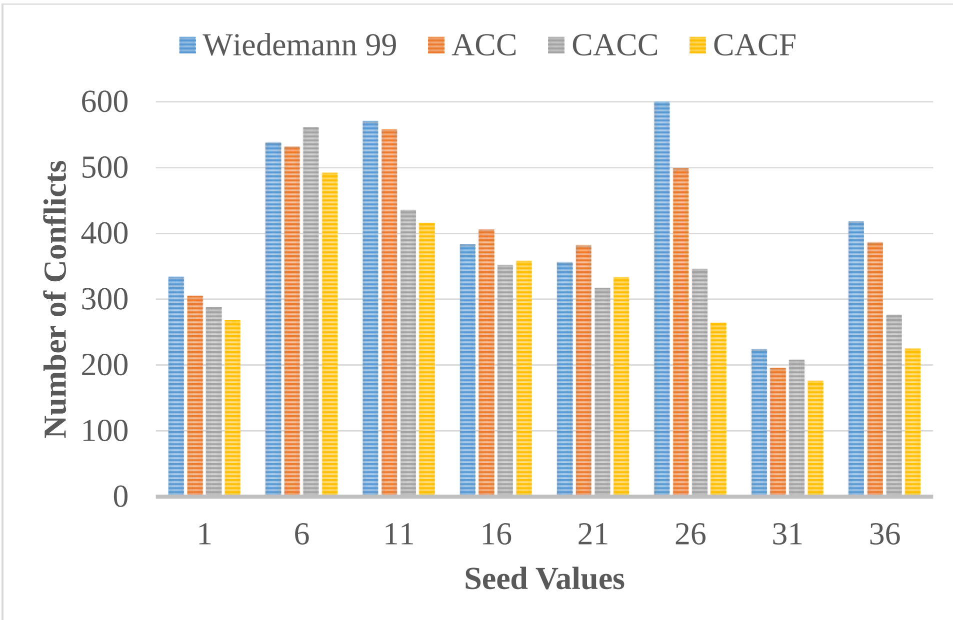

Figure 12. Comparison of the number of conflicts using different seeds at 45 mph

Table 3 and Figure 13 compare the number of conflicts at the speed limit of 50 mph estimated using eight different seed values for these four models. The new CACF from this study has more conflicts than the CACC model only happened at the seed value 21. For the other seven runs, the CACF model always has the least conflicts. When the seed value is 6, the new CACF model achieves reduction of conflict number by 57.70%, 54.64% and 11.64% compared with the Wiedemann 99, the ACC and the CACC models, respectively.

Table 3. Number of conflicts from the four different models at 50 mph

Seed Value	Wiedemann 99	ACC	CACC	The new CACF from this study
1	397	373	301	279
6	1367	1272	653	577
11	437	449	403	382
16	505	469	351	292
21	492	489	357	392
26	496	483	302	286
31	350	333	295	268
36	637	495	325	302

