EVALUATING THE SAFETY AND MOBILITY OF THE CUMULATIVE-ANTICIPATIVE CAR-FOLLOWING MODEL FOR CONNECTED AUTONOMOUS VEHICLES

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The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

MASTER OF SCIENCE

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ABSTRACT

The advancements of vehicle automation are progressively improving resulting in safer driving environments in addition to more efficient mobility and fuel cost savings. However, autonomous and connected autonomous vehicles (AVs, CAVs) require decades to achieve complete market penetration. It is important to investigate the coexistence of conventional and autonomous cars during such a transition period. Traditionally, adaptive cruise control (ACC) and cooperative ACC (CACC) models were used for the AVs to guide their car-following. Recently, the cumulative-anticipative car-following (CACF) model was developed with consideration of the cumulative influences from surrounding vehicles through vehicle-to-everything (V2X) communication. This study further evaluates the safety and mobility performances of the CACF model for CAVs in mixed traffic through various sensitivity tests using the VISSIM simulation platform. The results demonstrate that the CACF model has promising improvements in roadway safety and network performances compared with the Wiedemann 99 and CACC models in mixed environments.

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LIST OF ABBREVIATIONS

AHS	Automated Highway System
ACC	Adaptive Cruise Control
ADAS	Advanced Driver Assistance System
ADS	Automated Driving System
AIMSUN	Advanced Interactive Microscopic Simulator for Urban and Non-urban Network
ASCE	American Society of Civil Engineers
API	Application Programming Interface
AV	Autonomous Vehicle
BSM	Basic Safety Message
BTS	Bureau of Transportation Statistics
CACC	Cooperative Adaptive Cruise Control
CACF	Cumulative-Anticipative Car-Following
CAV	Connected Autonomous Vehicle
COM	Component Object Model
CORSIM	CORridor SIMulation
CTT	Cumulative Travel Time
CVHA	Cooperative Vehicle Highway Automation
DfT	Department for Transport
DS	Driving Simulator
DSRC	Dedicated Short-range Communication
DLL	Dynamic Link Library
EDM	External Driver Model
HCM	Highway Capacity Manual

HOV .... High Occupancy Vehicle

I2I .... Infrastructure-to-Infrastructure

IDM .... Intelligent Driver Model

ITS .... Intelligent Transportation System

LOS .... Level of Service

LiDAR .... Light Detection and Ranging

NHTSA .... National Highway Traffic Safety Administration

ODT .... Oregon Department of Transportation

PTV VISSIM .... Planung Transport Verkehr Verkehr In Städten – SIMulationsmodell

RSU .... Roadside Unit

SAE .... Society of Automotive Engineers

SSAM .... Safety Surrogate Assessment Model

TTC .... Time-to-Collision

TxDOT .... Texas Department of Transportation

USDOT .... United States Department of Transportation

V2I .... Vehicle-to-Infrastructure

V2V .... Vehicle-to-Vehicle

V2X .... Vehicle-to-Device

VMS .... Variable Message Sign

VMT .... Vehicle Miles Traveled

1. INTRODUCTION

1.1. Background

According to the United States Department of Transportation (USDOT) and the Bureau of Transportation Statistics (BTS), the US contains around 4.1 million miles of a highway network which recorded 37,461 fatalities/year in 2016 and approximately 2.4 million injuries/year [1] in 2015. The vulnerability of the transport infrastructure and human driving errors have created severe risks for different types of road users. The World Health Organization mentioned that road traffic injury is the eighth leading cause of death worldwide [2] and has reported around 1.35 million deaths globally in 2016 on roadway networks [3]. Further, an infrastructure report card by the American Society of Civil Engineers (ASCE) stated that Americans spent 6.9 billion hours delayed in traffic which is averaged to 42 hours per driver where traffic congestions cost the country 160 billion US dollars [4]. Additionally, 2 out of 5 miles of urban interstates are congested because of overcrowded traffic [4]. Hence, it implies that the safety of roadway systems, improved traffic operations, and mobility convenience is a major concern.

The future transformations of vehicle automation sectors promise potential benefits for the societies by delivering safe and convenient mobility options. The automated vehicle technologies are expected to revolutionize the traveler experience and traffic operations [5]. Self-driving cars or autonomous vehicles (AVs) are expected to have several automated driving operations and driving tasks that would allow the car to be driven with or with a need for a human driver [6]. As 90% of crashes are caused by human errors [7], it is projected that autonomous driving can save 30,000 lives per year in the USA, prevent around 5 million accidents and 2 million injuries and, preserving approximately 7 billion liters of fuel [8], which also yields similar lives save in UK [9]. Morgan Stanley estimated the benefits of self-driving cars towards the annual savings of the US economy up to 1.3 trillion US dollars and over 5.6 trillion global savings [10]. A study suggested that intelligent cars could increase the highway capacity of up to 273% [11]. Additionally, KPMG estimates the economic benefits of around 51 billion UK pounds to be gained from CAVs by 2030 [9]. Thus, the AV or CAV technology would improve safety and would impact the cost of transportation, traffic patterns, and traffic congestion [12]. In addition, it is expected that autonomous cars would minimize mobility costs, reduce risk to climate changes, allowing disable and elderly people to enjoy driving, and transform product delivery [13].

The AVs gather data from different sources such as sensors, cameras, GPS, 360-degree radars, other vehicles, and maybe also from infrastructure units if available. The human driver's intervention in the driving task depends upon the in-built technology in the autonomous car. The SAE International (Society of Automotive Engineers) has defined five levels of autonomous vehicles [14] which the National Highway Traffic Safety Administration (NHTSA) - USDOT also adopted in 2016 [15]. The Level 0 (no automation) is the conventional vehicles without ADS technologies where the human drivers are responsible for all the driving tasks including steering, accelerating, decelerating, and safe braking, with some supporting features such as automatic emergency braking, blind-spot warning, and lane-departure warning systems [16].

In Level 1 (driver assistance), some features of ADAS are included in the vehicle design to assist the driver for steering such as lane-centering and braking/accelerating such as adaptive cruise control (ACC), but one at a time [17]. The human driver is responsible for monitoring the surrounding traffic environment as well as fallback actions during dynamic driving. In Level 2 (partial automation), an ADAS system can control both driving functions such as lane-centering and braking/accelerating such as adaptive cruise control (ACC) at the same time. Still, the human driver must perform all the necessary operations of dynamic driving including monitoring the surrounding environment.

In Level 3 (conditional automation), the driver is necessary to control the vehicle but is not required to monitor the surrounding environment. An ADAS system can perform all the dynamic driving tasks under some circumstances excluding fallback performance. If the circumstances are not met, the vehicle's automated function would not operate. The human driver must be ready at all times to take full control of the vehicle upon the request of ADS.

SAE International defines Level 3 as the first stage towards automated driving where the driver is not driving the car. This level includes advanced assist features such as traffic jam chauffeur. In Level 4 (high automation), the vehicle is capable of performing all the driving tasks if all the circumstances are fulfilled. Therefore, the driver is not required to perform dynamic driving actions such as steering, accelerating, braking, monitoring surrounding traffic, and fallback performance actions. Additionally, pedals/steering may or not be installed in the vehicle. An example of a Level 4 vehicle is a local driverless taxi. In Level 5 (full automation), an ADS feature in the vehicle can perform all the dynamic driving tasks under all the roadway circumstances and every environment that otherwise requires a human driver’s intervention during normal operations. The human occupants in the vehicle are passengers and do not require to control the vehicle. The fully autonomous car can control the longitudinal and lateral control of the car i.e. keeping safe headway from the leading the vehicle and do the necessary lane-change [16].

Most current vehicles have acquired Level 1 or Level 2 ADAS technologies such as cruise control, hazard warning, and automated parallel parking. Level 1-3 requires a driver’s license to operate the vehicle with a license whereas Level 4-5 allows driverless operations. The maximum benefits of autonomous vehicles are predicted in Level 4 or Level 5 vehicles [6]. Currently, there exists an extensive competition in the automotive industry to acquire fully autonomous features for their vehicle design. Companies have been implementing Level 4 pilot projects to test AVs under certain circumstances such as specific road types, areas, and weather. For example, Waymo and Uber evaluate driverless taxi in Phoenix, Arizona region back in 2017 [18, 19].

The current challenges for the developers of AV technology are to enable the car with all the road conditions and driving scenarios that are expected to be faced by a conventional human driver. The early testing of Google's car shows potential benefits for reducing crashes and traffic injuries [20]. Waymo (formerly Google's self-driving car) has logged around 20 million miles on public roads [21] and Uber's autonomous car has also recorded millions of miles, to train the autonomous car with surrounding road and traffic conditions. However, some crashes were recorded for Waymo [22] and Uber [23] in Arizona, USA. The maturity of the AV technology requires extensive research and field tests to ensure the proper safety for road users.

The safety issue of the current AVs brought up attentions to the fact that although the AVs will have positive impacts on vehicle miles traveled (VMT), travel demands, traffic speed, and vehicle costs, they will also have negative impacts. For instance, zero occupancy vehicles would add additional travel miles to the system which may add further congestion in the existing traffic volume, however, it will increase the efficiency, better travel comfort, ease of parking operations, and utilization of vehicles for other household members rather than paying for the parking fee [6]. In addition, many other factors which may be negative or positive in some sense will influence the large entry of AVs into the fleet e.g. fail-safe technology, safety, privacy, security issues, personal choices, affordability, and infrastructure requirements [5]. Since the automotive industry requires many years of development, testing, and approval to completely reach Level 5 of self-driving vehicles [24], regardless of the progress made towards the technological advancement and improvements in the automation of driving, yet the proposed system requires more training under all normal conditions [25] to avoid potential vehicle malfunction crashes.

According to a study, the AVs transition phase from partial market penetration to fully autonomous driving will have different impacts on vehicle sales, fleet, travel, and other benefits as shown in Figure 1-1 [6] and would vary depending upon the market requirements and competitions among the automobile industry such as Google, Uber, Tesla, etc. The full penetration of AVs will follow the typical innovation S-curve and must pass through several technology innovation stages [6]. At the first stage, the AVs technology is proposed and developed, following the process of testing and necessary approvals, and then become commercially available in the market. At later stages, the technology will be reviewed, improved, and expands. Finally, the market diffusion occurs, maturation, and ultimately saturation and decline would occur. Litman predicts until 2045 half of the vehicles will be autonomous and by 2060 the autonomous market would fully occupy the roadway share. Between now and 2060 or later, AVs will share the roads with human drivers and partial AVs [6].

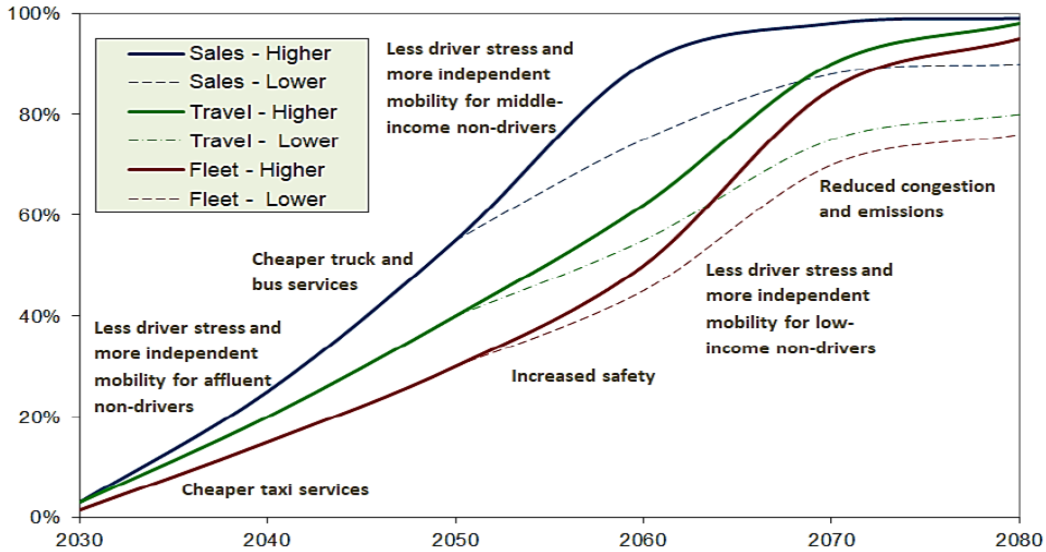


Figure 1-1. AVs sales, fleet, travel, and benefit projections [6]

1.2. Literature review

1.2.1. Difference between autonomous and connected autonomous vehicles

It is important to understand the difference between the terms ‘autonomous vehicle (AV)’, ‘connected vehicle (CV)’, and ‘connected autonomous vehicle (CAV)’. Atkins defines that an autonomous [26] is “a car that is capable of fulfilling the operational functions of a traditional car (e.g. driving, lane-change, parking, etc.) without the aid of a human operator” and a connected car is “a car that is equipped with a technology enabling it to connect and communicate with other devices within the car, and also to other surrounding cars and external networks (e.g. internet, navigation, environment data, etc.)”. Thus, an AV relies on the sensors installed in the vehicle that helps in inspecting the surrounding environment. Sensors such as the global positioning system (GPS) tells the position of the car and high-definition cameras to review other elements of traffic [27]. With the built-in software and smart algorithms, AVs can identify the obstacles on the road such as road markings, preceding and lead vehicle, vehicle on adjacent lanes, traffic signals, presence of pedestrians, cyclists, and other infrastructure installations. Autonomous driving has its benefits over traditional vehicles, however, communication with other vehicles and infrastructure is also an important element to ensure proper safety. For example, by Oct 2020, the Google-owned self-driving cars operated by Waymo has reached 20 million miles of autonomous driving[1] with a total of 36 crashes[2] in the mountain view area, California. Even with an extensive amount of training for machine-learning algorithms, accidents for Google's self-driving are mostly caused by other drivers due to human error[3]. Google AV steered into a bus[4] for not having proper communication with other vehicles resulting in a crash. A more severe example is Tesla's self-driving car where a tractor-trailer and AV encountered a fatal crash due to the failure in applying breaks by AV when the tractor-trailer made a left turn in front of the Tesla[5].

This type of collision involving self-driving cars could have been avoided with strong protocols of communication between the affected vehicles. In such a case, an advanced emergency message would have been prompted to the AV for the application of breaks. There is great evidence of gaining potential safety and capacity benefits [28] while combing 'autonomous' and 'connected' cars i.e. connected autonomous vehicles (CAV). The innovations in ITS technology (in the context of connecting and autonomous vehicles) are progressing rapidly all around the world due to challenging market competitions. CAV requires communication with a particular object of infrastructure, another vehicle, or a combination of the two or multiple objects. USDOT mentions three terms for explaining the communication of connected vehicles such as vehicle-to-vehicle (V2I), vehicle-to-infrastructure (V2I), vehicle-to-

[1]https://www.businessinsider.com/waymo-self-driving-vehicles-cover-20-million-miles-on-public-roads-2020-1
[2] https://www.businessinsider.com/cruise-waymo-apple-which-self-driving-cars-crash-the-most-2018-11#waymo-7
[3] https://www.businessinsider.com/self-driving-car-accidents-caused-by-humans-2018-9
[4] https://www.cnbc.com/2016/02/29/googles-self-driving-car-caused-an-accident-so-what-now.html
[5] https://www.nytimes.com/2016/07/01/business/self-driving-tesla-fatal-crash-investigation.html

device (V2X) [29] where the 'X' can be passenger, another vehicle, onboard device, or cloud technology [30], wireless sensors, and other navigation guidance tools. Figure 1-2 exhibits the communication channel of CAV through V2V and V2I communications, where a roadside unit (RSU) can be a traffic signal and other active traffic management sensors. I2I is referred to as infrastructure-to-infrastructure communication e.g. green wave of a traffic light for consecutive signalized junctions.

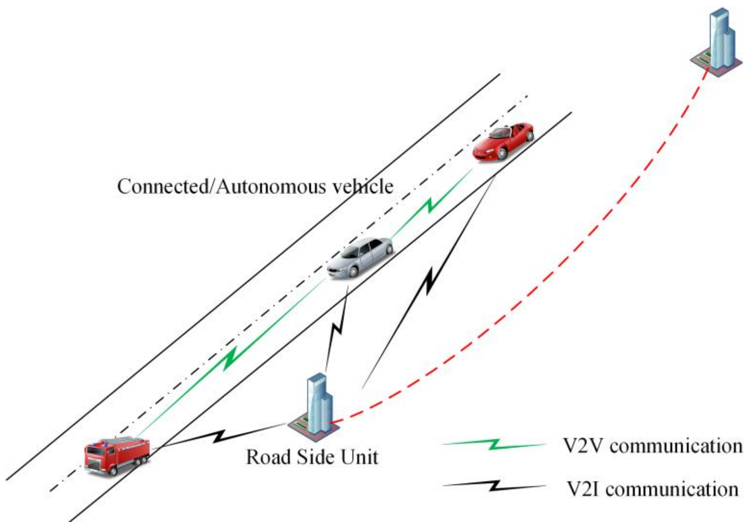


Figure 1-2. Connected vehicle communications through V2I and V2V [31]

Wireless technology such as dedicated short-range communications (DSRC), light detection and ranging (LiDAR) for 360-degree imaging, RADAR, Bluetooth, and cellular navigation system can perform the communication job for CVs [32]. DSRC is preferred over other communication channels because of fixed licensed bandwidth, fast network acquisition, low communication latency, and high reliability, interoperability, and security [33]. A basic safety message (BSM) is communicated through DSRC. A classic example of V2I communication is when a central control station at an intersection records the position of CAVs through the data transferred by the DSCR message set dictionary [34] (combing GPS and BSM signals) with a frequency transmission of 10 times per second [30].

The information received from nearby vehicles or/and the infrastructure enhances capacity, safety, and mobility of the traffic flow. In the traffic simulation platforms, CAVs conduct V2V communication by recording the position (coordinates), speed, desired acceleration/deceleration of other vehicles. Collision avoidance can be modeled if vehicles are aware of the headways and lane-change maneuvers of surrounding traffic. In a similar pattern, CAVs can conduct V2I communication by storing the status of traffic lights, road signs, detectors, and variable message signs (VMS). For instance, a vehicle approaching an intersection that already knows the status of the traffic light can manage the speed accordingly to enhance fuel efficiency and safety.

1.2.2. Advanced Driver Assistance System (ADAS) and Intelligent Transportation System (ITS) for Connected Autonomous Vehicles

The ADAS supports a driver for performing the driving task with safety, convenience, efficiency, and improving the overall driver's experience. Further ADAS can allow elderly and disable people to enjoy driving. The field of driving assist technologies has matured more in recent years. Currently, the scope of ADAS technologies is spreading around the automotive market quite rapidly [35]. Many of the advanced driving assistance functions are already available in today's motor cars such as lane-assistance, lane-departure warnings, adaptive cruise control (ACC), blind-spot detection, etc. [17]. Certain driving assistance tools have been developed by various ADAS companies and car manufacturers as shown in Table 1-1

Table 1-1. Available assistive driving technologies [36]

Vehicle manufacturer	Lateral movement			Forward movement		Reverse movement		Pre-crash systems			Parking task	Attention monitor	Congestion assistant
	Lane departure	Lane-keeping assistant	Lane changing/Blind spot detection	Adaptive cruise control	Front cross-traffic monitor	Rearview camera	Rear cross-traffic monitor	Brake assistant	Forward collision warning	Active protection			
Audi	Y	Y	Y	Y (radar)		Y		Y	Y	Y	Y(auto)		Exp. 2016 (w/o hand)
BMW	Y		Y	Y (radar)		Y		Y	Y	Y	Y(auto)	Y	Y (w/hand)
Ford/Lincoln	Y	Y	Y	Y (radar)		Y	Y	Y	Y		Y(semi)		Exp. 2017
Volvo	Y	Y	Y	Y			Y	Y		Y		Y	Exp. 2014
Mercedes-Benz	Y	Y	Y	Y (radar)	Y	Y	Y	Y	Y	Y	Y(semi)	Y	Y (w/hand)
Cadillac	Y		Y	Y		Y	Y	Y	Y		Y(semi)		
Infiniti/Nissan	Y	Y		Y (radar)		Y	Y	Y					
Acura/Honda	Y	Y	Y	Y		Y			Y				
Lexus/Toyota	Y	Y	Y	Y (radar)			Y	Y		Y	Y	Y	
Kia	Y		Y	Y (radar)		Y	Y	Y		Y	Y		
Hyundai	Y	Y	Y	Y (radar)			Y	Y					

Note: Information is obtained from the sources up to 2015, where ‘exp’ means expected

The intelligent transportation system (ITS) has shown great supports for hi-tech advancement both in highways and in-vehicle technologies which the CAVs are highly dependent on [37]. To date, there are a substantial amount of ITS applications in use such as active traffic management and monitoring, traffic signals, on-board vehicle navigation system (e.g. Google maps), smartphone application, and other connected vehicle technologies [30]. The primary reason for the ITS application is to improve network efficiencies such as the reduction in traffic congestion, alleviate driver's safety and security.

Both the ADAS and ITS systems come under the concept of a term known as 'automated highway system (AHS)' or more recently another term used called 'cooperative vehicle-highway automation (CVHA)' which usually employs assistive technologies such as LiDAR, RADAR, V2V, and V2I systems [36, 38].

1.2.3. Forward movement and car-following models

In the forward movement of an autonomous vehicle, the car-following model is an important element of any traffic flow theory, micro-simulation models, or car autonomation, which states the behavior of individual vehicles [39]. The car-following model describes how the drivers interact longitudinally with the preceding vehicle (leader) in the same lane [40]. Different researchers explain the acceleration behavior, safety gap, and reaction time of the subjected following-vehicle in numerous conditions.

1.2.3.1. General Motors (GM) car-following model

A stimulus-sensitivity-framework which creates a consistent set of acceleration driving behaviors was proposed by General Motors (GM) research laboratories [41, 42]. This framework calculates the driver's reaction time through acceleration/deceleration values by subtracting the leader's current speed from the speed of the following subjected vehicle. This simple GM model is a basis for other car-following models with varying sensitivity parameters [43]. The simple linear-car following model is developed with a constant sensitivity parameter [44] and the model notations are simplified in [43] which is described as:

$$a_n(t) = \alpha . \Delta V_n^{front}(t - \tau_n) \tag{1}$$

where $a_n(t)$ is the acceleration applied by driver 'n' at a time 't', $\Delta V_n^{front}(t - \tau_n)$ is the leader relative speed recorded at the time$(t - \tau_n)$, $\tau_n$is the driver's reaction time and α is a constant term.

The basic GM linear model has an impractical approach because the spacing between the leading and the following vehicle does have its impact on stimulus. The GM model was further expanded to consider the non-linearity behavior in the sensitivity of relative distance between the following and leading vehicle, and the sensitivity of relative speed for the subject vehicle [42]. The extended model is named on the name of authors as Gazis-Herman-Rothery (GHR) model which was established in 1961. The GHR model notations are simplified in [43] which is explained as:

$$a_n(t) = \alpha . \frac{V_n(t)^\beta}{\Delta X_n^{front}(t - \tau_n)^\gamma} . \Delta V_n^{front}(t - \tau_n) \tag{2}$$

where $V_n(t)$ is the speed of the subject 'n' vehicle n measured at a time 't', $\Delta V_n^{front}(t - \tau_n)$ is the relative speed of the leading vehicle and ΔX_n^{front} $(t - \tau_n)$ is the relative spacing measured at the time $(t - \tau_n)$. $\tau_n$is the driver's reaction time and $\alpha > 0, \beta, \gamma$ are constant parameters. Researchers extend the GM model to overcome other limitations such as driver attentiveness [45], [46] and modeling behavior based on critical headway [47].

1.2.3.2. Safety-distance or collision avoidance car-following model

Unlike the GM family models that describe the relationship of stimulus-response type function, the safety-distance model always maintains a safe distance between the following and the lead vehicle. These collision avoidance models are based on the basic newton's equation of motion that explains that the collision would be unavoidable if the lead vehicle behaves unpredictably [39]. The basic and old rule of safety-distance quoted by Pipes in 1953 [40] is "A good rule for following another vehicle at a safe distance is to allow yourself at least the length of a car (about 15 ft) between you and the vehicle ahead for every 10 miles of hour speed at which you are traveling". The first general acceleration model was developed by Gipps in 1981 that record car-following (vehicle ahead) and free-flow (no vehicle ahead) conditions. This model confirms a 'no-collision' behavior between the follower and the leader if the time-gap is equal or greater than 3T/2 (safe-headway), and the follower's approximation about the leader's deceleration is equal or larger than the leader's actual deceleration value (apply limits to a driver's braking rate) [48].

The acceleration model has two limitations that the desired speed must not surpass, and a critical safe headway should be maintained. The model consists of acceleration (Eq. 3) and deceleration (Eq. 4) components that correspond to empirical formulations [48, 49] as

$$v_n^{acc}(t+T) = v_n(t) + 2.5.a_n.T\left(1 - \frac{v_n(t)}{v_n^d}\right).\sqrt{0.025 + \frac{v_n(t)}{v_n^d}} \tag{3}$$

$$v_n^{decc}(t+T) = -T.d_n + \sqrt{T^2.d_n^2 + d_n\left\{2[x_{n-1}(t) - x_n(t) - (S_{n-1})] - T.v_n(t) + \frac{v_{n-1}(t)^2}{d'_{n-1}}\right\}} \tag{4}$$

where, T = reaction time, n, n-1 = follower and leader, respectively, $v_n(t)$,$v_{n-1}(t)$ = vehicle speed of follower and leader respectively at the time 't', v_n^d,a_n = follower's maximum desired speed and maximum acceleration respectively, d_n,d'_{n-1} = respectively the most severe braking that the follower wishes to undertake and his estimate of the leader's most severe braking capability (d_n> 0 and d'_{n-1} > 0), x_n(t), x_{n-1}(t) = longitudinal position of the follower and leader at the time 't', S_{n-1} = intervehicle spacing at a stop. It includes the length of the leader's vehicle added to the follower's desired intervehicle spacing at the stop. The output result is the speed of each vehicle at a time 't' corresponding to its previous timestep speed.

Gipps' model has gained numerous extensions, modifications, and calibration by various researchers [50-52]. Most of the leading micro-simulation tools use the Gipps model [53-56] as a default driving behavior because of its simple calibration that requires the common-sense assumption about human driving behavior. One of the weaknesses of the safety-models [57] is that the model does not consider the driver's perception. Further, a minor variation causes an end to the reaction for the following driver.

1.2.3.3. Psycho-physical car-following model

Another approach of car-following models is psycho-physical or action point models[39]. The GM-type model has two behavioral limitations [58, 59] including drivers reacting to arbitrary small changes in the stimulus e.g. relative speed and the driver following the lead vehicle remaining affected by the actions of its leader even when the distance is very large and that the follower's response dismisses as the relative speed is zero. The psychophysical model uses a 'perceptual threshold' which is a function of (i) space headway and (ii) relative speed for the following vehicle pairs was further developed by Wiedemann and Reiter [60]. The drivers react to changes in spacing or relative velocity only when the threshold values are reached. In this way, it also records the driver's attentiveness for small spacing and lack of the following behavior for larger spacings [43].

The Wiedemann car-following model is a famous psycho-physical car-following model. The driving behavior of humans is naturally distributed [60] which essentially means that each driver has different driving capabilities for perception, reaction, and estimation of the surrounding traffic environment, safety needs, desired speed, and aggressiveness towards maximum acceleration/deceleration values. Similarly, the same principle applies to vehicle abilities in exercising basic features such as maximum speed and maximum acceleration/deceleration. According to Wiedemann, the varying behavior of drivers can be explained by normal distributions. Hence, this car-following model uses several ranges of different random parameters for the calculation of threshold values and the driving functions such as minimum and maximum following distance [60]. For example, the desired minimum following distance at low-speed differences is denoted by the threshold of ABX. At higher speeds, the driver would undervalue the safe distance and drive closely unlike at slower speed with safe gaps. The ABX can be estimated as:

$$ABX = AX + BX \tag{5}$$

$$BX = (BXadd + BXmult * RND1_n) * \sqrt{v} \tag{6}$$

where, $BXadd$ and $BXmult$ are calibration parameters. $RND1n$ is a normally distributed parameter for desired front-to-rear distance that depends on the driver safety. The speed v is defined as:

$$v = \begin{cases} v_{n-1} & for\ v_n > v_{n-1} \\ v_n & for\ v_n \leq v_{n-1} \end{cases} \tag{7}$$

The Wiedemann model uses thresholds for defining different car-following regimes. However, a study shows that the thresholds are not constant and vary according to speed ranges and driver’s behavior. Therefore, instead of using a single parameter value, a driver’s profile should be used for accuracy [61].

1.2.3.4. Optimal Velocity Model (OVM) car-following model

Traffic flow observes instabilities which usually creates congestion in highways and freeways. A dynamic model is required to model this behavior of instability. The optimal velocity model (OVM) describes the dynamical formulation of traffic congestions (traffic jam) using the equation of motion for each vehicle. In this traffic flow model, the stimulus is a function of the following headway and all the drivers possess constant sensitivities. The assumptions of the OVM model include that 1) each driver responds to a stimulus from the preceding vehicle and has a legal velocity of V, 2) each driver controls the acceleration/deceleration observing the motion of the preceding vehicle to maintain a safe velocity, and 3) no response-lag time was considered. The OVM dynamical equation is obtained as [62]:

$$\ddot{x}_n(t) = \mathrm{a}\{\mathrm{V}(\Delta x_n) - \dot{x}_n(t)\} \tag{8}$$

Where $\Delta x_n = x_{n+1-} x_n$, is the headway of vehicle n (following) and n+1 (preceding), t = time, n = total number of vehicles, a = driver’s sensitivity constant (independent of the vehicle), x_n = position for the nth vehicle with respect to time (t), V= optimal velocity of a vehicle n, the calculated optimal velocity $\mathrm{V}(\Delta x_n)$of a vehicle (n)depends on the following distance of the preceding vehicle number (n+1).

The velocity (V) of a vehicle increase as the headways (Δx_n) gets larger but does not surpass the maximum allowable velocity. Similarly, the velocity reduces to minimal value as the headways get narrower to prevent the crash. The optimal velocity function $\mathrm{V}(\Delta x_n)$is defined as described as:

$$V(\Delta x_n) = \tanh(\Delta x - 2) + \tanh(2) \tag{9}$$

Using the above equation, the driver manages the acceleration and braking behavior, and would never pass the preceding vehicle in any case. This model ensures that traffic flow creates congestion phenomena instead of accidents. A noticeable weakness of the OVM outlined in research [57] is that the model develops idealistically large acceleration in some conditions.

1.2.3.5. Intelligent Driver Model (IDM) car-following model

A car-following model for mixed traffic condition is named as Intelligent Driver Model (IDM). This model describes the acceleration as a function of the gap $S_\alpha(t)$, the speed $V_\alpha(t)$ and the speed difference $\Delta V_\alpha(t)$ between vehicle α and the vehicle in front [63] as:

$$\frac{d}{dt} v_\alpha = a.\left(1 - \left(\frac{v_\alpha}{v_0}\right)^{\delta} - \left(\frac{S^* \, v_\alpha.\Delta v_\alpha}{S_\alpha}\right)^2\right) \tag{10}$$

where δ is the acceleration component, S^* is the desired gap, a is the maximum acceleration, and v_0 is the free speed.

As shown above, the IDM model considers factored maximum acceleration and minimum headway to achieve the desired velocity and to maintain a minimum gap with the lead vehicle respectively. Researchers have formulated the potential following behavior of autonomous vehicles, advance driver assistance features such as adaptive cruise control (ACC), and cooperative adaptive cruise control (CACC) [64] using the IDM algorithms as a basis of model construction.

1.2.3.6. The adaptive cruise control (ACC) car-following model

The adaptive cruise control (ACC) is an advanced feature of conventional cruise controls in vehicles, which is designed to provide relief to the driver and convenience by releasing the stress of the need to continuously match his speed with the leading vehicle [65]. The ACC examines the leading traffic in the same lane through cameras, laser, or radar sensors [36, 65, 66] and record their speed and headway and adjusts its own speed to maintain a safe gap from the leading vehicle. If the desired safe gap is diminishing and/or the leading vehicle is slowing down, the ACC vehicle will adjust its speed accordingly. Similarly, if the gap ahead is clear (e.g. front car accelerates or changed a lane), the ACC vehicle will accelerate to achieve the desired cruising speed. Thus, the ACC system does not rely on the V2V communication between the leading and the following vehicles but on the speed detection sensors on board of the vehicle itself.

1.2.3.7. The adaptive cruise control (ACC) and CACC car-following model

The cooperative adaptive cruise control (CACC) system, on the other hand, relies heavily on the V2V communication between the leading and the following vehicles. The vehicles equipped with the ACC system can communicate with only one preceding vehicle and adjust its speed and headway accordingly. Whereas CACC vehicles communicate with a series of cars in the range of communication, and the decision control about the recommended speed, headway and acceleration is with the leader (first car) in the traffic stream. Therefore, the leading vehicle sends a message about its recommended speed and (sometimes lane assignment) to the following vehicle. Once the signal is received, the following vehicle will adjust its speed and desired distance without the involvement of the driver [66]. The ACC and CACC acceleration mathematical model [65, 67, 68] is described in the following as

$$a_c = k_v * (v_p - v_f) + k_s * (s - v * t_d) \text{ – for ACC} \tag{11}$$

$$a_c = k_a * a_p + k_v * (v_p - v_f) + k_s * (s - v * t_d) \text{ – for CACC} \tag{12}$$

$$a = \max[a_{min,} \min(a_c, a_{max})] \tag{13}$$

Where, a_c – control acceleration with the liner function, a – acceleration in the next step of the objective vehicle, a_p – acceleration of the preceding vehicle, t_d – time gap, 1.4 sec for ACC, 0.5 sec for CACC, v_p – speed of the preceding vehicle, v_f – speed of the following vehicle, a_{min} – maximum allowed acceleration = (2m/s^2), a_{max} – maximum allowed deceleration (-3m/s^2), and k_a, k_v, k_s are constant factors. (k_a= 0; for ACC).

The CACC enables the vehicle to follow each other with tight distances. Hence, it provides traffic flow stability and improved throughput by increasing highway capacity up to a lane drop [65]. No definite consensus or the definition of CACC has been fixed at this stage as the concept of CACC is still under development. This system is expected to provide smooth, safe, and efficient driving behavior. However, the reduced gap between the two vehicles is only possible if both vehicles are equipped with the CACC technology. Further, at least 40% of market penetration is required to acquire some benefits of the CACC technology [65]. More recently, Van Arem developed a car-following model for CACC called as the cooperative following (CF) using automated longitudinal control combined with intervehicle communications [65, 69]. The CF model forms platoons by connecting vehicles with each other and keeping a tight distance. The CACC platoon can be considered as a train, with the first vehicle of the platoon being the locomotive (leader) and the rest of the railcars follow the instructions of the leader[68].

Many researchers have investigated the impact of ACC and CACC car-following models under varying market penetration using VISSIM software. This thesis will further explore the implications of CACC in mixed traffic later in the methodology and results section.

Another feature to assist forward movement is called Front cross-traffic monitoring/alert (FCTA). This feature use cameras, radars, and a color display screen to detect the vehicles or bicyclist at T-intersections [36]. The vehicle is vulnerable at these intersections because of a lack of sight distance. Once the object is under the system's trajectory, FCTA identifies the object and shows it to the user through an interactive display. If there exists a risk, a user is warned and the system boosts the braking power applied by the driver until is it sufficient to prevent the vehicle from a collision or otherwise reducing the amount of possible damage [36].

1.2.3.8. The Cumulative Anticipative Car-Following Model (CACF)

Recently, the research group of Yang [70] developed a Cumulative Anticipative Car-Following Model (CACF) for connected autonomous vehicles (CAVs), which implements V2X communications (e.g. V2I sensors embedded in the roadways in addition to V2V) for real-time traffic data of multiple surrounding vehicles for car following. The acceleration of this CACF model can be described as:

$$a_c = k_a * a_p + k_v\left(v_p - v\right) + k_d * (r - t_{system} * v + (-1)^c * |\ (X_d - X_r)|) \qquad (14)$$

$$a_d = max[\ a_{min}, \min(\ a_c, a_{max})] \qquad (15)$$

where, a_c – is the control acceleration of the ego vehicle, a_d – desired acceleration in the next step of the objective vehicle, a_p – actual acceleration of the preceding vehicle, t_{system} – time gap, 0.5 sec (if preceding vehicle is an automatic car), otherwise 1.4 sec, v_p – actual speed of the preceding vehicle, v – actual speed of the following vehicle, a_{min} –maximum allowed acceleration = ($2m/s^2$), a_{max} – maximum allowed deceleration ($-3m/s^2$), X_d – predicted clearance (distance) based on the "desired" data of the preceding vehicle, X_r – predicted clearance (distance) based on the "real (current)" clearance of the preceding vehicle, r – is a real end-to-front clearance (or distance) between preceding and lead vehicle and is given by $r = x_p - x - l_p$, c – is equal to 0 if $X_d > X_r$ and r > X_s(safe distance), and 1 otherwise, X_s (safe distance) = Standstill distance (CC0) + Gap Time (CC1) * current velocity (v) [71], $k_a = 1.0$, $k_v = 0.58$, k_d = 0.1 are constant gains, and greater than zero respectively, x, x_p: current coordinate (position) of following and preceding vehicle respectively, and l_p is length of the preceding vehicle.

The CACC vehicles rely on the V2V communication channel where each vehicle is expected to have a communication capability for the effective implementation of the logic. Hence, until a significant market penetration of connected autonomous cars is achieved, the application of CACC would be a challenge. On the other hand, the CACF model considers all available communication means such as V2I, V2V, and others. Although the transition phase of conventional vehicles or semi-automatic cars towards fully operational autonomous cars requires decades and the effective V2X communication would remain a challenge until substantial amounts of automatic vehicles are available in the market, the needs to consider the V2X communication into the car-following models are still very attractive. However, since this is a very new model developed in May 2020 [70], up to now, there is no analysis for how this model would work in the mixed driver environments. In this thesis, we will further investigate this model for its potential future wider applications in the mixed driver environments before a full penetration of CAVs.

1.2.4. Lateral (lane-keeping and lane-changing) and reverse movements

1.2.4.1. Lane-keeping and lane-changing

Various systems can be used for vehicle maneuvering on a multi-lane highway for lateral movements such as lane-keeping, lane-changing, and left-turn assist. Autonomous vehicles are equipped with various technologies such as cameras, GPS, radars, and laser, and LiDAR sensors to inspect the surrounding elements while driving. For lane-keeping, vehicles are assisted through built-in cameras above the central rearview mirror and positioning systems to monitor lane-markings. If the vehicle is going off-track, a ‘lane-departure warning (LDW)’ system is activated automatically to warn the driver of a possible exit from the current lane or prepares the driver for maintaining a lane-discipline through automated steering and/or braking as a ‘Lane-keeping assistant’ [36].

For lane-changing, short-range radar sensors [36] were used to observe the surrounding traffic zones to the sides and back of the car as the driver decides to change the lane from his/her current lane, for providing drivers warning on the presence of traffic in the target lane for potential adjacent vehicle in the blind spot location. If the driver ignores the warning and initiates the lane maneuvering, another strong message is transmitted to avoid the side crash.