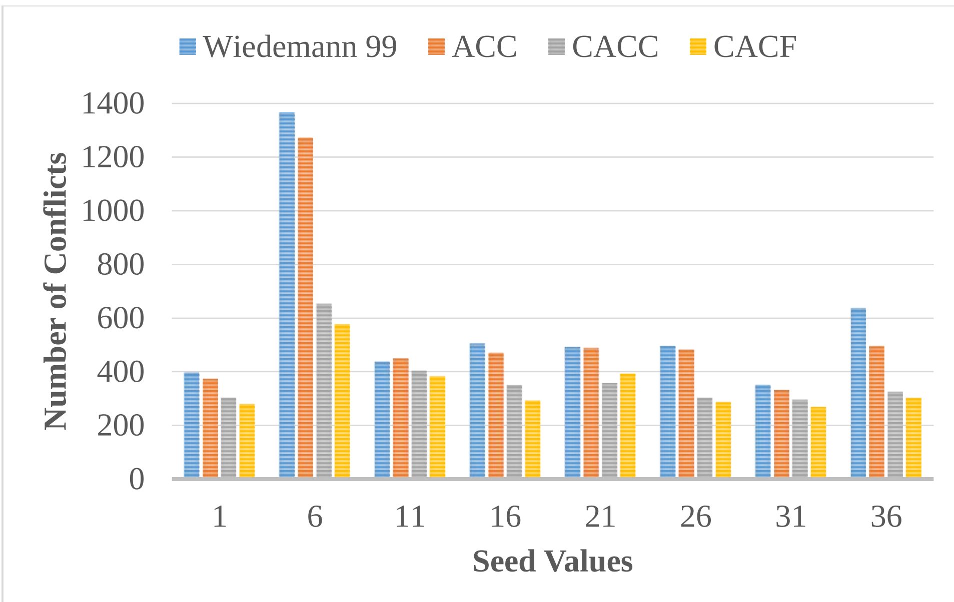

Figure 13. Comparison of the number of conflicts using different seeds at 50 mph

Table 4 and Figure 14 compare the number of conflicts at the speed limit of 55 mph estimated using eight different seed values. Different from the speed limit of 45 and 50 mph, the new CACF has the minimal conflicts in all of the simulations. When the seed value is 6, it reduces 64.67%, 63.35% and 26.17% conflicts compared with the Wiedemann 99, ACC and CACC models.

Table 4. Number of conflicts from the four different models at 55 mph

Seed Value	Wiedemann 99	ACC	CACC	The new CACF from this study
1	384	325	282	256
6	1973	1902	944	697
11	824	771	595	561
16	977	1047	605	551
21	762	783	539	534
26	836	727	482	457
31	232	225	204	181
36	450	469	294	260