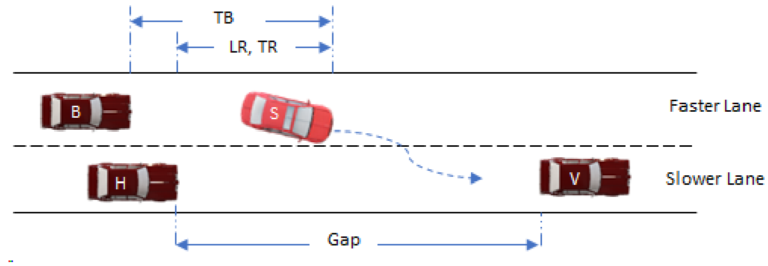
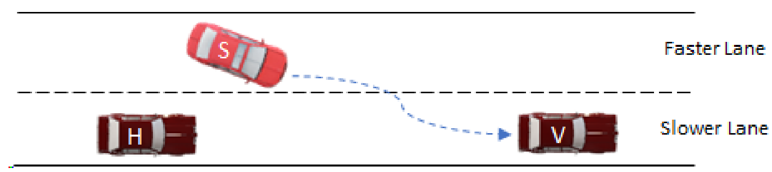
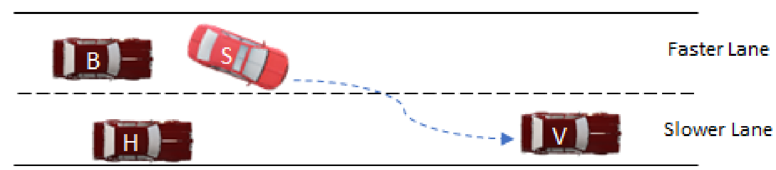
The lane-change system uses lane-change models to define the driver’s decision as to when it is possible to change a lane or not to change a lane in a multi-lane road network system [72]. The concept of lane changing is followed by the gap acceptance models. As the driver finds a safe gap (critical gap), the lane change rule initiates immediately. Mostly lane-changing models are based on a ‘set of rules’ [73] that enables the driver to make a decision when it is necessary to change a lane to reach the desired destination. Lane-changing can be categorized into two categories such as mandatory lane-change and discretionary lane-change [74]. One of the famous lane-changing models is developed by Gipps in 1986. ‘Gipps’ model explains the structure of lane-changing maneuvers in an urban driving situation which covers the influence of traffic signals, obstructions, and other vehicle types such as the presence of heavy vehicles in a mixed traffic stream [75]. The ‘Gipps’ models focus on the risk of the possible collision between vehicle to vehicle, vehicle to obstructions, and other logical driving behaviors.

Later, Sparmanns investigated the human behavior towards lane-changing process on one-way roads. A lane-change can be characterized as slower-to-faster and faster-to-slower lanes depending upon the desires and needs of the driver. It is important to have safety as a priority element before the initiation of the lane-changing process such as estimating optimum distances and speed differences of the lead and back vehicle on the particular lanes. There are six types of lane-changes defined by Sparmanns, including four types for faster lane-change and two types for slower lane-change respectively as shown in Table 1-2 and Table 1-3 [76].

In addition, for left turn assistance, the laser scanners installed in front of the vehicle senses the on-coming traffic and sends a signal to the driver to apply the brake or/and otherwise, the vehicle decelerates to stop automatically [66]. LiDAR is an optical remote sensing technology that measures the distance to a target or other features of a target (e.g. shape, size, design, etc.) by illuminating it with a light, often by using pulses from a laser [77] [78], which is normally installed on the roof of autonomous cars which provides 360-degree imaging. However, this system is in the development stage, yet complex and expensive [32] and AVs and CAVs rely on the data quality of the LiDAR to provide smooth and safe operation.

However, up to now, there is no investigation on how the development of a recent car-following model CACF would impact the lateral movements of the CAVs, which will be investigated in this thesis. It is important to note that, ACC and CACC are car-following models which only control the longitudinal behavior of the following cars in the same lane. If a user needs to perform the lateral operations additionally, a desired lane-change logic needs to be added in the ACC/CACC models accordingly.

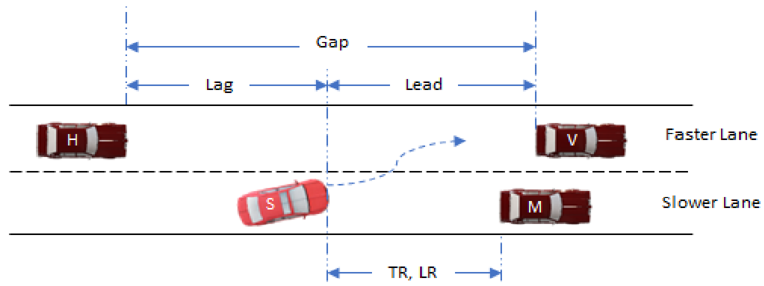
Table 1-2. Lane-change to a slower lane and relevant two types [76]

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

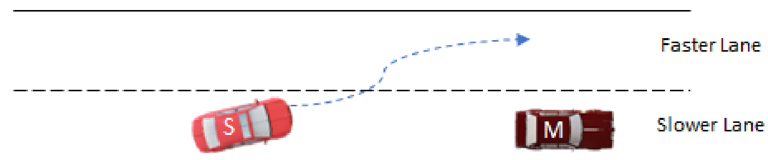
S = lane-changing vehicle
M = front vehicle on an actual lane
V = front vehicle on a faster lane
H = following vehicle on a faster lane
GAP, TR, TB = Time headways [s]
LR = Distance for reaction [m]

Table 1-3. Lane-change to a faster lane and relevant four types [76]

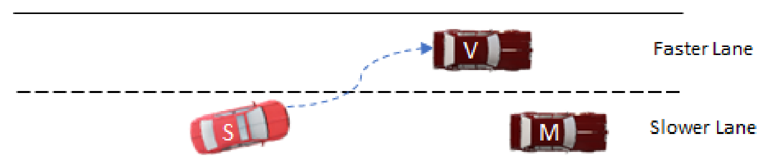
Faster lane-change



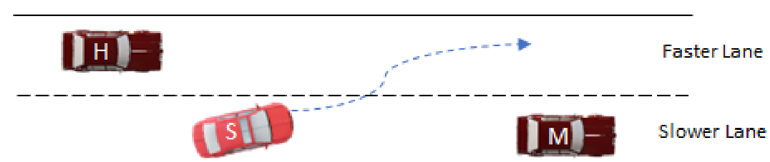
Type-1: FREE lane-changes



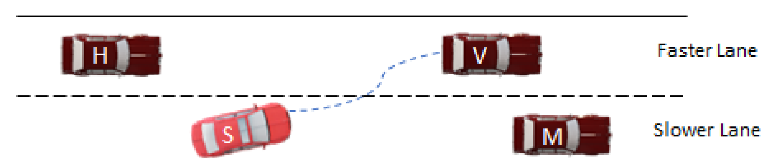
Type-2: LEAD lane-changes



Type-3: LAG lane-changes



Type-4: GAP lane-changes



S = lane-changing vehicle
M = front vehicle on an actual lane
V = front vehicle on a faster lane
H = following vehicle on a faster lane
LAG, LEAD, GAP, TR = Time headways [s]
LR= Distance for reaction [m]

1.2.4.2. Reverse movement and others

For reverse movement, there are rearview camera and rear cross-traffic monitoring available [36] for assisting drivers when applying the reverse gear. An interactive display shows the position of the car while pushing the vehicle in a reverse direction. As soon as the driver is close to the obstructions, the sensors (e.g. reverse-traffic monitoring) alerts the driver for the possible accident. The in-vehicle cameras and onboard sensors alert the driver before the occurrence of a potential crash and/or otherwise help in the reduction of crash damage. Parking assistance is generally activated when the vehicle is in reverse gear status and speed is below 10 miles per hour. Drivers use parking assistance technologies to find adequate parking spaces and in some cases, the vehicles can automatically park themselves after finding the required parking space [36].

In addition, there are attention monitoring systems on vehicles sometime to monitor the driver's fatigue level through facial recognition analysis. The system is trained to detect certain prolonged facial features such as closed eyes or not looking ahead, as well as some steering behaviors that suggest the onset of drowsiness. If the system encounters the driver's fatigue, it generates a warning so that the driver may stop or rest [36].

Driving in congested highways and long-queuing conditions is a hectic and stressful activity. The recent technologies e.g. congestion assistant or traffic jam assist (TJA) takes full control of driving and provide relief to the driver from the tedious task of driving during traffic jams. Under this system, the primary lateral (e.g. lane-keeping) and longitudinal control (e.g. accelerative or deceleration, breaks) are ceded by the driver. Some manufacturers like Mercedes S-class provide TJA system though the driver is expected to keep the hand on the steering wheel [36, 66].

1.2.5. Transport simulation models

Transport simulation models broadly contain three types of models such as: macroscopic, mesoscopic, and microscopic. The use of each model varies depending upon the level of details required for network analysis. The macroscopic models are used by transportation planners to manage large-scale traffic networks [79] such as freeways, corridors, urban congestions [80], and also for forecasting travel demands. The macroscopic model uses deterministic traffic stream characteristics (speed, flow, and density) [72, 81]. The individual vehicle interaction such as conflict management, gap-acceptance, and other discrete vehicular characteristics cannot be modeled by macroscopic models.

The mesoscopic models combine both macroscopic and microscopic simulation models. The mesoscopic models provide less reliable individual vehicular characteristics as compare to micro-simulation however these tools have better performance for typical planning analysis techniques [81]. The microscopic models record the individual vehicle's physical and operational characteristics for each simulation time step based on car-following, lane-changing, and gap-acceptance logics. Microscopic simulation is essential for complex roadway geometry, congested urban networks, pedestrian movements, road safety, and other proposed transportation improvements [81] followed by the impacts of detours.

The micro-simulation models consist of several objects that enable users to develop actual traffic flow systems. It includes different roadway network elements such as road design, signals system, vehicle types, driving behaviors, and other parameters. The driving behavior logics are defined in such a way that it illustrates the real human driving phenomenon on a typical highway. The significant logics behind a certain driving behavior includes a gap acceptance model, speed adaption, ramp merging, overtaking, lane-changing, and car-following models [82]. The driver does two types of tasks during driving such as longitudinal interaction (acceleration of own vehicle, maintaining a safe speed and gap from the preceding vehicle) and lateral communication (lane changing and overtaking) [83]. The following sections provide a brief introduction to important elements of driving behavior.

There are several traffic micro-simulation packages available commercially in the market today that simulate various real-world network configurations, problems, and solutions. Each computer simulation software package employs different car-following behaviors, lane-change, and gap-acceptance models as discussed in the previous section. The four most popular simulation tools are AIMSUN, CORSIM, PARAMICS, and VISSIM [72, 82, 84].

The AIMSUN (Advanced Interactive Microscopic Simulator for Urban and Non-urban Network) uses Gipps' safety distance models and developed by Traffic Simulation System, Barcelona, Spain. This tool is potentially famous for modeling traffic dynamic assignment, incident management, and ITS applications such as ramp metering and vehicle guidance systems [53]. AIMSUN is mostly used in Europe but now a wide-use is observed in the U.S. which can simulate urban streets, freeways, interchanges, and roundabouts [84]. Additionally, one of the reasons for the selection of this tool by modeling practitioners is its strong 3-D animation capabilities.

In 1988, FHWA developed CORSIM (CORridor SIMulation) software by combining previous micro-simulation tools such as; (1) NETSIM (NETwork SIMulation) which simulates urban traffic streams whereas; (2) FRESIM (FREEway SIMulation) which simulates complex freeway networks. The car-following logic of NETSIM is that the lead vehicle moves to a new position (i.e. coordinate) as the simulation time proceeds with one time-step. The following vehicle is then moved to a new location in a way that reads the lead vehicle such as if the lead vehicle decelerates at the maximum deceleration limit, the following vehicle will stop at a speed of zero to prevent the vehicle crash with the lead vehicle[85]. The FRESIM uses Pitt car-following model that can be considered as a stimulus-response model. The logic for this model works idealistically the same as the GM-type model such that the following vehicle always maintains a safe space-headway [86]. CORSIM has the most application in the U.S because of its reliability for driving behaviors and vehicle performance models [84].

The PARAMICS tool was developed by the UK Department for Transport in 1990. This software uses the Fritzsche car-following model that is an acceleration model based on psycho-physical logic[87]. The Fritzsche model records human perception in five different regimes: free following; following 1; following 2; closing in; and danger. Each regime has a specific threshold value in the relative speed/space ($\frac{\Delta X}{\Delta V}$) diagram for the psychophysical follower-leader pair [82]. For example, the driver will only react to the vehicle if the change in speed falls within the specified threshold.

The PTV VISSIM (VISSIM - Verkehr In Städten –SIMulationsmodell) is one of the most predominant micro-simulation tools developed by a German company PTV Vision (Planung Transport Verkehr) in 1992. VISSIM uses a psychophysical car-following model which was first developed by Wiedemann in 1974 [58] and further enhanced in 1992 by Wiedemann and Reiter [60] which is now called Wiedemann 99 car-following model. This simulation tool is capable of performing complex network and capacity analysis including signalized junctions, transit operations, passenger commute, corridor modeling, multimodal systems, active traffic management, emission modeling, connected vehicles, and facility operations such as airport and terminals [71].

In VISSIM, the Wiedemann model decides how the following vehicle behaves based on the distance and difference of speed to the vehicle ahead. The model used numerous random numbers, statistical distributions, and stochastic variations that ensure each car has different behavior in each time-step [30]. Similarly, the lane-change algorithm works on the rule-based model as explained earlier [75, 76]. This software package allows the user to adjust the parameters of lane-change, gap-acceptance, and car-following models that make this tool stand-out from other commercially available simulation tools in the market.

This thesis focuses only on VISSIM software which is explained in more depth following the next sections and chapters. The primary reasons for selecting this micro-simulation tool include 1) application of external driver models through APIs, 2) use of a psychophysical car-following model as it is based on the assumptions and perceptions of the driver behavior, 3) allowing the user to calibrate the car-following model parameters, 4) robustness of the graphic user-interface; built-in features for connected autonomous vehicles, and 5) effective evaluation techniques for capacity and safety.

1.2.6. Impacts of autonomous vehicles and connected technologies on traffic flow

As stated in the introduction, the advent of autonomous and connected vehicles will bring potential benefits to the traffic engineering perspectives along with the number of unique challenges for the users and concern authorities. With the continuous penetration of AVs and CAVs into the market, they will continue impacting significantly to traffic engineering parameters such as road capacity, delays, travel times, cost factors, and safety.

1.2.6.1. Implications of AVs and CAVs on traffic speed, capacity, and travel times

The AVs/CAVs would initially maintain larger headways as compare to traditional human-cars due to a conservative behavior. As a consequence, the road capacity would reduce and the average speed of overall traffic would slow down at the first stage. However, the increasing penetration of AVs and cooperative driving (e.g. platooning) in the market share will eventually reverse the process by improving the mobility, safety, and environmental gains [88-91]. The human-driving has a stochastic behavior and is modeled more hesitant to accept risk. The AV/CAV on the opposite has deterministic driving behavior and the driving dynamics are predictable. Hence, the calibration parameters and other constants used in the existing car-following models as discussed previously (e.g. Wiedemann psycho-physical car-following model 1974 or 1999) need to be revised for autonomous cars [88].

The AVs will have the potential to improve the capacities of urban intersection network, freeways, merge/diverge, and weaving segments by (1) keeping constant parameters, and (2) faster speeds with tightly spaced vehicles. If there is further increment in traffic after the optimal density is achieved, headways tend to reduce and become more constant (i.e. smaller standard deviation). In due course, it will approach jam density and hence both the flow and speed will become zero [5].

It is obvious that the impacts AVs and CAVs on freeway operations and capacity are dependent on the fleet mix, market penetration, lateral and longitudinal communication, and other car specific parameters such as desired acceleration/deceleration, speed, and headways). The maximum throughput (i.e. 2,400 v/h/ln for a freeway) will increase when autonomous cars maintain shorter gaps and decrease with larger headways [5]. Another study evaluated the effectiveness of collaborative merging behaviors of connected vehicles in freeway ramp operations. Using VISSIM, MATLAB, and Car2X module, an optimization-based ramp control approach and gradual speed limit control approach was developed. Subsequently, the proposed operational strategies were implemented in a simulation platform to assess average speed, delay, and throughput against no control strategy (default behavior). The results indicated that the control strategy effectively coordinated all merging vehicles at freeway on-ramps and significantly improves network safety [92].

Atkins conducted detailed research for the Department for Transport (DfT) of UK on the impacts of CAVs on traffic flow for the UK road network. CAVs are modeled for different longitudinal (i.e. VISSIM driving behavior CC0 to CC9), lateral (i.e. lane-changing parameters), and other driving behavior parameters (i.e. the observed vehicle, look ahead distance, and look back distances). The benefits of CAVs towards average delay and the average journey time is calculated for different market penetration as shown in Table 1-4. The strategic road network consists of motorways, free-flow, and controlled intersection, as well as merge and diverges sections. The base scenario has 0% CAVs fleet whereas others have a combination of Level II (driver assistance) to Level IV (full automation) CAVs fleet. The average delay and journey time is significantly improved by 50.54% and 11.87% respectively for 100% market penetration of Level IV CAVs. Further, the result strongly suggests a higher percentage of market penetration to gain the benefit of vehicle automation. For instance, at 25% CAVs penetration, the improvements are negligible [93].

Table 1-4. VISSIM simulation results for CAVs performance at the strategic road network [93]

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

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

A study by peter et al. investigated the impacts of increasing AVs penetration rates for 3 different desired speeds. The VISSIM network is a single-lane link with linearly distributed desired speeds between a minimum and maximum values such as 50 km/h (48-52), 100km/h (99-101), and 130 km/h (125-135). The market penetration increases from 0-100% with 10% increasing intervals. The trends show that higher capacities can be achieved at higher speeds. Additionally, the increase in capacity is nearly linear for up to 0-60% AVs penetration whereas the gap slightly increases for higher penetration rates (>60%) [89].

1.2.6.2. Estimating traffic flow benefits for ACC and CACC models

Several studies have investigated the potential benefits of autonomous and connected cars for varying market penetrations and time gapes (i.e. headway) utilizing techniques such as ACC and CACC through microscopic traffic simulation. A study found that ACC increases speed in congested conditions even at a lower market penetration of 20% yet some bottlenecks can be formed at locations where drivers turned off their ACC systems [94]. In 2007, Kesting et al. analyzed the ACC results for travel-time delay and found that using ACC at 10 percent market penetration, the individual driver's maximum travel-time delay was reduced to 30 percent, and the cumulative delay-time was reduced to 50 percent. Additionally, the simulation results observed a significant reduction in queue lengths [95].

However, not all the researchers found positive impacts of ACC on the traffic flow. For example, Shladover et al used the AIMSUN simulation software and modeled the traffic dynamics using ACC with varying market penetrations. The study showed that conventional ACC does not have any positive impacts on the highway capacity as the drivers behave in a similar pattern to manual driving where a typical system gap is maintained [96]. A study by Davis in 2004 showed at 10 percent or less market penetration and high speeds, congestions occur. Further, positive impacts are only found starting at a 20 percent penetration rate, while a measurably reduced travel time is only found at a 50 percent rate [97]. In a simulation experiment by Calvert et al, it was found that improvements in traffic flow are observed for market penetration above 70% [98]. Therefore, according to the available literature review on the impacts of ACC over traffic capacity, congestion, delays, and speeds advocate that potential benefits are only available at higher market penetration rates.

Mixed results of the positive and somewhat negative impact of CACC market penetration have been found by different researchers. A study used MIXIC traffic-flow simulation to analyze the impacts on traffic after the introduction of CACC. The study reveals that the variance of the vehicle's speed in one lane and speed differences between each lane were decreased. The same researcher also found that road capacity decreased with the decreasing rates of CACC market penetrations which is unlikely to the expectation of roadway capacity as shorter and uniform headways on actual increases the capacity [99]. It is however uncertain that this result is because of the CACC implementation or the limitation of the mandatory lane-change model of the MIXIC [36].