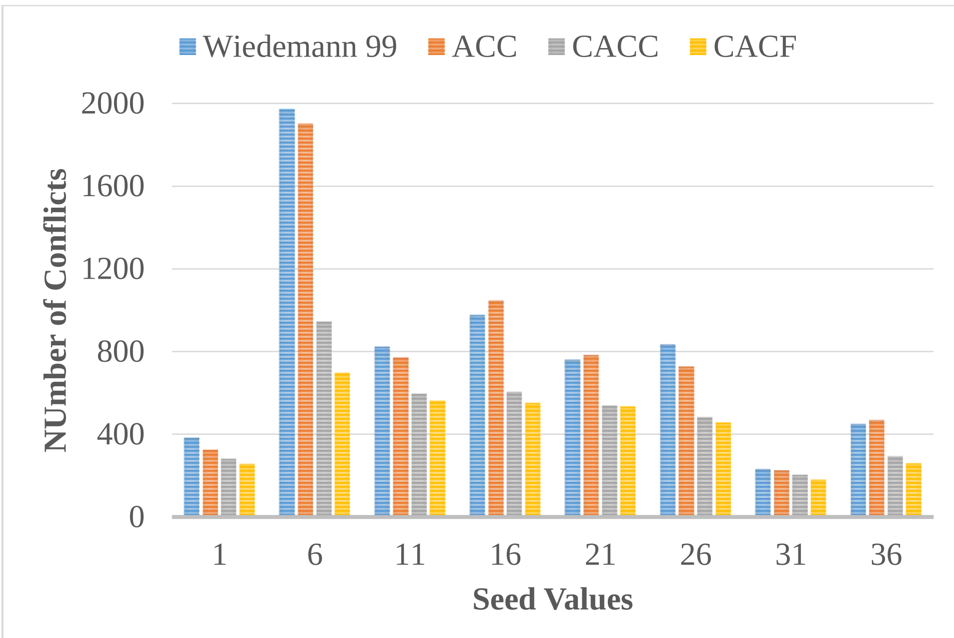

Figure 14. Comparison of the number of conflicts using different seeds at 55 mph

Table 5 and Figure 15 compare the number of conflicts at the speed limit of 60 mph estimated using eight different seed values for the four models. The new CACF has the best performance at speed limit of 60 mph compared with 45, 50 and 55 mph. When the seed value is 1, the new CACF reduced 83.63% conflicts compared with the ACC model which is 12.13%, 25.20% and 21.23% when the limit speed is 45, 50 and 55 mph, respectively. The average reduced conflict rate of the new CACF model when compared to the Wiedemann99 model is 24.01%, 35.12%, 39.12% and 60.37% at speed 45, 50, 55 and 55 mph, respectively. The average reduced conflict rate when compared to the ACC model is 21.04%, 31.45%, 36.53%, and 63.07% at speed 45, 50, 55 and 55 mph, respectively. And the average reduced conflict rate when compared to the CACC model is 9.30%, 6.59%, 9.87%, and 15.09% at speed 45, 50, 55 and 55 mph, respectively.

Table 5. Number of conflicts from the four different models at 60 mph

Seed Value	Wiedemann 99	ACC	CACC	The new CACF from this study
1	589	946	164	155
6	3297	2464	968	733
11	1337	1512	682	535
16	1286	1329	676	576
21	1730	1733	744	633
26	1340	1700	814	727
31	444	377	315	251
36	578	851	230	210

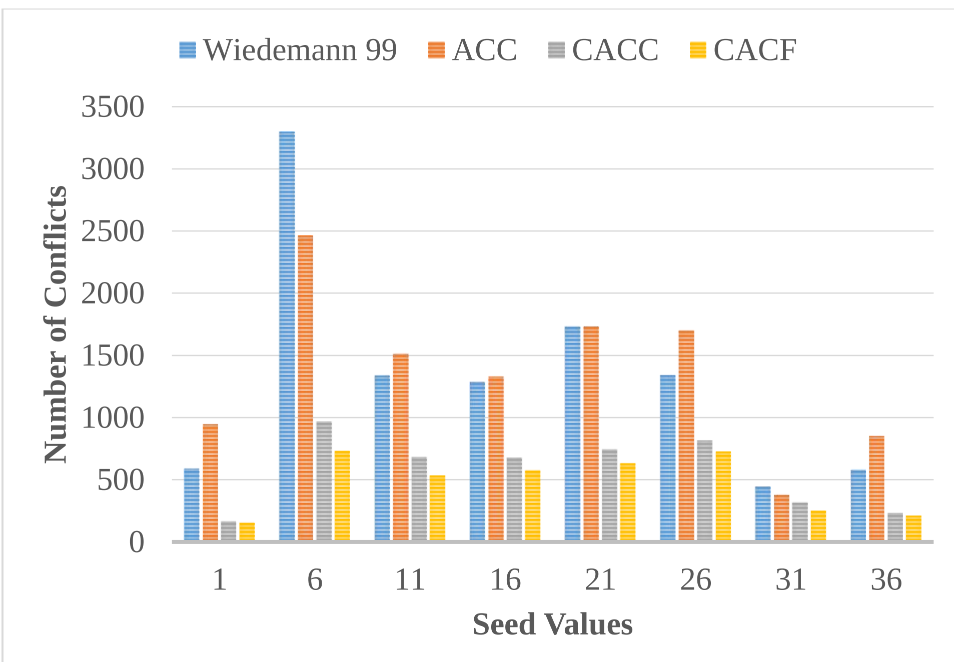

Figure 15. Comparison of the number of conflicts using different seeds at 60 mph

Based on the results compared between Tables 2 to 5 and Figures 12 to 15, the number of conflicts has a significant dependence on the speed limit for all models. In a general observation, the number of conflicts positively relates to the speed limits. For all conditions, the Wiedemann 99 or the ACC models have the maximum number of conflicts while the new CACF model has the lowest number of conflicts. In other words, the new CACF model can significantly reduce the number of conflicts under all different scenarios with eight different seed numbers, such as different car lengths, different accelerations, and different number of vehicles, when compared with other models. Comparing with the conflicts number of the Wiedemann99, ACC and CACC models, the average reduced conflict rates of the new CACF model increases as the limit speed increases.