In contrast, Shladover et al founded a substantial increment in the roadway capacity. The experiment consists of all vehicles equipped with the CACC system and maintains a 0.5 s time gap, the outcomes showed the potential increase of capacity up to 4,400 v/h/ln [100, 101]. Another study by Van Arem et al. uses the MIXIC simulation model to analyze the traffic stability and throughput for the shockwave effect by limiting the highway capacity (i.e. dropping a four-lane highway to a three-lane highway) and examined the impacts of CACC by incorporating good vehicle dynamics and driving behavior [65]. The study proved that the shockwave effect could be mitigated as well as the average speed of traffic increased for higher market penetrations of CACC such as greater than 60 percent [65].

In a similar pattern, Zhao et al. considered a simulation of manual, ACC, and CACC vehicles in VISSIM to analyze the reaction towards shockwaves and benefits of a platoon (i.e. 6 CACC vehicles with a closed time-gap). The formation of the platoon is simulated by an API (application programming interface) where several maneuvers are modeled such as forming, splitting, dismissing, and joining a platoon. The results indicated that lane capacity improves significantly with the increasing penetration of CACC vehicles [68].

In 2012, Shladover et al conducted another AIMSUN simulation study that consists of manually driven, ACC, CACC, and HIA (Here I am, a manually driven vehicle equipped with DSRC). The HIA vehicle is capable of sharing location and speed information to other vehicles, therefore it acts as a CACC once followed by another CACC. The message transmitted by HIA vehicle follows the same proposed strategy by USDOT where all vehicles would be at least equipped with a vehicle awareness device (VAD) which can broadcast GPS (actual location), speed, and heading information. By doing this, HIA vehicles can be treated as a leader to the CACC platoon [96].

The CACC vehicles assumed that the drivers hold the capability of higher dynamic response i.e. actual gap that the driver selects in a field testing [102-104], which provides them the confidence to follow the vehicles safely with shorter gap settings. The simulation results show that the per lane capacity would increase from 2,000 to 4,000 vehicles. Another point to note, even at low CACC penetration, benefits can be achieved ensuring that the rest of the manually driven vehicles are equipped with VAD. The maximum per lane capacity is logged about 3,389 vehicles at 90 percent CACC and 10 percent ACC in the absence of manual vehicles

[96]. Further, research indicated that the platooning of vehicles could increase the highway lane capacity by up to 500 percent [105].

Finally, some studies investigated the capacity benefits from CACC towards specific events such as merging, on-ramps, and HOV (high-occupancy vehicle) lanes. For example, a concept of cooperative merging was introduced for by Davis, where he found that if the on-ramp traffic demand is moderate, the cooperative merging improves the throughput by 20 percent as well as increases up to 2.2 miles in distance traveled per 600 seconds for a 50 percent penetration rate [106]. Another study found significant improvement in the highway capacity when CACC vehicles were given priority access to HOV lanes with a penetration rate of as low as 20 percent [107]. The optimum headway setting for an effective CACC system was analyzed by Calvert et al. The study modeled the initial default headway of 1.2 s and later discovered that the optimum headway for a CACC system is 0.9 s. The system shows significant improvement for market penetration between 50 percent to 75 percent [108].

1.2.6.3. Estimating benefits through V2V and V2I communications

The recent developments in the area of ITS and wireless communications have equipped the road users with more awareness about the future traffic conditions such as live traffic congestion maps, navigations maps, detailed routes including turn by turn information to reach the destination, detours, the current speed of the driver, position of the car, estimated travel times of a complete journey, and any other blockage or incident along the routes. In a similar pattern, many opportunities can be availed by the drivers through real-time vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I) channel, which provides an additional communication capability to the autonomous vehicles with the surrounding vehicles and the roadside infrastructure units.

Some of the V2V applications are already discussed in the previous discussion such as ACC and CACC. Another example of V2V communication, for instance, the drivers have the updates of an upstream traffic incident or hazard. The drivers can calculate expected travel time from their position and the incident [36], or in other cases, a driver can decelerate in advance to maintain the desired safety distance and to avoid any head-on collision. Using the same concept of V2V communications, Yeo et al proposed a hazard alert system where a system provides lane-specific information to the vehicles and found a potential decrease in traffic congestion at higher penetration rates [109].

Similarly, the examples of V2I applications can include the communications between the vehicle and the traffic signal lights, traffic regulatory signs, VMS, dictations form road embedded sensors, and other roadside unit inventory. For example, a sensor embedded in the road records the speeds of the vehicles and delivers the information to other vehicles. Similarly, a vehicle receives a warning from a traffic signal for crossing the intersection at the red light. For the successful deployment of V2I technologies in real-world settings, the DOT plans to provide funding of $100 million [110].

Several researchers evaluated the operational benefits of V2I communication for improving the intersection capacity, safety, fuel consumption, and CO_2 emissions [111-114]. A study evaluated the effectiveness of V2I communications towards the intersection capacity and safety. The vehicles were modeled using the VISSIM COM (component object model) application where a vehicle records the status of a traffic light and adjusts its speed decision before reaching the traffic signal ahead to improve the intersection delay, reduce the number of stops, and increase the overall throughput at the junction [30]. Another sensitivity study established a novel coordination method for intersection management in a connected vehicle environment. It divides the road network into three different regions such as area, core area (e.g. junction box), and free driving. Additionally, a buffer-assignment mechanism is then developed to communicate the AVs for the adjustment of its entry time and corresponding speed in the intersection core area. The VISSIM simulation results show a significant decrease in the number of stops and travel delays of up to 77% and a substantial reduction in fuel consumption [115].

The conclusion from several studies which are discussed in this section explains that both V2V and V2I have potential benefits towards the improvement of the system's capacity and sustainability. The connected autonomous vehicles (CAVs) follow each other with closer gaps and stable traffic flow speeds and hence generates improved traffic operations [65, 68]. A typical journey through an urban road network or a freeway network involves several complicated scenarios that require human inputs at every stage. Therefore, a system that combines V2V and V2I communication can ensure significant improvement in vehicle throughput and safety benefits. The real-time V2V and V2I wireless communication broaden the spectrum of technology innovations for transport planners, traffic engineers, car manufacturers, and software developers.

1.2.6.4. Safety benefits of AVs and CAVs

The previous sections outlined various studies mentioning the expected benefits of connected autonomous vehicles through the roadways. This section discusses the future safety benefits of self-driving vehicles. As almost 90% of the car crashes involved human errors [7], self-driving cars can reduce crash rates and insurance costs by 90% [116], however, this does not include associated additional risk for the innovating technologies [66, 117]. The Texas Department of Transportation (TxDOT) evaluates the potential gains of vehicle automation and communications on the safety and operations of the roadway network. The study developed a document that can be used as the best practice for TxDOT and other agencies for the adoption of CAV technologies for the long term [66]. This thesis is focusing only on the simulation-based surrogate safety benefits of AVs and CAVs. Researchers have used a safety sensitivity analysis tool named 'Safety Surrogate Assessment Model (SSAM)' and developed by FHWA named which is discussed in section 2.5 to evaluate the crash severity and number of crashes.

A study by Mark et al. evaluated the safety benefits of AVs for a signalized intersection and roundabout for varying market penetration. The results show significant improvement in the safety event at shorter headways. For signalized intersection, the number of conflicts reduces by 20% to 65% for the penetration ranging from 50% to 100%. Similarly, for the roundabout, the conflicts are reduced by 29% to 64% with full market penetration [118]. Another study evaluates the effectiveness of communication in mixed traffic i.e. CAVs and conventional vehicles when passing an intersection. The CAVs share their information with surrounding connected vehicles near an intersection and pass the intersection with improved efficiency and safety [119].

Another researcher developed a decision-making CAV control algorithm using VISSIM API to control longitudinal and lateral decisions on motorways operations. The results showed potential improvement in safety and traffic flow even at lower market penetration e.g. 12-47% conflicts reduction for 25% CAVs penetration whereas 90-94% conflicts reduction for 100% CAVs penetration [120]. In 2016, Martin evaluated the safety benefits for connected vehicles using two applications, (1) cumulative travel time (CTT) intersection control algorithm for V2I communication and (2) Platooning for V2V communications. VISSIM and SSAM tools evaluated the changes in the level of safety for connected vehicle applications [30]. The results showed significant improvement in safety for CACC and CTT applications. However, up to now, there is no investigation on how the CACF model of an AV or CAV would impact the traffic or safety of road users.

1.3. Problem statement

The safety and mobility of vehicular traffic are dependent on driving behaviors and infrastructure of the roadways. As mentioned in the previous section, human errors are the main cause of road crashes. Autonomous and connected cars are expected to improve the current scenario of traffic operations. However, at this stage, AVs and CAVs are still in the development stage which requires various trails in field and machine learning through autonomous driving miles on real road networks. Until the complete market adoption of autonomous technology, a long transition period of coexistence between conventional and automatic cars would exist. It is important to study and develop the expected driving behavior of future autonomous cars. Further, the future challenges also comprise of potential interaction of automatic cars with manual vehicles and/or infrastructure units. Based on the extensive literature review, there are several observations found:

1) AV/ CAVs would benefit the traffic and safety of user in some extents.
2) The V2X from ITS would benefit the AV and CAVs. Among the various car-following models available for an AV or CAV, the ACC/CACC model considers V2V and the most recent CACF model is the only model considers V2X, especially V2I. However, no in-depth analysis on how the CACF model would impact the traffic and safety of the road users.
3) There are many simulation tools available for simulating traffic, micro-simulation modeling is a good tool to evaluate a new car-following model. Among various tools, VISSIM is a good tool to be applied for investigating the safety behavior of

AV/CAVs. Two approaches can be adopted for modeling AVs and CAVs in a simulation tool including calibrating the existing driver model and driving behavior parameters for AVs and CAVs, and by implementing the externally developed algorithm.

1.4. Research objectives

Based on the observations in last section, in this study, we will focus on evaluating the safety and mobility of the CACF model which is a new model available for AVs/CAVs using VISSIM microsimulation. The specific research objectives for this thesis are listed below:

1) A comprehensive literature review for existing car-following models, advanced driving assist technologies, impacts of AVs and CAVs on traffic flow and safety, and the capabilities of simulation tools for modeling the autonomous behavior of cars.
2) Set up the CACF model in VISSIM with other conventional and autonomous related car-following models such as the Wiedemann 99 and CACC models.
3) Conduct various sensitivity tests of the CACF model on numbers of cars and distance to be considered in communication, lane changes, time delay, etc. for mixed traffic streams under varying market penetration rates.
4) Analyze and compare the results of the CACF model with that from the related car-following models such as the Wiedemann 99 and CACC models.
5) Evaluate the safety and mobility effects of the cumulative-anticipative car-following (CACF) logic for automatic cars.

1.5. Organization of the dissertation

The thesis is organized into five chapters, Chapter 1 presents an introduction and a comprehensive literature review in the area of autonomous and connected vehicles, intelligent transportation systems, advanced driving assistance technologies, transport simulation models, and the impacts of AVs and CAVs on different traffic flow parameters. In Chapter 2, the VISSIM model was developed for all the interested car-following logic. A framework of the VISSIM simulation model for sensitivity tests is presented in Chapter 3. The results of the sensitivity tests are described in Chapter 4 accordingly. Finally, Chapter 5 discusses the outcomes of this study and concludes.

2. MODELING OF CONNECTED AUTONOMOUS VEHICLES IN VISSIM

The behavior of autonomous and connected driving is predictable and deterministic unlike the stochastic behavior of human drivers. However, the existing car-following models (e.g. Wiedemann psycho-physical model) for human drivers and other driving behavior parameters (e.g. lane-change, gap-acceptance, acceleration/deceleration distributions, etc.) in the traffic simulation software need to be modified or replaced with external driving models such as ACC/CACC and CACF models for autonomous cars. This section describes how to implement the car-following models in the VISSIM software (Version 2020) and associated external APIs for the modeling of autonomous driving, platoon formation, connected driving, advance driver assistance options, and recommendations for driving behavior parameters.

Although many car manufacturers and other companies have already built partial autonomous vehicles (i.e. SAE automation level 1-3) or working towards the production of fully autonomous driving, the companies are restrictive in revealing the information of car-following algorithms. Also, the concept of autonomous driving is in the development stage and this process varies for different manufacturers. Therefore, the analysis using VISSIM simulation can model the expected driving behavior of autonomous vehicles and can inspect the associated risk before the vehicles are ready to be driven on the roads.

2.1. AV/CAV related features in VISSIM

The CoEXist[6] is a European Commission funded project which prepares the concerned authorities for a transition phase during which both the automated vehicles (i.e. AVs and CAVs) and conventional vehicles will co-exist on the roadways. The basic effort for this project is to

[6] https://www.h2020-coexist.eu/

bridge a gap between emerging AV's technology, transport planning, infrastructure development, and enabling city authorities to effectively deploy AVs using the best practices [121]. The CoEXist project has simulated real examples of AVs in four European cities such as Milton Keynes-UK, Stuttgart-Germany, Gothenburg-Sweden, and Helmond-Netherland [7]. The outcomes of this exercise provide resources to the authorities for the potential impacts of automated technology and market penetration of AVs and CAVs.

The AV-ready framework develops specialized tools for microsimulation and macroscopic modeling of autonomous and connected cars. The VISSIM 2020 is the latest version released by the PTV Group which contains all the updated AV related tools that are developed under the CoEXist study. However, PTV Group has initially provided autonomous features[8] starting from VISSIM 9[9], VISSIM 10, VISSIM 11[10] [11], and now VISSIM 2020[12]. The following section introduces some of the autonomous features in VISSIM 2020. To facilitate autonomous driving, the CoEXist project develops multiple additional tools to simulate the expected behavior of future autonomous and connected cars [134]. A brief introduction of additional AV features are outlined below, however, the complete details and guidelines are provided in PTV VISSIM 2020 user manual [71]:

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[7] https://www.h2020-coexist.eu/what-is-coexist/

[8] https://www.ptvgroup.com/en/solutions/products/ptv-vissim/areas-of-application/autonomous-vehicles-and-new-mobility/

[9] Webinar: Why Simulate Connected & Autonomous Vehicles on our Transport Systems? https://www.youtube.com/watch?v=Jrc3hUG4wjs&t=2717s

[10] What is new in PTV Vissim/Viswalk 11 https://www.ptvgroup.com/fileadmin/user_upload/Products/PTV_Vissim/Documents/PDF/PTV-Vissim_What-is-new-in-Vissim-11_EN.pdf

[11] CoEXist Vissim Webinar - Autonomous vehicles new features and how to? https://www.youtube.com/watch?v=C_bouqPNSw4

[12] What is new in PTV Vissim/Viswalk 2020 https://www.ptvgroup.com/fileadmin/user_upload/Products/PTV_Vissim/Documents/Release-Highlights/Vissim_2020_what_s_new.pdf

Desired speed spread: Since it is expected that autonomous cars will have deterministic behavior unlike the random behavior of human drivers, the spread of values for individual vehicles can be reduced for several functions such as desired acceleration, desired deceleration, maximum acceleration, and maximum deceleration. Similarly, the distribution function such as the desired speed is an important factor for a link capacity and travel times. In VISSIM, this desired speed value is assigned to each vehicle and the vehicle wishes to match this speed throughout the simulation network. However, due to the varying speed of other surrounding vehicles, human behavior towards accepting the risks, and congestions in the network, a large spread of desired speeds can be observed. The automated cars are expected to have lower spread as they will obey the speed limit regularly. The conventional vehicle has a spread of desired speed values ranging from 88km/h (55 mph) to 130kmh (80 mph) whereas the automated vehicles have a minimal spread of values ranging from 99km/h(61.5mph) to 100km/h (62.1mph).

Use implicit stochastics: This option is provided under the 'driving behavior - autonomous driving' window tab of VISSIM. If this option is unchecked (default is checked for conventional cars), a vehicle would not use any internal stochastic variations. This will affect safety distances, desired acceleration/deceleration, and other uncertainties for braking decisions.

Headway based on leader vehicle class: This AV feature is available under the 'driving behavior – car following' window tab of VISSIM. It is a specialized feature that allows users to set different desired safety distances (i.e. CC0 and CC1 for Wiedemann 99) for each vehicle class of the leading vehicle. For example, a connected car follows another connected car with a close safety distance unlike a connected car would follow a conventional car with higher safety distances.

Enforce absolute braking distance: This AV feature is available under the ‘driving behavior-autonomous driving) window tab of VISSIM. If this option is checked, the affected vehicle would stop without a collision even if the vehicle ahead comes to an immediate rest. It is expected for AVs and CAVs to be equipped with a smart braking system that can foresee the situation (i.e. next simulation run timestep) because of strong connectivity with the vehicles and the surrounding infrastructure.

Increased acceleration: This AV feature can be selected through an attribute list of driving behavior. It is dependent on the behavior of a leading vehicle (current acceleration value) and improves the capacity of a network. The concept of ‘increased acceleration’ is to enable the following car to accelerate at a desired acceleration (not more than a maximum acceleration) if the leading vehicle is accelerating. The human drivers are not aware of the future behavior of the leading vehicle; hence the vehicles fall behind in the case where the vehicle ahead accelerates more than the following vehicle. The automated cars can read the acceleration value of the vehicle ahead using V2V technology. Therefore, if a user sets an input value of 100%, the AVs or CAVs will accelerate to reach the desired acceleration in the event where the leading car is accelerating [71, 122].

Platooning possible: This AV feature is available under the ‘driving behavior-autonomous driving) window tab of VISSIM. The current version (2020) allows users to form a platoon without any need for an external code scripting. Rules of platoon formation are fixed and well defined in the software user manual. However, a scripting effort is still needed to develop the desired behavior of vehicle connectivity and cooperation.

Communication and cooperation: Communications between vehicles (conventional or autonomous) are improved by introducing two options under the lane-change tab for driving behavior in of VISSIM 2020. The first option is ‘cooperation lane-change’ which facilitates the process of a lane change in such a way that the trailing vehicle in the target lane would move to another side of a lane and providing room for lane change-vehicle. The second option is ‘advanced merging’ where a lane-changing vehicle would initiate the process earlier so that no disruption of the traffic occurs and therefore the capacity of the network increases. The vehicle cooperation can also be modeled by choosing smaller headways between vehicles through CC0, CC1, CC2, and CC6 parameters in VISSIM.

The CoEXist project also introduces three AV-ready driving logics in VISSIM 2020 under driving behaviors such as cautious, normal, and aggressive. Each driving logic uses different parameters for Wiedemann 99 car-following model, lane-change, and following behaviors as shown in Table 2-1. The concept is defined below as [71]:

AV cautious: The vehicle maneuvers in a safe manner at all the time and maintains larger headways. This logic is conservative if compared with default urban (motorized) driving logic.

AV normal: This logic behaves similar to a default urban (motorized) driving behavior. Additionally, the vehicle can sense the vehicle’s distance to other vehicles in the range and their real-time speed.

AV aggressive: The vehicle is ‘all-knowing’ of the entire traffic situation, equipped with traffic situation prognosis, and maintains a minimum gap to other vehicles. This aggressive logic leads to cooperative driving.