4.2. Average, Minimum, and Maximum Number of Conflicts

Table 6 compares the total, average, maximum, and minimum number of conflicts of the four models at four different speed limits of 45, 50, 55, and 60 mph. It can be seen from Table 6 that the new CACF model significantly reduced the number of conflicts when compared with the other three models at all four speed limits. When compared with the CACC model, the average conflicts reduced 31.38, 26.13, 56.00, and 96.63 at the speed limit of 45, 50, 55, 60 mph. When compared with the ACC model, the average conflicts reduced 91.38, 198.13, 344.00, and 886.50 at speed limit of 45, 50, 55, 60 mph. When compared with the Wiedemann 99 model, the average conflicts reduced 111.5, 237.88, 367.63, and 847.63 at speed limit of 45, 50, 55, 60 mph. The developed CACF model also generated the lowest number of total, maximum, and minimum number of conflicts.

Table 7 compares the percentage of reduced conflict from the new CACF model with the other three models for the total, average, maximum, minimum number of conflicts at speed limit of 45, 50, 55, 60 mph. When compared with the CACC model, the average conflicts reduced 9.02%, 7.00%, 11.36%, and 16.83% at speed limit of 45, 50, 55, 60 mph. When compared with the ACC model, the average conflicts reduced 22.40%, 36.33%, 44.04%, and 64.99% at speed limit of 45, 50, 55, 60 mph. When compared with the Wiedemann 99 model, the average conflicts reduced 26.05%, 40.65%, 45.68%, 63.97% and xx at speed limit of 45, 50, 55, 60 mph.

Table 6. Comparison of the four models for the total, average, maximum, minimum number of conflicts at speed limit of 45, 50, 55, 60 mph

Speed Limit	Model Name	Total	Avg	Max	Min
45 mph	Wiedemann 99	3424	428	600	224
	ACC	3263	408	558	195
	CACC	2783	348	561	208
	The new CACF from this study	2532	317	492	176
50 mph	Wiedemann 99	4681	585	1367	350
	ACC	4363	545	1272	333
	CACC	2987	373	653	295
	The new CACF from this study	2778	347	577	268
55 mph	Wiedemann 99	6438	805	1973	232
	ACC	6249	781	1902	225
	CACC	3945	493	944	204
	The new CACF from this study	3497	437	697	181
60 mph	Wiedemann 99	10601	1325	3297	444
	ACC	10912	1364	2464	377
	CACC	4593	574	968	164
	The new CACF from this study	3820	478	733	155

Table 7. Percentage of reduced conflict from the new CACF model for the total, average, maximum, minimum number of conflicts at speed limit of 45, 50, 55, 60 mph

Speed Limit	Model Name	Total	Avg	Max	Min
45 mph	Wiedemann 99	26.05%	26.05%	18.00%	21.43%
	ACC	22.40%	22.40%	11.83%	9.74%
	CACC	9.02%	9.02%	12.30%	15.38%
50 mph	Wiedemann 99	40.65%	40.65%	57.79%	23.43%
	ACC	36.33%	36.33%	54.64%	19.52%
	CACC	7.00%	7.00%	11.64%	9.15%
55 mph	Wiedemann 99	45.68%	45.68%	64.67%	21.98%
	ACC	44.04%	44.04%	63.35%	19.56%
	CACC	11.36%	11.36%	26.17%	11.27%
60 mph	Wiedemann 99	63.97%	63.97%	77.77%	65.09%
	ACC	64.99%	64.99%	70.25%	58.89%
	CACC	16.83%	16.83%	24.28%	5.49%

4.3. Total Number of Stops at Different Time Interval

The developed new CACF model not only can reduce the number of conflicts, but also has the potential to reduce the number of stops for vehicles. Table 8 compares the average number of stops of each simulation time interval for all four models at a speed limit of 45, 50, 55, 60 mph. Table 9 shows the percentage of the reduced number of stops from the new CACF model compared with the other three models at speed limit of 45, 50, 55, 60 mph. Since HCM (TRB 2010) recommends the 15-minute flow rate as a peak hour factor for most of the capacity analyses and the 15-minute interval provides a better statistical representation of traffic output in terms of travel time, delays, queue and other parameters as compared to the 60-minute hourly time interval. For each simulation run, the length of the simulations is 4500 seconds which are divided into five travel intervals, with 900 seconds' warm-up time for the simulation to become in a steady state. Based on the stops number of each time interval, we can find that the developed model reduces the average number of stops for almost every time interval when compared with other three models. Compared with the Wiedemann99, ACC, and CACC models, the new CACF model has the maximum percentage of reduced stops occurs at the time interval 3600- 4500, 2700-3600, 900-1800 with 63.16%, 50.00% and 18.18%, respectively. It proves that the new CACF model can be applied to AVs to reduce the traffic congestion by reducing the number of vehicles' stops.

Table 8. Comparison of the number of stop at speed limit of 45, 50, 55, 60 mph

Speed Limit	Time Interval	Wiedemann 99	ACC	CACC	The new CACF
45 mph	900-1800	14	9	8	8
	1800-2700	10	9	8	7
	2700-3600	9	10	9	10
	3600-4500	17	14	10	7
50 mph	900-1800	21	11	11	9
	1800-2700	9	8	6	5
	2700-3600	16	16	8	8
	3600-4500	19	11	7	7
55 mph	900-1800	44	33	18	16
	1800-2700	18	17	10	12
	2700-3600	17	14	10	10
	3600-4500	37	52	13	10
60 mph	900-1800	88	40	12	12
	1800-2700	64	28	11	8
	2700-3600	24	18	10	5
	3600-4500	170	94	28	25

Table 9. Percentage of reduced number of stop for different time intervals from the new CACF model at speed limit of 45, 50, 55, 60 mph

Speed Limit	Time Interval	Wiedemann 99	ACC	The new CACC
45 mph	900-1800	42.86%	11.11%	0.00%
	1800-2700	30.00%	22.22%	12.50%
	2700-3600	-11.11%	0.00%	-11.11%
50 mph	900-1800	57.14%	18.18%	18.18%
	1800-2700	44.44%	37.50%	16.67%
	2700-3600	50.00%	50.00%	0.00%
55 mph	900-1800	63.64%	51.52%	11.11%
	1800-2700	33.33%	29.41%	-20.00%
	2700-3600	41.18%	28.57%	0.00%
60 mph	900-1800	86.36%	70.00%	0.00%
	1800-2700	87.50%	71.43%	27.27%
	2700-3600	79.17%	72.22%	50.00%

4.4. Average Velocity

Table 10 compares the average speeds in each time interval for each seed for all the four different models with a speed limit of 45, 50, 55, 60 mph. For the average velocity, the new CACF model increases 0.31%, 0.63%, 1.09%, 2.70% compared with the Wiedemann 99 model at the speed limit 45, 50, 55, 60 mph, respectively. When compared with the ACC model, it increases 0.38%, 0.80%, 1.36%, 3.75% at the speed limit 45, 50, 55, 60 mph, respectively. And when compared with the CACC model, it increases 0.09%, 0.14%, 0.15%, 0.48% at the speed limit 45, 50, 55, 60 mph, respectively. For the sample variance, the new CACF model increases 51.61%, 71.07%, 65.43%, 57.96% at the speed limit 45, 50, 55, 60 mph when compared with the Wiedemann 99, increase 57.14%, 74.78%, 59.66%, 61.42% at the speed limit 45, 50, 55, 60 mph when compared with the ACC model, and increases 15.38%, -5.00%, 0.70%, 41.70% at the speed limit 45, 50, 55, 60 mph, when compared with the CACC model. The new CACF model has a higher average speed and lower sample variance than the ACC model and the Wiedemann 99 model, which indicates the AVs with the new CACF model will have faster and more stable speeds. Although the CACC model has a slightly higher average speed and lower sample variance when compared with the newly developed model, the differences were not significant when compared with other two models.