Table 2-1. Driving behavior parameters for three different AV-ready logics

Driving Parameters	CoEXist AV-ready driving behaviors		
	AV cautious	AV normal	AV aggressive
Following behavior			
Max look ahead distance (m)	250.0	250.0	300.0
Number of interaction objects	2	2	10
Number of interaction vehicles	1	1	8
Car-following (Wiedemann 99)			
CC0 (m)	1.5	1.5	1.0
CC1 (sec)	1.5	0.9	0.6
CC3	-10.0	-8.0	-6.0
CC8 (m/s2)	3.0	3.5	4.0
CC9 (m/s2)	1.20	1.5	2.0
Lane-change			
Necessary lane change - max deceleration (m/s2) for own vehicle	-3.5	-4.0	-4.0
Necessary lane change - max deceleration (m/s2) for trailing vehicle	-2.5	-3.0	-4.0
Necessary lane change- -1m/s2 per distance (m)	80	100	100
Necessary lane change – accepted deceleration (m/s2) for own vehicle	-1.0	-1.0	-1.0
Necessary lane change – accepted deceleration (m/s2) for trailing vehicle	-1.0	-1.0	-1.5
Safety distance reduction factor	1.0	0.6	0.75
Max deceleration for cooperative braking (m/s2)	-2.5	-3.0	-6.0
Cooperative merging	No	Yes	Yes
Autonomous driving			
Enforce absolute braking distance	Yes	No	No

Although it is convenient to model the anticipated behavior of autonomous and connected cars by modifying the existing VISSIM car-following model and using the existing AV/CAV features in VISSIM 2020 such as headway, safety distance, acceleration functions, or speed distributions, it has its drawback that it uses the same driving logic as by other conventional human-driven vehicles i.e. Wiedemann Model 74 or 99. Further, VISSIM contains about 190 parameters for car-following, lane-change, gap-acceptance, and others which makes it very difficult to calibrate the model [123]. In addition to the existing AV/CAV features available in the VISSIM 2020, another way to model AVs & CAVs or V2V & V2I communication in VISSIM is by writing external scripts using the VISSIM COM interface, Driver Model (DLL) – interface, and DrivingSimulator-interface, which will be introduced next, which is the approach used in this study.

2.2. VISSIM APIs to integrate ACC/CACC and CACF car-following models

The VISSIM-APIs (Application Programming Interfaces) are an add-on module which allows user to integrate external applications into the VISSIM [71] and thus enhancing the user's experience. It includes COM-Interface, DriverlModel-DLL, DrivingSimulator-DLL, EmissionModel-DLL, and SignalControl-DLL [71]. The advanced communication features of automated vehicles such as V2V (vehicle-to-vehicle) or V2I (vehicle-to-infrastructure) are modeled through VISSIM APIs by various researchers [30, 68, 120, 122]. The concept of ACC, CACC and CACF car-following models have been previously explained in Chapter 1.2.3 and based on the mathematic descriptions of these models, in this section, the codes of the external driver models (ACC, CACC, and CACF) were manually written as explained in Chapter 1.2.3 and integrated into the VISSIM APIs for further analysis.

2.2.1. Component Object Model (COM)

The Microsoft COM (Component Object Model) provides communication, connection, and access to different applications. The data and functions contained in the VISSIM application can be accessed externally through the COM-Interface using different programming languages such as VBA, Python, C++, C#, MATLAB, and JAVA [124]. It can access each vehicle's attribute (e.g. current position, acceleration, orientation on the lane, vehicle's receiving traffic light status, etc.) during a simulation run and can also edit some of the parameters (e.g. arrival pattern of vehicles in the network, create or remove vehicles, etc.). As per the requirement of the user to run the scripts for a specified amount of time, VISSIM "event-based" COM scripts only activate during the user-defined simulation time value or if required it stays active throughout the simulation period. The software package contains a detailed instruction document of COM-Interface explaining the procedures for accessing the objects and attributes. COM-Interface assist in modeling the behavior of autonomous and connected vehicles such as platooning, shorter and steady headways, and the vehicle adjusting the speed to arrive at an intersection at the status of the green traffic light. The VISSIM package contains some AVs related COM scripts examples files for users.

2.2.2. Driving simulator DLL and External driver model DLL

The Driving simulator Interface connects the VISSIM software to a real-world driving simulator (DS) hardware (e.g. containing a steering and wheel pedals) or any other external vehicle simulation program with the developed algorithms (for a single vehicle or multiple vehicles). For example, a DS controls a specific vehicle type in a network while the rest of the vehicles are using the VISSIM default car-following and lane-change behaviors. The information is exchanged between the VISSIM and a DS for each simulation time-step. VISSIM provides the information for the surrounding traffic (e.g. position, acceleration/deceleration, speed, etc.) to the DS, and in return, the DS provides back the current position and orientation of the simulator vehicles [125]. The DS provides an opportunity for the users to model AVs and CAVs using the data from the real-world autonomous cars and built-in sensors on the roadways.

The External Driver Model DLL API module enables the user to completely replace the internal-car following model (i.e. Wiedemann 74 or 99) and lane-change models by a user-defined algorithm for selected or all vehicle type. The external driver model (EDM) such as ACC, CACC, and CACF models can control the longitudinal (acceleration and deceleration), lateral (lane-change) behavior of the vehicles. VISSIM provides two EDM source files in the API package. The first file is the "DriverModel.h" which is the header file for a driver model DLL and shouldn't be changed by a user. The header file contains the definitions of all "types" and "number" constants that are used by VISSIM when a "DriverModel" call the DLL functions [126]. The second file is the "DriverModel.cpp" file which is the main source file [126]. The user-defined car-following logic code is programmed using C++ language which outputs a DriverModel.cpp file. The CPP file can be compiled to Dynamic Link Library (.DLL) file using the Microsoft Visual Studio software. The VISSIM package also contains an example of a DLL code file and a Visual Studio Project (.vcproj). The prepared DLL file can be loaded for a specific vehicle type using VISSIM GUI.

During a simulation run, VISSIM calls the DLL code for each affected vehicle using the EDM (ACC, CACC, and CACF car-following models) for each simulation time-step and decides the behavior of the vehicles. The current state of the affected vehicle and surrounding vehicles is delivered to DLL and in return, the developed code computes the longitudinal behavior i.e. acceleration/deceleration values, and lateral behavior i.e. lane-change values. Finally, the DLL file passes the computed values back to VISSIM in the current simulation-time step [126] as shown in Figure 2-1. The DriverModel-DLL is a potential tool for modeling the autonomous and connected behavior of vehicles such as cruise controls, platooning, and getting real-time traffic data of surrounding vehicles e.g. headway, current speed, current acceleration, and current lane.

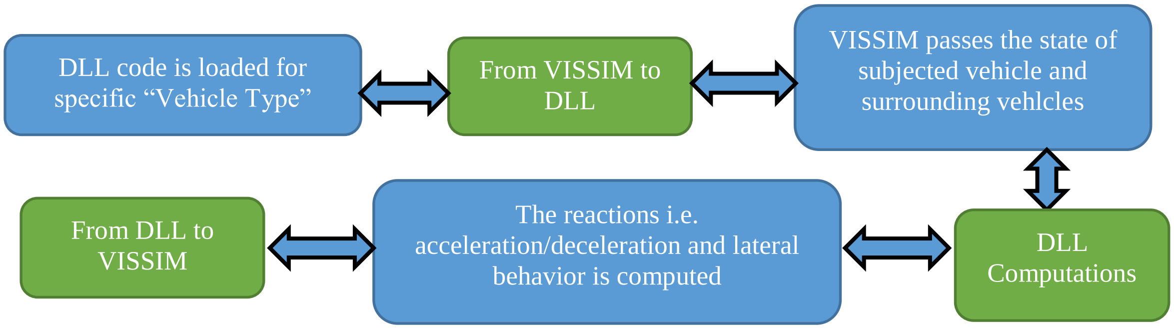

Figure 2-1. VISSIM and External DriverModel-DLL working procedure

Zhao et al. developed an external driver model using ACC/CACC framework through VISSIM API i.e. DriverModel-DLL [68] and Yang developed an external driver model using CACF framework through VISSIM API [70]. As shown in as shown in Figure 2-2 [68], the following steps explain the procedure of implementing the ACC/CACC or CACF DLL files into the VISSIM:

1. Development of a VISSIM simulation network (e.g. links, connectors, etc.).
2. Writing code in C++ for ACC and CACC.
3. Compiling the code into a DLL file.
4. The DriverModel-DLL is loaded into VISSIM for a specific vehicle type.
5. VISSIM reads the DLL logic for each time step.
6. Using the “Set” function, the driver behavior is sent from VISSIM to DLL for every time-step.
7. Using the “Get” function, the update driver behavior is sent from DLL to VISSIM.
8. Using the “Execute” function, VISSIM moves the driver (i.e. DLL affected vehicle).

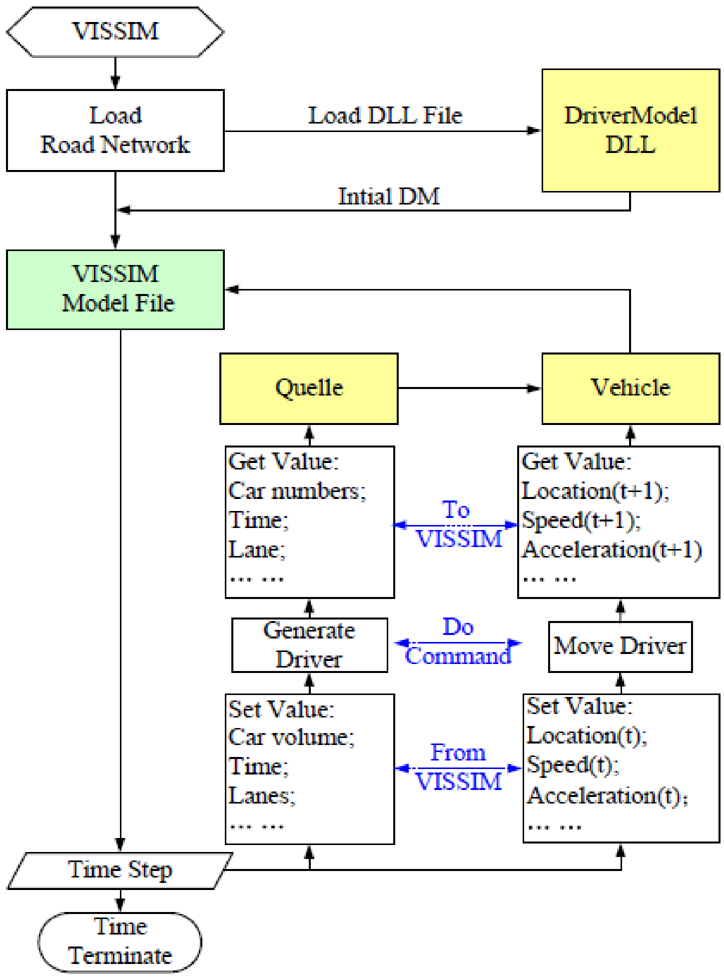

Figure 2-2. The flowchart for DriverModel-DLL and VISSIM [68]

2.2.3. Loading EDM DLL application in VISSIM

With the EDM DLL (for ACC/CACC and CACF car-following models), the user-defined External DriverModelDLL file can be loaded into the VISSIM following the procedure as shown in Figure 2-3 and detailed below:

1. Develop the proposed algorithm code using the “DriverModel.cpp” file provided in the VISSIM installation package. The code can be developed using any text editor.
2. At the next step, open a “DriverModel.vcxproj” file which is provided in the package in Microsoft Visual Studio 2019 software as shown in flowchart in Figure 2-3. Paste the developed code under the DriverModel.cpp.

3. Check for any coding errors and build a solution. The EDM DLL file is ready to be imported in VISSIM.
4. Under "Vehicle Types", check "External driver" and locate the developed DLL file as shown in Figure 2-4.

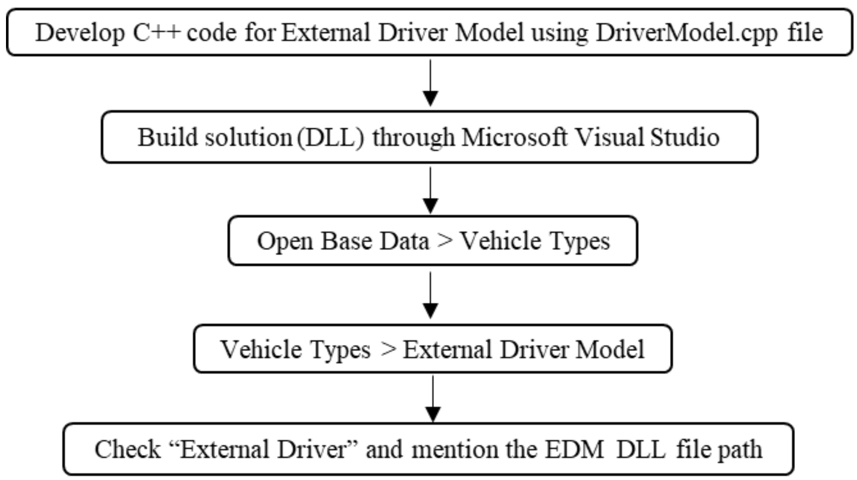

Figure 2-3. Flowchart for loading EDM DLL application in VISSIM

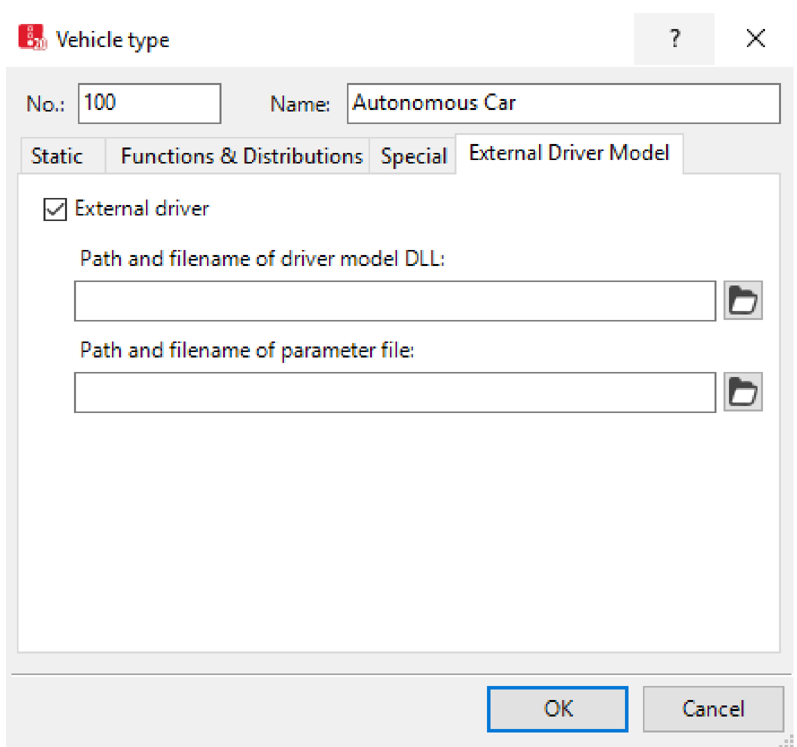

Figure 2-4. VISSIM Vehicle Type window for selection of EDM DLL model (Source: VISSIM Software)

2.2.4. Typical time gaps for ACC, CACC, and CACF car-following models

In different car-following model, the time gap is different. According to the International Standard Organization (ISO), the time-gap is the distance divided by vehicle speed [127]. The distance is measured from the front end of the following car to the rear-end of the leading car. The time gap has a potential impact on network capacity and road safety. It becomes critical in emergency scenarios where the driver needs to react and takes a decision immediately A shorter-time gap may increase the traffic flow, however, the safety would be compromised.

The time gap for human driving includes perception-reaction time and duration for the application of breaks. The car-following models define different time-gap values depending upon the model's sensitivity and safety behavior. The human-drivers typically require more time-gap as compare to those vehicles equipped with adaptive cruise control technology because of the active communication between the following and leading vehicles.

Since the ACC control algorithm use ADA systems such as forward ranging sensors to inspect and measure the headway and sometimes matching the speed with the forward vehicle [67], the system provides convenience to the driver by releasing the stress of continuously matching the speed with the leading vehicle [65, 101]. The time-gap for the ACC system has a typical range of 1.0 to 2.0 seconds [67], however, a fixed value of 1.4 seconds is used in several studies as a midpoint value [65, 67, 68, 101].

The CACC control includes vehicle-to-vehicle communication to the existing capabilities of ACC control [67] to enhance the cooperation between vehicles. The CACC system collects data from multiple preceding vehicles and can form platoons. Unlike ACC, in this system, the vehicles follow each other with closer gaps which results in the improvement of the highway capacity. The typical time gap of 0.5 seconds is used for modeling CACC control [65, 67, 68, 100, 101].

The CACF model uses a time gap value of 0.5-seconds as was used in the CACC model because it is functioning on the same principles. Such as recording the variations in the speed, acceleration, headways, etc. of the preceding vehicle through vehicle-to-everything communication.

2.3. Wiedemann car-following model in VISSIM

Although the CoEXist study provides three default AV-ready driving behaviors in the VISSIM package along with some additional features as discussed in the previous section and there are approaches to enter external car-following models into VISSIM, yet the Wiedemann-99 car-following model still is the most popular car-following model which had been used for a lot of other studies with different parametric values for the autonomous vehicle's simulation. A recent study by Karlsruhe Institute of Technology-Institute for Transport Studies and PTV Group investigated the following behavior of autonomous vehicles for the Wiedemann car-following model using the data collected through CoEXist project of three test vehicles out of which two are real-world autonomous vehicles that drive autonomously on public roads under normal traffic conditions [128]. The leading vehicle is manually driven whereas the following two cars are in the autonomous driving mode. The autonomous cars are equipped with two longitudinal control communications such as CACC (autonomous car communicate with the leading vehicle) and degraded CACC (dCACC - autonomous car do not communicate with the leading vehicle). Hence the longitudinal behavior of two autonomous cars is analyzed to proposed the adjustment in Wiedemann’s model for autonomous driving behaviors as shown in Table 2-2. Also, it is important to mention that most of the urban driving would have active dCACC mode because the leader is sometimes lost at a traffic light or a manual vehicle cut in the platoon formations [129].

Table 2-2. Parameters for AV simulation using Wiedemann 99 model [129]

Parameter	**Autonomous CACC (communication with the leader)**	**Autonomous dCACC (no communication with leader)**
CC0	4	6
CC1	0.3, 0.6, 1.0	1.0
CC2	0	0
CC3	-40	-40
CC4	0	0
CC5	0	0
CC6	0	0
CC7	0.25	0.25
CC8	3.5	3.5
CC9	1.5	1.5

The Atkins's study also suggested model parameters for different SAE levels (i.e. Level 2 to Level 4) autonomous cars as shown in Table 2-3. The level 3 AVs are subdivided into four categories depending upon the aggressiveness of the driving parameters. The two user-defined merging behavior parameters are defined as [93]: 1) ‘minimum time-gap’ is to measure the minimum time required by a vehicle on the mainline to achieve minimum headway at its present speed, and 2) minimum clearance or headway is to measure the minimum headway required by a vehicle to merge into the mainline.

In another study, Peter et al. investigated the impacts of autonomous and conventional vehicles on the traffic flow for different market penetrations using Wiedemann-74 (for urban roads) and Widemann-99 (for freeway) car-following models. A python script was used to perform at least 20 simulations runs for varying combinations of parameters. The capacity of the

VISSIM single-lane link network is calculated against two variables i.e. CCO (standstill distance in meters) and CC1 (headway time in seconds). The desired speed distribution of a freeway network is set at 100 km/h (linear distribution 95 km/h to 105 km/h). The CC0 values are varied from 0.30 m to 0.90 m whereas CC1 values are ranging from 0.50 s to 1.50 s [89].

The CC2 (following variation) which is a longitudinal oscillation represents the stochastic behavior of a human driver. Thus theoretically, CC2 can be set to 0 for AVs due to the stable behavior of autonomous driving. The impact of the CC2 parameter is significant throughout a traffic network. The capacity jumps up to 4,000 veh/h per lane for headway values smaller than 0.60 s which is indeed a massive increase in the traffic network capacity. Similarly, if it is assumed for AVs to have stable behavior (CC2 = 0), the network capacity increases massively up to 106% (from 3,244 to 6,686 veh/h per lane). However, a disturbance in the traffic flow is observed for headways lower than 0.5 sec which seems to represent that the results are touching the theoretical ceilings of the Wiedemann 99 car-following model [89].