Table 10. Comparison of average speed at speed limit of 45, 50, 55, 60 mph

Velocity		Wiedemann 99	ACC	CACC	The new CACF
45 mph	Mean	44.48 mph	44.45 mph	44.66 mph	44.62 mph
	Standard Error	0.10	0.10	0.06	0.07
	Standard Deviation	0.56	0.59	0.37	0.39
	Sample Variance	0.31	0.35	0.13	0.15
50 mph	Mean	48.98 mph	48.90 mph	49.36 mph	49.29 mph
	Standard Error	0.25	0.27	0.14	0.13
	Standard Deviation	1.41	1.50	0.78	0.75
	Sample Variance	1.97	2.26	0.60	0.57
55 mph	Mean	53.21 mph	53.07 mph	53.87 mph	53.79 mph
	Standard Error	0.51	0.47	0.30	0.30
	Standard Deviation	2.89	2.67	1.69	1.70
	Sample Variance	8.33	7.14	2.86	2.88
60 mph	Mean	56.23 mph	55.66 mph	58.03 mph	57.75 mph
	Standard Error	0.95	0.99	0.52	0.62
	Standard Deviation	5.39	5.62	2.93	3.49
	Sample Variance	29.02	31.62	8.61	12.20

4.5. Summary

The simulation results from the case study on the safety features of the number of conflicts in eight different seeds, the total/average/minimum/maximum number of conflicts, the total number of stops at the different time interval, and the average velocity among four models, indicate that the newly developed CACF model can significantly improve the safety of AVs in mixed traffic conditions. Specifically, when compared with other three common models, the Wiedemann 99 model, the ACC model, and the CACC model, the new CACF model can significantly reduce the number of conflicts under different scenarios in eight different seed value 1, 6, 11, 16, 21, 26, 31, 36. It generates the lowest number of total, average, maximum, and minimum number of conflicts. It can be applied to AVs to reduce the traffic congestion by reducing the number of vehicles' stops and the new CACF model has a slightly lower average speed and sample variance than the ACC model.

5. CONCLUSIONS AND FUTURE WORK

In order to improve the safety of AVs in mixed traffic conditions, this study develops a new CACF model. The new CACF model considers the information of the multiple preceding vehicles and cumulates the influences of the changed distance, velocity and acceleration of multiple preceding vehicles. Instead of averaging all of the influences of the preceding vehicles, the new CACF model filters the data and sums selected influences which can support the AVs to make quicker and safer decisions. Simulations are performed on a case study to evaluate the effectiveness of the new model. The comparison between the new CACF model with the other three different models which including Wiedemann 99 (in-build models of VISSIM), ACC, and CACC models from 128 simulations runs demonstrates that the new model outperforms in term of safety. More detail conclusions are shown as below:

1) For eight different seed values (1, 6, 11, 16, 21, 26, 31 and 36), the new CACF model can significantly reduce the number of conflicts under all scenarios when compared with other three models at limited speed 55 and 60 mph;
2) Based on the data combine from eight different seed values, the new CACF model generates the lowest number on the total, average, minimum, maximum number of conflicts at the four analyzed speed limits;
3) The new CACF model can reduce traffic congestion since it has the smallest stop sign at most of the conditions when limited speed is 45, 50, 55 mph and it has the smallest stop sign at all of the conditions when limited speed is 60 mph;
4) Based on the average speeds of the vehicles run at the four 15 minutes' time interval:900s-1800s, 1800s- 2700s, 2700s- 3600s, 3600s- 4500s, the new CACF model has a slightly

lower average speed and sample variance than the CACC model and higher average speed and sample variance than the Wiedemann 99 and ACC model.

However, the results based on the conditions that the ACC, the CACC, and the new CACF models only simulate at the freeway with only one lane, while there is one value per parameter such as the penetration rate of the autonomous vehicles, TTC, CC0, CC1 and so on. In the future, the four models will be applied to compare at the roads with more than one lane. The various autonomous vehicle penetration rate and the sensitivity of the will be tested on the simulation to prove the effectiveness of the new CACF model at more traffic conditions.

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