Table 2-3. Parameter variation for Wiedemann model and VISSIM user-defined attributes [93]

Capability levels		CC0	CC1	CC7	CC8	CC9	Min. clearance or headway (front/rear)	Safety distance reduction factor	User-defined Minimum time-gap	User-defined Minimum clearance or headway
Level 2		1.5	0.9	0.25	3.5	1.5	0.5	60%	3	5
Level 3	Cautious	2.5	1.8	0.1	3.2	1.2	0.8	90%	3.6	6.5
	Normal cautious	2	1.2	0.2	3.4	1.4	0.6	70%	3.2	5.5
	Normal assertive	1	0.8	0.3	3.6	1.6	0.4	50%	2.8	4.5
	Assertive	0.5	0.6	0.4	3.8	1.8	0.2	30%	2.4	3.5
Level 4*		0.5	0.6	0.4	3.8	1.8	0.2	30%	2.4	3.5

*Level 4 vehicles are subject to use a fixed desired speed distribution. Rest all the categories uses the VISIM default desired speed distribution according to a link type.

VISSIM treats each car as a separate driver-vehicle unit that differs in characteristics from all other surrounding traffic. The traffic flow logic not only interacts with the vehicle ahead (longitudinal communication) but also the vehicle in the two adjacent lanes (lateral communication). VISSIM does not specify the four driving states of the Wiedemann model but it delineates a more detailed description for the current driving state of the vehicle. A user can edit several parameters that control the driving behavior of a vehicle [71] such as (1) following logic, (2) car-following, (3) lane-change, (4) lateral behavior, signal control, and others.

Since the Wiedemann-99 car-following model is still very popular, this study also included the analysis of the Wiedemann-99 car-following model as a reference for comparison. The detailed parameters that control the following logic of vehicles used for the Wiedemann-99 car-following model used in this study are detailed in Table 2-4. and Figure 2-5.

Table 2-4. VISSIM Following logic parameters [71]

Parameters	**Explanation**
Look ahead distance	Defines the minimum and maximum distance for the vehicle to interact with the other vehicles.
Number of interaction objects and vehicles	Defines the number of preceding vehicles and objects (stop sign, signal controller, etc.) which the vehicle observes downstream or adjacent.
Look back distance	Defines the minimum and maximum distance for the vehicle to look back on other vehicles.
Standstill distance for static obstacles	This is the parameter borrowed from Wiedemann’s model i.e. AX already defined in the previous section. If selected the vehicle would use the user-input value otherwise the default normal distribution (0.5; 0.15)
Behavior during recovery from a speed breakdown	During the event of a breakdown, a user can specify the number of parameters such as speed, acceleration, safety distance so that the vehicle can recover to attain the desired following distance.

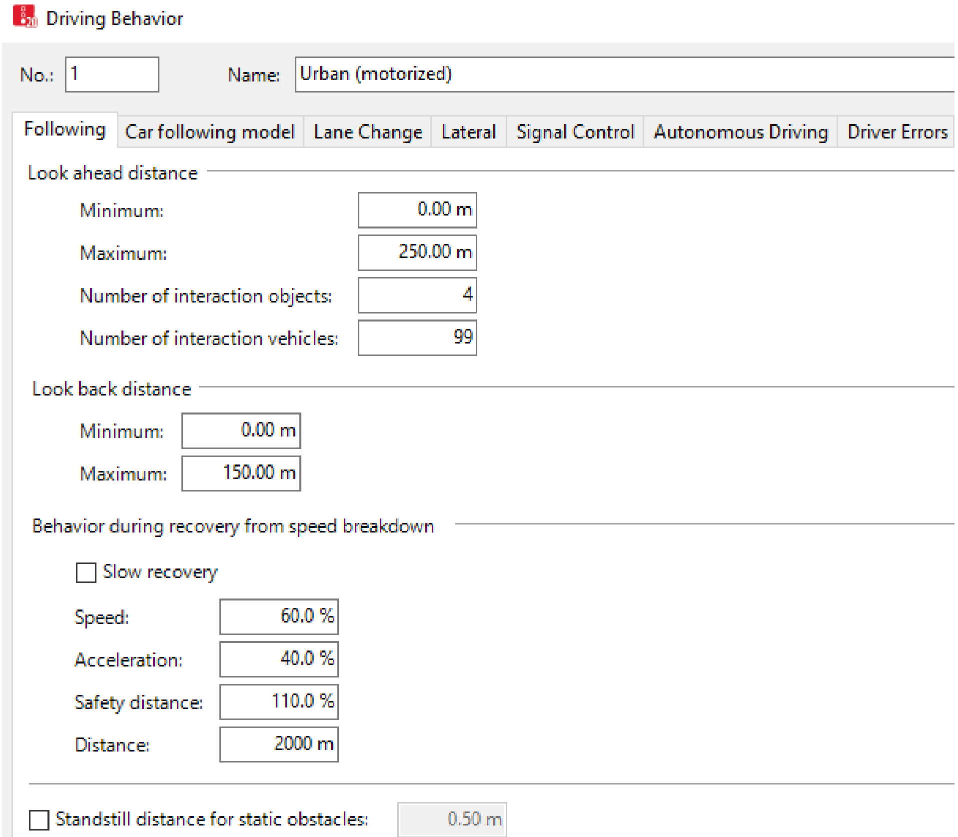

Figure 2-5. Following parameters under VISSIM driving behavior (Source: VISSIM Software)

The Wiedemann 99 suggests using this model for freeway with no merging areas. The model parameters affect the saturation flow rate of vehicles in simulation. This model is complex in nature which contains at least nine parameters enabling the user to control the following behavior of the driver. The details of the Wiedemann 99 car-following model parameters are shown in Figure 2-6. A detailed description of each parameter is presented in Table 2-5.

Table 2-5. VISSIM Wiedemann 99 car-following parameters[71]

Variable		Description	Default Value
Thresholds for Safety Distance (Δx)	CC0	**Standstill Distance:** Desired minimum distance between the two standing vehicles (lead and following) at v=0 [mph]. The value for this parameter is fixed.	4.92 ft (1.50 m)
	CC1	**Headway Time (Gap):** Desired time in seconds between the two vehicles (lead and following). The higher the value, the more cautious the driver is. Thus, at a given speed v [mph], the safety distance dx_safe is computed to: **dx_safe = CC0 + CC1 * v**. The safety distance is defined in the model as the minimum distance a driver will keep while following another car. In the case of high volumes, this distance highly influences the capacity of the network.	0.90 sec
	CC2	**Following Variation:** This is an added value to a safety distance. Restricts the longitudinal oscillation (distance difference) as a driver moves closer to the car ahead. Hence if this value is set to 30 ft, the following distance will be dx_safe and dx_safe + 30ft. The default value is 13.12ft which results in a quite stable following process	13.12 ft (4.00 m)
	CC3	**Threshold for Entering 'Following' State:** Time in seconds before a vehicle starts to decelerate in order to reach the required safety distance (negative). Hence, it defines the number of seconds a driver needed to decelerate earlier reaching the safety distance (dx_safe).	-8.00 sec
Thresholds for Speed (Δv)	CC4	**Negative 'Following' Threshold:** Defines a negative speed variation between the following process. This parameter controls the speed differences of Wiedemann's 'following-state'. A smaller value generates a more sensitive driving behavior to the acceleration or deceleration of the preceding vehicle. The default value models a potentially tight following condition for the following drivers.	-0.35
	CC5	**Positive 'Following Threshold':** Defines a positive speed variation between the following process. This parameter controls the speed differences of Wiedemann's 'following-state'. A smaller value generates a more sensitive driving behavior to the acceleration or deceleration of the preceding vehicle. The default value models a potentially tight following condition for the following drivers.	0.35
	CC6	**Speed Dependency of Oscillation:** Influence of distance on speed oscillation. If set to 0, the speed oscillation is independent of the distance. Whereas for larger values, lead to a greater speed oscillation with increasing distances.	11.44
Acceleration Rates	CC7	**Oscillation Acceleration:** minimum acceleration/deceleration during the following process.	0.82 ft/s^2 (0.25 m/s^2)
	CC8	**Standstill Acceleration:** desired acceleration when starting from a standstill (limited by maximum acceleration defined within acceleration curves).	11.48 ft/s^2 (3.50 m/s^2)
	CC9	**Acceleration at 50 mph (80 km/h):** Desired acceleration at 50 mph (limited by maximum acceleration defined within acceleration curves)	4.92 ft/s^2 (1.50 m/s^2)

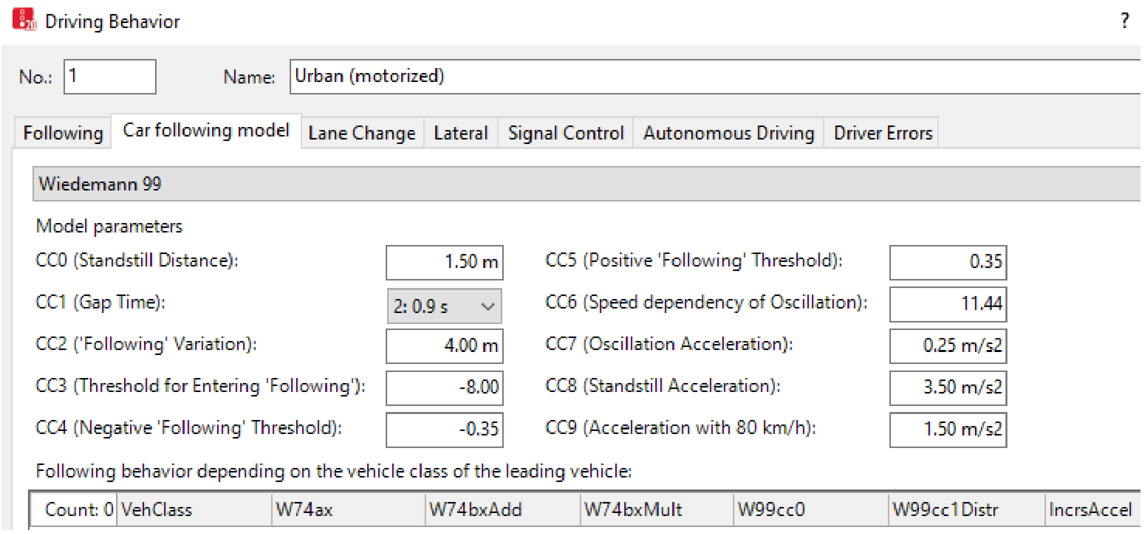

Figure 2-6. Parameters for Wiedemann 99 car-following model in VISSIM (Source: VISSIM Software)

Some of the following behavior for a human-driver to the leading vehicle class can be adjusted under the car-following model tab such as CC0, CC1, and "increased acceleration" if the following car is using the Wiedemann-99 model. For example, a conventional car would maintain a narrower safety gap for another conventional car, however, the safety gap would increase for leading autonomous vehicles or vice versa. In this study, the human-driver is assumed to maintain a similar driving behavior for both leading vehicle classes such as conventional cars or autonomous cars.

2.4. Lane-change model parameters under VISSIM driving behavior

The VISSIM lane-change model is based on Sparmann's model as discussed in Chapter 1 [130]. Additionally, there are two types of lane-changing procedures available in the software package including necessary lane-change (or mandatory lane change) and free-lane change (or discretionary lane-change). In the necessary lane-change, the driver must change its lane to reach the next connector of a route. VISSIM controls this behavior by a parameter called 'maximum acceptable deceleration' for lane changing vehicle (own) and the vehicle which will be its follower in the target lane (trailing vehicle) after the lane-change is completed as shown in Figure 2-7. The free lane-change method is initiated when the vehicle demands to obtain the benefits of speed increment while maintaining the desired safety distance in the target lane. This safety distance is computed by the speed of the lane-changing vehicle (own) and the trailing vehicle in the target lane [71]. Table 2-6 outlines some of the important parameters that control the lane-changing logic of vehicles.

Table 2-6. Lane-change logic parameters [71]

Parameters	**Explanation**
General behavior	Defines the behavior for overtaking by two methods such as (1) free lane selection in which vehicles can overtake on each lane, (2) slow-lane rule which allows overtaking on freeways.
Necessary lane change (route)	This parameter is subdivided into two columns for own (subject) vehicle and a trailing (target) vehicle. It consists of three sub-components as shown in Figure 5. The deceleration thresholds for the own and trailing vehicle are defined to adjust the aggressiveness of the necessary lane-change [130]. The 'Maximum deceleration' (upper bound value) and 'Acceptable deceleration' (lower bound value) are the limits of deceleration value while performing a lane change. The '-1m/s^2 per distance' is the reduction rate which defines the pace at which the Maximum deceleration will reduce with the increasing distance from the emergency stop distance.
Waiting time before diffusion	The maximum amount of time a vehicle can wait at the emergency stop before making a lane-change. If the vehicle is not successful in this defined period, it is removed from the network.
Minimum clearance	The minimum distance that must be available between the lead and preceding vehicles after a lane-change.
Safety distance reduction factor	A drop in the safety distances for vehicles involved in lane-change maneuvers. Smaller the value, the more aggressive lane-change.
Maximum deceleration for cooperative breaking	Defines the maximum deceleration which the trailing vehicle would accept to help the maneuver of lane-changing vehicles.
Cooperative lane-change	Through the use of this option, the trailing vehicle in the target lane would move to another side of a lane and providing room for lane change-vehicle.

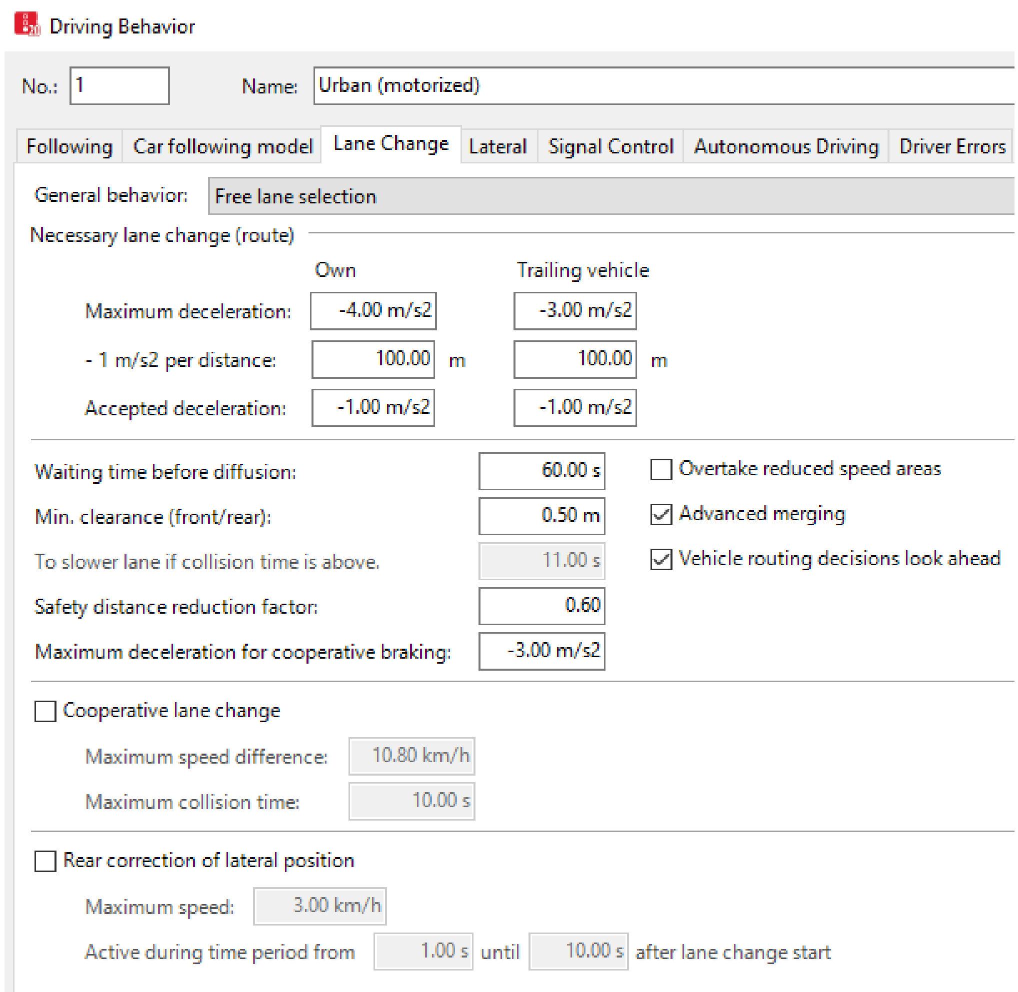

Figure 2-7. Lane-change parameters under VISSIM driving behavior (Source: VISSIM Software)

The lateral control of a vehicle is maintained through a lane-change model. A brief description of the conventional lane-change models is discussed previously in Chapter 1. In this study, a lane-change rule has been defined for a connected automatic car in addition to the car-following logic of the CACF model. In the CACF model, since there is no lane-changing analysis performed before, this study develops a lane-changing algorithm or framework for the CACF model and implements the developed logic to the VISSIM for analysis. The VISSIM API would replace the internal default lane-change rule if a user-defined lateral control algorithm is implemented. During the lane-change process, the vehicle performing a lane-change operation would consider the same weight factor for the order of preceding cars. For example, if one of the leading vehicles in the range of communication observes a breakdown, the CACF car would immediately initiate a lane-change process if the desired safety conditions are met. Since the maximum deceleration allowed in the CACF model is limited to -3 m/s^2, therefore, this value is considered as a reference conservative approach for breakdown events in downstream traffic.

In the developed CACF lane-changing framework, it is a two-stage process for the lane change as shown in Figure 2-8. In Stage 1, the autonomous car records the acceleration/deceleration behavior of the preceding stopped vehicle or slow-moving vehicle in downstream traffic. If the acceleration value of the preceding car in the range of communication drops to -3m/s^2, the lane-change logic is triggered. In Stage 2, the lane-changing vehicle look for a safe distance in the adjacent lane i.e. 'Back distance (upstream)' and 'Front Distance (downstream)'. If the adequate distance available for lane-change maneuvers, the autonomous car will change a lane accordingly otherwise waits for clearance or stays in the current lane. Two sets of safe distances (i.e. front and back) are considered from previous studies such as cautious [131] and aggressive [132] behaviors accordingly. This lane-change logic is implemented for a two-lane basic freeway segment only. The lane-changing ego vehicle communicates with both conventional as well as connected autonomous cars. Chapter-3 and Chapter-4 present a sensitivity test setup and evaluations for the multi-lane CACF model accordingly. This lane-change logic optimizes network efficiency by reducing unnecessary delays and enhancing network safety.

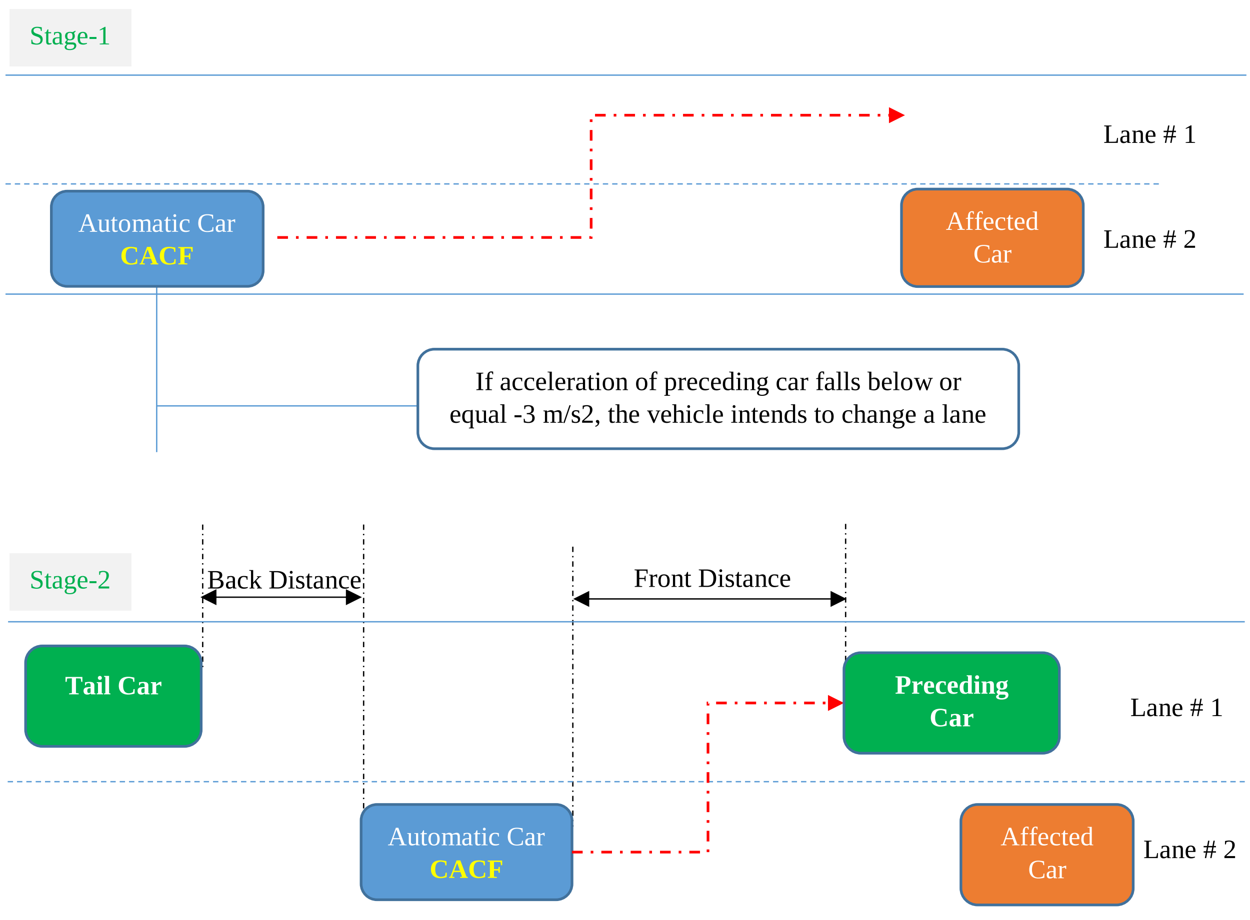

Figure 2-8. Lane-change logic for connected autonomous car

2.5. Safety Surrogate Assessment Model (SSAM) integration with VISSIM

2.5.1. The safety surrogate assessment model

The Safety Surrogate Assessment Model (SSAM) is a software package developed by FHWA to evaluate the safety of roadway traffic conflicts from the output of micro-simulation models. Currently, the software is compatible with four traffic simulation software such as VISSIM, PARAMICS, AIMSUN, and TEXAS. The SSAM uses the trajectory (.trj) file resulted from a successive simulation run and analyze the severity and counts of traffic conflicts. The tool enables the user to analyze the surrogate measures of proposed or innovative traffic facilities that have not been built. Additionally, it provides basic visualization and statistical features to facilitate the analysis and also to help in traffic report generation [133]. The SSAM analyzes the vehicle-to-vehicle interaction using the information from the trajectory file and develops a database of all instances found through a simulation run. The SSAM tool is an open-source software which is free to download upon a submission a request to the FHWA authority.

Further, the output of SSAM includes surrogate safety measures and types of conflict such as lane-change, rear-end, or path crossing as well as the velocity change (if the conflict event has happened) to estimate the severity of the incident [30]. The term ‘conflict’ is defined by Amundsen et al. as ‘an observable situation in which two or more road users approach each other in space and time for such an extent that there is a risk of collision if their movement remains unchanged’ [134]. The traditional approach of traffic safety analysis is to collect traffic collision data from roadway locations. The level of safety is analyzed by the frequency of collision and the collision type such as fatality, injury, or property damage [30]. The drawback of using the traditional approach of traffic safety is due to poor quality reporting of collision incidents, assumptions about the causes, improper and outdated data, and uncertainty for a future collision as incidents need to happen before it can be considered as a potential collision. Alternative methods are required for evaluating the safety of roadway location and also to evaluate the potentials safety risks involved during vehicle-to-vehicle maneuvers such as lane-change, shorter gaps, cross conflicts at junctions, and platooning operations.

The traffic conflict technique considers recording the occurrence and potential severity of the conflicts between vehicles on a roadway, allowing for the immediate evaluation of unsafe driving behavior before the collision happens [134]. Perkins et al. first introduced the concept of traffic conflicts in 1986 where they defined other events of traffic that have higher frequency then collisions and those events can lead to collisions. The research involved identifying the events where the drivers take aggressive measures to avoid the collision such as hard braking, rapid lane-change, and indicating areas with a higher risk of collisions [135]. The reasons involved in the events of a traffic conflict can lead to future crashes. Therefore, it is important to evaluate the severity of traffic conflicts and likewise mitigate in advance before the collision occurs in real-world traffic conditions.

In 2003, Gettman et al. developed a detailed report on the investigation of evaluating surrogate measures of safety from the leading microscopic traffic simulation models such as CORSIM, VISSIM, SIMTRAFFIC, PARAMICS, AIMSUN, TEXAS, and others for intersections [136]. The SSAM validation report provides a regression technique that is employed to develop a relationship between the actual crash frequency and the conflict frequency evaluated by the SSAM tool. The non-linear regression mathematical model for crashes as a function of conflicts is given by [133];

$$Crashes\ per\ year = 0.119 * (conflicts\ per\ hour)^{1.419} \tag{16}$$

In this study, the SSAM-3 version was used for safety analysis.

2.5.2. VISSIM-SSAM workflow

With the SSAM-3 selected to be used for safety evaluation, it is needed to integrate the SSAM with VISSIM for analysis. The workflow of integrating SSAM into VISSIM as shown in Figure 2-9 include a three-stage process. At the first stage, a micro-simulation model is developed by incorporating all the necessary network objects such as links, connectors, vehicle inputs and routes, speed and acceleration distributions, signal systems, driving behaviors, etc. In the second stage, a rigorous exercise of fine-tuning the simulation network is conducted through multiple simulations runs until the expected and acceptable behavior is attained. At the last stage, the model is calibrated to evaluate the traffic conditions. VISSIM generates a vehicle trajectory file (.trj) which is an input to the SSAM tool. A .trj file is generated for each successive simulation run. However, the size of the .trj file is big and requires an ample amount of computation time when processes in the SSAM tool. The latest release of PTV VISSIM 2020 has provided an additional feature under SSAM evaluation configuration, now a user can choose a specific ‘section’ from a network and VISSIM will only generate a .trj file for the prescribed section rather than the whole VISSIM network. This helps in reducing the size of the .trj file as well as the computation time.

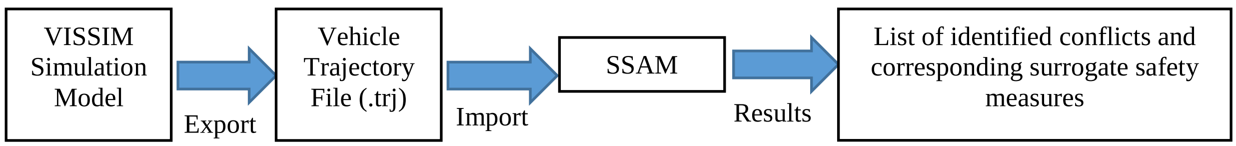

Figure 2-9. Procedure for VISSIM-SSAM workflow

The SSAM tool uses two threshold attributes for surrogate measures of safety such as time-to-collision (TTC) and post-encroachment-time (PET) to define which vehicle-to-vehicle interactions are classified as conflicts. The TTC is explained by Amundsen et al. as ‘an observable situation in which two or more road users approach each other in space and time to such an extent that there is a risk of collision if their movements remain unchanged’ [134]. The default value of TTC in the SSAM tool is 1.5 sec as suggested in the previous researches [137, 138]. TTC is the most commonly used surrogate measure of safety by researchers which requires the projection of the vehicle trajectories into the future, based on the information before the evasive maneuver takes place [30]. The definition of TTC in the SSAM manual [133] is presented in Table 2-7. This study used different TTC values to evaluate the sensitivity of traffic simulation.

The PET is a surrogate measure where two vehicles reach at the same time and space value. Cooper defines PET as the moment (in time) where the ‘offending’ vehicle departs the zone (space) where a potential collision has occurred and the moment (in time) that the other ‘non-offending’ vehicle arrives at the same potential collision zone (space) [139]. However, PET is not a potential surrogate measure for conflict severity as it does not require speed and distance measurements [140]. The default value of PET in the SSAM tool is 5 sec as suggested by Hyden [141]. This research has used the default software value while conducting safety analysis. The definition of PET in the SSAM manual [133] is presented in Table 2-7.

The type of conflicts such as rear-end, lane-change, or crossing is classified based on the ‘conflict angle (θ)’ in a case where the link and lane information of both vehicles are not available [133]. The conflict angle $(\theta) < 30°$ is rear-ended conflict; conflict angle $(\theta) < 85°$ is lane-change conflict; otherwise conflict angle $(\theta) > 85°$ is crossing conflict. The classification of conflicts is shown in Figure 2-10. However, if the link and lane information is provided by the simulation model in the trajectory file, the type-of-conflicts may vary depending upon the relationship of both the vehicles. A rear-end conflict is defined when both the vehicle occupies the same lane (and link) at the start and the end of the conflict event. Similarly, a lane-change conflict is defined when either vehicle ends the event in a different lane (same link) as compare to the started. Lastly, if either of the vehicles changes a link over the course of the event, the classification of conflict type is defined through conflict angle as discussed previously [133]. For example, a simulation model that contains only a one-lane link freeway network produces only have rear-end conflicts. A two-lane link freeway model produces both the rear-end and the lane-change conflicts. Finally, a typical intersection can produce all three types of conflicts.

Table 2-7. Definitions for surrogate measures of safety computed by SSAM tool [133, 136]

Surrogate measures of safety	**Definition**
TTC – Time-to-collision (minimum)	Expected time for two vehicles to collide if they remain at their present speed and on the same path. tMinTTC = Time in the simulation when minimum TTC conflict value recorded
PET - Post-encroachment time (minimum)	The time between when the first vehicle last occupied a position and the time when the second vehicle subsequently arrived at the same position. A value of zero indicates a collision.
MaxS – Maximum speed	The maximum speed of either vehicle throughout the conflict.
DeltaS – Difference in vehicle speeds	The difference in speed of the two vehicles at the minimum TTC (time-to-collision)
DR – (initial) deceleration rate	The rate at which crossing vehicles must decelerate to avoid a collision.
MaxD – Maximum deceleration	The maximum deceleration of the second vehicle, the crossing or following vehicle.
MaxDeltaV – Maximum change in velocity	The maximum change between the conflict velocity and the post-collision velocity.
FirstDeltaV/SecondDeltaV	The change in conflict velocity and post-collision velocity.
Conflict type	The type of conflict as rear-end, lane-change, or crossing movement.

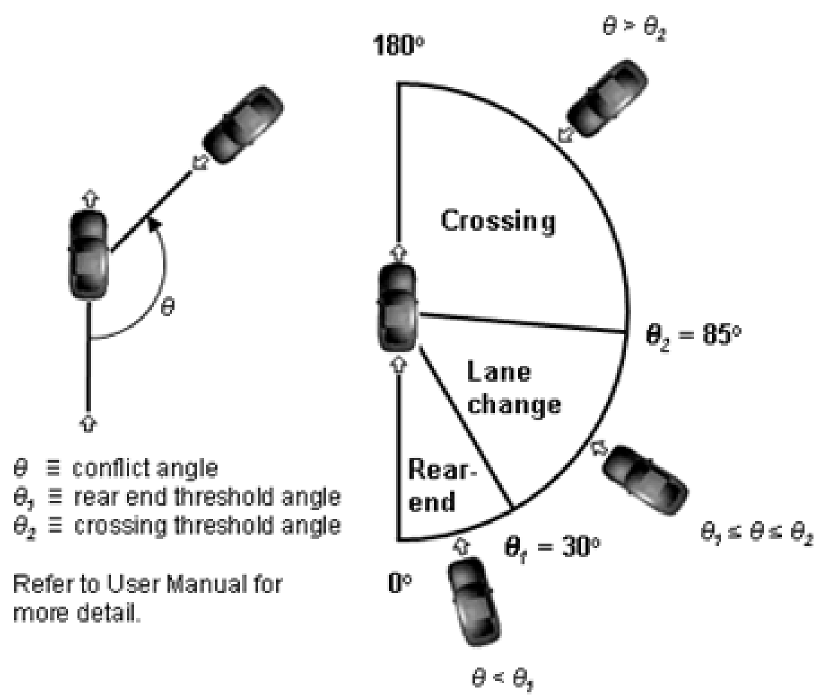

Figure 2-10. Conflict threshold angle diagram (Source: SSAM Software)

2.5.3. VISSIM simulation studies using the SSAM tool

The SSAM is a popular tool or evaluating the safety of roadway facilities and traffic conditions. It is used by both academic types of research and real-world industry projects. Traffic engineers used this tool to evaluate the potential safety surrogate measures of future traffic facilities such as crossing movements at intersections, merge/diverge locations, weaving problems especially at cloverleaf and other interchanges, roundabouts, all-way stop, and yield conditions, etc. Additionally, mitigation measures can be effectively analyzed and also compare the safety benefits of different alternatives. On the other hand, researchers have used the SSAM tool to conduct a sensitivity analysis of the simulation models and also to evaluate the dynamics of driving behavior algorithms, especially for autonomous and connected vehicles. This section outlines some of the previous research work establish using the SSAM tool.

A study investigated the relationship between the field measured conflicts and conflicts evaluated by SSAM using the microsimulation tool. A 2-day video is recorded for an urban signalized intersection (four approaches) to extract vehicle trajectories using automated computer vision techniques. The surrogate measures such as TTC and location is compared with the results of VISSIM-SSAM conflicts. After applying the two-step calibration for field conditions and VISSIM model behaviors, heat maps are produced to compare both the conflicts. The study suggested a proper calibration of the VISSIM model before the application of the SSAM tool [123]. Another study by Filmon et al. investigated the impacts of VISSIM driving behaviors (car-following model and lane-change) on the safety of simulated vehicles. Using the SSAM tool and results from the VISSIM simulation model, it is found that the Wiedemann-99 car-following model parameters i.e. CC1 to CC5 greatly influence the safety of the vehicles. Further, the lane-change parameters such as 'Safety distance reduction factor – free lane-change', 'Maximum deceleration of trailing vehicles – necessary lane-change', and a lane change distance (found in the link's connector window under the lane-change tab) also affects the safety of simulation vehicles. As a result of this study, the authors have concluded that the safety of simulated vehicles can be ensured by proper calibration of VISSIM driving behavior parameters [142].

Another study by Mark et al. explores the impacts of safety and other traffic operational parameters such as delay, against varying AV's penetration for a signalized intersection and a roundabout. This section discusses only the safety impacts of AVs for an intersection facility. Two sets of AVs driving behavior parameters were adopted from Atkins [143] and PTV [144] studies respectively. After a sensitivity analysis of AV-AV interaction, the SSAM tool is used by setting the TTC threshold to 0.75 sec and 1.0 sec while keeping PET value to 5 as default. The study shows that the number of conflicts reduces significantly by increasing AVs market penetration i.e. conflicts reduced by 20% to 65% for AVs penetration between 50% and 100% as well as statistically significant at $p\text{-value} < 0.05$. Additionally, comparing the results of both the TTC thresholds, 0.75 sec shows a consistent decline in the number of AV-AV conflicts up until 100% AVs penetration [118]. Several other studies have indicated that improvements in traffic safety can be achieved by incorporating AVs and CAVs in the traffic stream as well as increasing the market penetration in different roadway facilities such as a roundabout, intersections, and freeways [30, 119, 145].

2.6. Other VISSIM simulation parameters

The settings of VISSIM simulation parameters have a great influence on the simulation results. Different sets of values create variation in the output results and hence generating stochastic distributions. Some of the important parameters are explained here with the adopted input values for the sensitivity study in next chapter.

2.6.1. Simulation period

The simulation period is the time in seconds for a single simulation run. For example, 3600 seconds account for 1 hour of simulation. For valid analysis, it is important to provide a “warmup“ and “cooling down” period at the start and end of the simulation respectively. At the start of a simulation, the network is empty which may lead to faulty results because of no congestion. Hence, providing a warmup period would allow vehicles to occupy the network in advance before conducting the actual simulation analysis. Similarly, a cooling down period would help in eliminating the remaining queues or bottleneck in the network. For this study, a simulation period of 5400 seconds (1.5 hours) is selected where 0-900 seconds is a warmup period and 4500-5400 seconds is a cooling down period. The simulation evaluation time is from 900-4500 seconds divided into four intervals each of 15 minutes accordingly. However, the safety analysis using the SSAM tool is evaluated for the whole simulation period i.e. 5400 seconds.

2.6.2. Simulation resolution

The simulation quality and behavior of vehicles or pedestrians are affected by the simulation resolution. The real-time position of a vehicle is calculated in each second for each timestep [71]. The resolution value range is from 1 to 20 where a low value leads to jerky results and higher value results in smooth traffic and high-quality simulations. [71]. In this study, a default simulation resolution of 10-time step(s)/simulation second is used for the smooth experience of simulation.

2.6.3. Random seed and random seed increment

The “random seed” parameter defines the randomness of traffic patterns across different simulation runs. For example, two simulation runs with the same network configuration and random seed number would produce the same results [71], and therefore no change in the measure of effectiveness (MOE) would be recorded e.g. the total number of vehicles, average travel time, etc. In real-life experience, the arrival rate of vehicles, traffic speed distributions, acceleration functions, and other vehicular characteristics have random distributions. When a user sets a unique seed value for multiple simulation runs, VISSIM assigns different stochastic distribution and functions for each simulation run which alters the traffic flows accordingly [71]. This is important when comparing results of different simulation runs to draw various statistical conclusions. The "random seed increment" adds to the random seed number value for each consecutive simulation run. In this study, an initial random seed value of 1 with a random seed increment of 5 is used for multiple simulation runs.

2.6.4. Number of simulation runs

The number of simulation runs enables the user to gather enough data to produce a true statistical average. Oregon Department of Transportation (ODOT) defines a minimum of 10 simulation runs for different random seeds [146]. The FHWAs' Traffic Analysis Toolbox defines an equation for calculating the number of simulation runs as described below [147].

$$N = (2 * \ t_{0.025,N-1} * \ \frac{s}{R})^2 \tag{17}$$

where R = 95% confidence interval for a true mean, s = standard deviation for a selected MOE parameter, N = number of simulation runs required, and $t_{0.025,N-1}$ = Student's t-statistics for two-sided error of 2.5% (total 5 3%) with N-1 degrees of freedom (for 4 runs, t = 3.2, for 6 uns t= 2.6, and for 10 runs, t = 2.3). (Note: there is one less degree of freedom than car runs when looking up the appropriate values of t in the statistics table).

The number of simulation runs can be calculated using any MOE parameter such as average speed for specified time-interval. In this study, 10 simulation runs have been used as minimum requirements defined by ODOT.

2.6.5. VISSIM evaluation configurations

The vehicles and network performances are extracted through a number of parameters available in the "Evaluation Configuration" window for each successive simulation run. A user defines various network objects such as Data collection points, Vehicle travel times, Queue counters, Nodes, etc. in advance before simulating the vehicles on the network. Further, the evaluation time in seconds is another input through which VISSIM calculates the results for specified time intervals. Some additional parameters can be recorded by checking the parameters under the "Direct Output" tab e.g. vehicle record, data collection (raw), SSAM (vehicle trajectory file explained in the next section), etc. The analysis period for this study starts from 900 seconds and ends at 4500 seconds (1 hour) for mobility evaluations where the time interval is divided into four datasets of 900 seconds (15 minutes). The safety analysis (using vehicle trajectory file) is of 5400 seconds period.

2.6.6. Simulation safety analysis

VISSIM generates a vehicle trajectory ".trj" file for each successive simulation run if the "SSAM" option is checked under the "Direct Output" tab. The trajectory files are stored in a given destination folder under the "Evaluation Configuration" tab. The vehicle trajectories describe the course of vehicle position through the network [71]. VISSIM simulation safety analysis is computed through the exported vehicle trajectory files using the FHWA safety analysis tool (SSAM). A discussion about the SSAM tool and its integration with VISSIM is previously presented in section 2.5. In this study, a total of 10 trajectory files are exported and analyzed for each set of user inputs such as speed values, vehicle inputs (volume), different external driver models.

2.7. Summary

This chapter discussed the modeling capabilities of the VISSIM 2020 software along with the findings of the CoEXist project which introduces various AV-ready (autonomous ready) tools for the expected behavior of AVs and CAVs. Further, VISSIM APIs such as COM-Interface, Driving Simulator, and External Drivel Model DLLs are defined briefly. The VISSIM APIs provide an additional capability to the user for integrating the external applications into VISSIM. For example, a user-defined car-following model would replace the default internal driving behavior of VISSIM using the application of External Driver Model DLL. Additionally, the importance of the time gap in the car-following models as well as the typical values for ACC, CACC, and CACF car-following models are presented.

Additionally, a brief description of the parameters of-VISSIM the default Wiedemann car-following model, VISSIM lane-changing model, and a proposed two-stage lane-change logic for connected autonomous cars are discussed together with a review of various simulation studies. Afterward, the integration and the workflow of VISSIM and SSAM software are explained along with a review of different simulation studies. Finally, the VISSIM simulation parameters such as the number of simulations runs, random seeds, simulation period, simulation resolution, and evaluation configurations are discussed.

3. SENSITIVITY STUDY TEST SETUP USING VISSIM

This chapter outlines the sensitivity test setup of driving behaviors for three different car-following models including VISSIM default driving behavior (Wiedemann 99), CACC models, and the recent CACF model. The results from these sensitivity tests will be used to evaluate the safety and mobility of the CACF model in next Chapter.

3.1. Setting up sensitivity test matrix

In this study, the sensitivity of the VISSIM default driving behavior using Wiedemann 99 model was analyzed as a reference for comparison. To evaluate the safety and mobility performances of the CACF model, seven sensitivity tests were performed for the CACF model in addition to the CACC model for further comparison and validation, as shown in Table 3-1 for more details. Among the seven sensitivity tests, six of the analysis cases were performed using a single-lane network and the sensitivity test 7 was conducted to investigate the influence of lane changes on the CACF model. More descriptions of each sensitivity test were further explained in the sections below.

Table 3-1. A summary of all sensitivity tests

<table>
<tr><th rowspan="2">Sensitivity test</th><th rowspan="2">Description</th><th colspan="2">Evaluations</th></tr>
<tr><th>Mobility</th><th>Safety</th></tr>
<tr><td colspan="4">Sensitivity test for Autonomous Vehicles using VISSIM default driving behavior</td></tr>
<tr><td>Reference: VISSIM default driving behavior using Wiedemann 99 model</td><td>The mobility performance is investigated for Wiedemann-99, AV-cautious, AV-normal, and AV-aggressive driving behaviors for varying market penetration rates</td><td>The average results of mobility performance from each driving behavior are compared.</td><td>-</td></tr>
<tr><td colspan="4">Sensitivity test for CACF and CACC models using a single-lane network</td></tr>
<tr><td>Test 1: Maximum throughput for the CACF model</td><td>The maximum attainable throughput (capacity) of the CACF model is investigated along with other mobility parameters for varying market penetration rates.</td><td>The average mobility benefits such as capacity, travel time, delay, and speed are computed.</td><td>-</td></tr>
<tr><td>Test 2: Mobility Performance of the CACC and CACF Models for “No-crash” Scenario</td><td>The mobility performance for CACC and CACF models is compared for varying market penetration rates.</td><td rowspan="2">Average mobility performance for travel time, delay, and speed are compared for each model respectively.</td><td></td></tr>
<tr><td>Test 3: Mobility and Safety Performance of the CACC and CACF Models for “With-Crash” Scenario</td><td>The mobility and safety performance are investigated and compared for CACC and CACC models for varying market penetration rates.</td><td>The safety analyses of CACC and CACF models are performed for a crash scenario using a range of TTC values from 1.0 sec to 3.0 sec.</td></tr>
<tr><td>Test 4: Impacts of Acceleration Coefficients of the CACF on Safety for “With-crash” Scenario</td><td>The safety performance of the CACF model for 3 different sets of acceleration coefficients is investigated for varying market penetration rates.</td><td rowspan="2">-</td><td rowspan="3">The safety analyses are performed for each case scenario through the computation of the number of rear-end conflicts.</td></tr>
<tr><td>Test 5: Impacts of V2I Communication range on safety for “With-crash” Scenario</td><td>The safety performance of the CACF model for various communication ranges as well as different capability of communicating with ‘n’ number of cars ahead is compared respectively against varying market penetration rates.</td></tr>
<tr><td>Test 6: Impacts of Communication Signal Response Delay on Safety and Mobility for “With-crash” Scenario</td><td>The mobility and safety performance of the CACF model for signal response delay is investigated and compared for varying market penetration rates.</td><td>Average delays are compared for each case of signal response delay.</td></tr>
<tr><td colspan="4">Sensitivity test of CACF model for multi-lane (2 lanes) network</td></tr>
<tr><td>Test 7: The Behavior of the Multi-lane CACF model for safety</td><td>The safety performance of a multi-lane network is compared using VISSIM default lane-change control technique as well as CACF lane-change logic for varying market penetration rates.</td><td>-</td><td>The safety analyses are performed for each case scenario through the computation of the number of lane-change conflicts.</td></tr>
</table>

Note: The blank fields show insignificance either for mobility or safety analysis. Hence, no analyses are performed accordingly.

3.2. Sensitivity tests on VISSIM default driving behavior using Wiedemann 99 model

Researchers have adjusted the default driving behaviors of VISSIM such as the Wiedemann 99 car-following model, lane-change behaviors, gap-acceptance, etc. for modeling the expected behavior of the autonomous vehicles. This study has also evaluated the mobility benefits of three AV-ready driving behaviors such as AV-cautious, AV-normal, and AV-aggressive available in the VISSIM 2020 software package (refer to Chapter 2).

The VISSIM network consists of a 2-lane basic freeway segment with no merging, diverging and weaving segments as shown in Figure 3-1 where the black cars are conventional manual cars and red cars are using autonomous driving behavior. The length of a road network is about 5 km long with a design speed value of 75 mph (approx. 120 kph). As per Highway Capacity Manual (HCM) 2000, the maximum free-flow speed for a basic freeway segment is 75 mph and the maximum service flow rate ranges from 820 to 2400 passenger cars/hour/lane (pc/h/ln) for Level of service (LOS) A to LOS E respectively [148]. Although the maximum throughput is expected at LOS E, yet the traffic flow becomes unstable due to heavy congestions which leads to a network failure i.e. LOS F. The traffic shockwave or bottleneck reduces the average speed of traffic and increases the average density of the network. Therefore, to analyze the worst-case scenario i.e maximum achievable capacity for passenger cars in a basic freeway segment, LOS E with 2400 pc/hr/ln service flow rates, and the desired speed of 75 mph (approx.. 120 kph) was considered for conventional vehicles using W99 model. On the other hand, autonomous vehicles will have additional throughput as compared to conventional vehicles. Hence, an extreme value i.e. 5000 pc/hr/lane for a vehicle input is set in the VISSIM to evaluate the maximum benefits from each driving behavior.

The driving behavior for manual cars is “freeway (free lane selection)”. The simulation time is set to 5400 sec (90 minutes) where the initial warm-up period between 0 to 900 sec and final cooling-down period between 4500 and 5400 sec was not included in the analysis. The travel time measurements are collected for a 3 km road segment starting from 1000 meters and ending at 4000 meters. The AV market penetration values investigated include 0%, 20%, 40%, 60%, 80% and 100%.

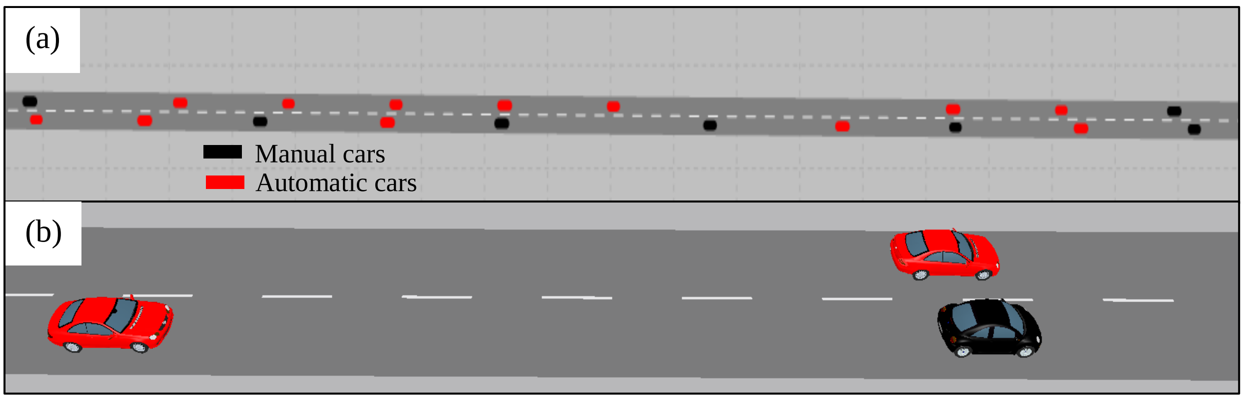

Figure 3-1. Basic freeway segment for a 2-lane network using VISSIM default car-following behavior (a) 2D graphics and (b) 3D graphics

The AVs are expected to have little variations in the driving behaviors, unlike the human drivers which have stochastic variations in driving capabilities. Additional functions have been defined for AVs including desired acceleration, maximum acceleration, desired deceleration, maximum deceleration, and speed distribution. Figure 3-2 shows the comparison of default versus modified maximum acceleration function and 120 km/h speed distribution. The safety distance between the two cars is calculated using Eq. (18). Hence, using different CC0 and CC1 values for each behavior type, the safety distance can be calculated as:

$$\text{Safety Distance} = CC0 + CC1*V \tag{18}$$

Table 3-2 shows the results of the safety distances using various VISSIM AV features. The values are calculated for 75 mph (33.5 m/s).

Table 3-2. Safety distance for different driving behaviors

Behavior Type	Safety Distance (m)
W99 (CC0 = 1.5 m, CC1 = 0.9 sec)	31.65
AV cautious (CC0 = 1.5 m, CC1 = 1.5 sec)	51.75
AV normal (CC0 = 1.5 m, CC1 = 0.9 sec)	31.65
AV aggressive (CC0 = 1.0 m, CC1 = 0.6 sec)	21.1

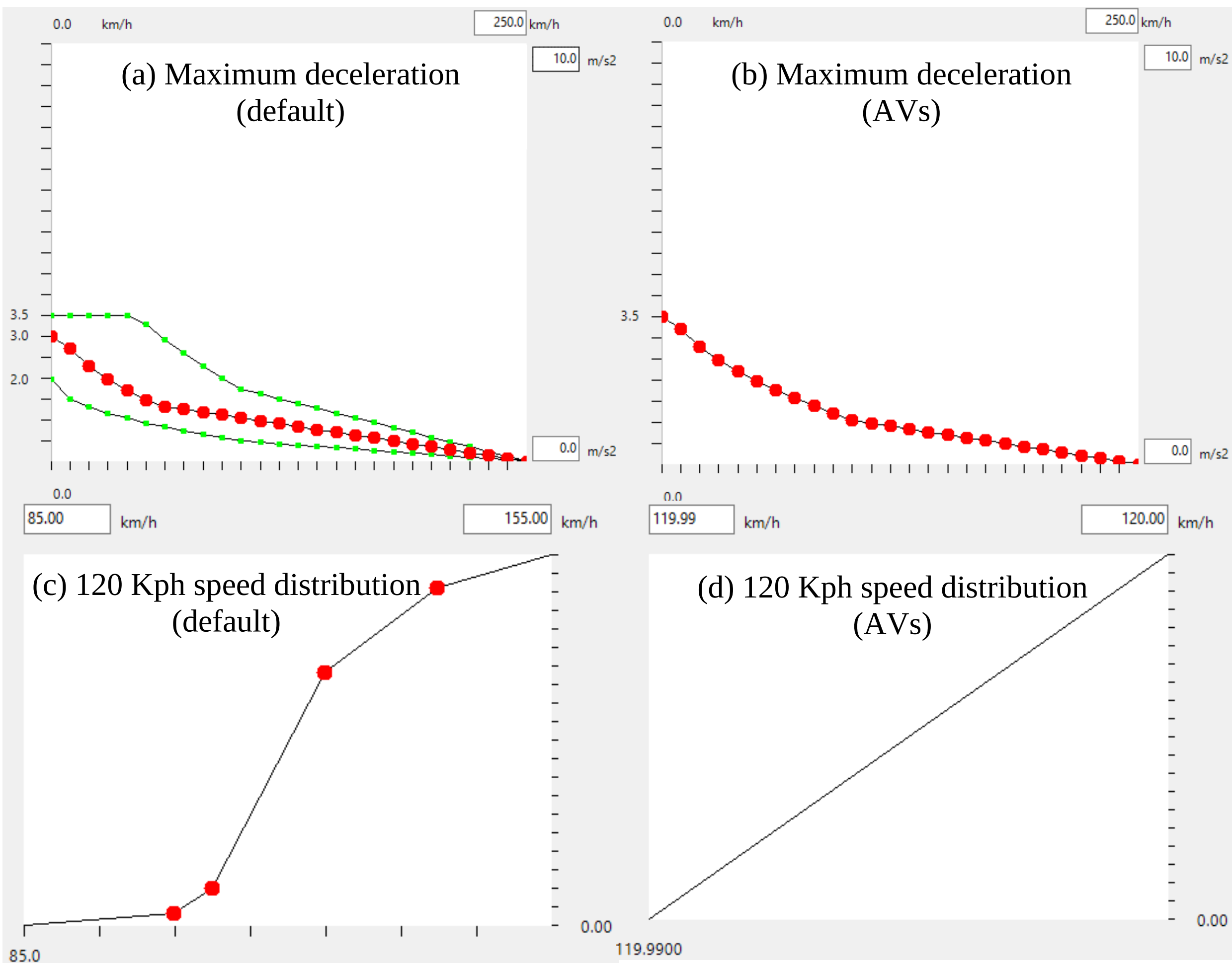

Figure 3-2. Acceleration function and distribution for conventional and autonomous cars (Source: VISSIM Software)

3.3. Sensitivity tests for the CACC and CACF models

The VISSIM network configuration is divided into two categories, including a single-lane freeway network and a multi-lane freeway (two-lanes) network for conducting various sensitivity tests. First, the single lane network was critically investigated thoroughly for understanding the behavior of the CACC and CACF models. After comparing the performance of both the models, the CACF model was implemented in a multi-lane (two-lanes) network to further evaluate its safety and mobility benefits of the CACF model in a multi-lane environment.

3.3.1. Sensitivity test 1 - maximum throughput for the CACF model

The sensitivity test 1 consists of a single-lane 5 km freeway network and two network objects including vehicle travel time measurements and data collection points. The "vehicle travel time measurements" are positioned between 1000 meters to 4000 meters i.e. 3 km stretch which is used to calculate the average travel time from each simulation run. Similarly, the data collection point is placed at the end of a link which provides several evaluation parameters such as the number of vehicles arrived, acceleration, distance traveled, etc. by all vehicles during each successive simulation run. The simulation is conducted for 0% (no AVs) until 90% market penetration with 10% increment rate. For example, for 70% market penetration, 30% are using VISSIM default human driving behaviors. At 100% penetration, the results are not significant and therefore it is not considered in any sensitivity analysis.

Since this simulation test is to evaluate the maximum expected mobility benefits from the CACF model, the vehicle input is set to an extreme value of 10,000 vehicles/hour/lane. VISSIM would generate a maximum logical number of the car's arrival for each run. The desired speed is 75 mph (120.7 kph) for all the vehicles, however, the conventional car uses the default 120 kph distribution in VISSIM, and AVs (external CACF model) uses a strict desired speed of 75 mph (120.7 kph) with no stochastic distribution. The driving behavior for manual cars is "freeway (free lane selection)".

3.3.2. Sensitivity test 2 – mobility performance of the CACC and CACF models for "No-crash" scenario

Using the same VISSIM network configuration as explained previously in sensitivity test 1 (Section 3.3.1), in sensitivity test 2, the mobility performance of the CACC and CACF models are analyzed for 65 mph (104.7 kph) with 1680 veh/hr/lane. This scenario is named "no-crash" because no potential traffic disturbance is created in the simulation through various network objects such as "stop signs" or "reduced speed areas" etc. Since traffic volume is moderate for a single lane network i.e. "LOS C" and therefore the operational performance showed no bottlenecks or significant shockwaves during each simulation runs.

3.3.3. Sensitivity test 3 – mobility and safety performance of the CACC and CACF models for "with-crash" scenario

The sensitivity test 3 uses a similar configuration network as discussed previously in section 3.3.1. Additionally, a vehicle breakdown spot is modeled in the downstream where a specific vehicle type would first decelerate aggressively until reaching a speed of zero. A "stop sign" with a dwell time of 0.2 sec is located at 4000 meters position of a single lane network. The input volume of "breakdown-vehicle" is kept 1% for all the market penetrations. For example, at 70% market penetration, 29% is a manual car (with no breakdown function) and 1% is a manual car (with breakdown function). The reason to introduce an accident spot is to evaluate the safety implications of the CACC and CACF models, respectively. During a simulation run, vehicles in upstream react to downstream breakdown vehicles and hence generate traffic congestion or traffic bottlenecks. In Figure 3-3 (2D graphics) and Figure 3-4 (3D graphics), green cars are externally controlled vehicles such as the CACC and CACF cars, black and red cars are conventional vehicles where the red-car is a breakdown vehicle.

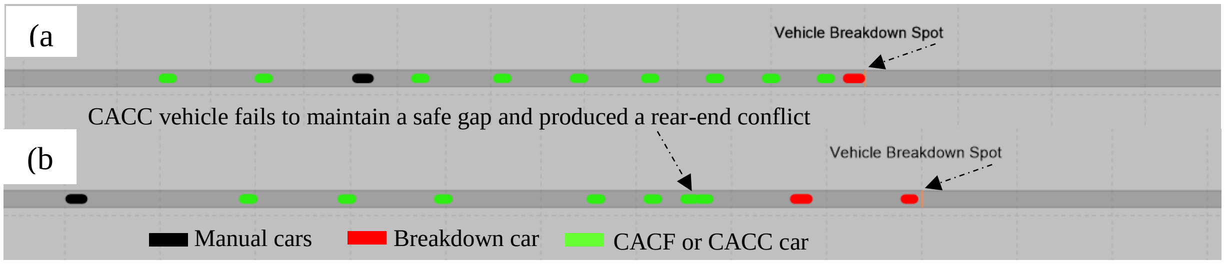

Figure 3-3. Performance of externally control vehicles for a crash scenario (a) CACF model and (b) CACC model – 2D graphics

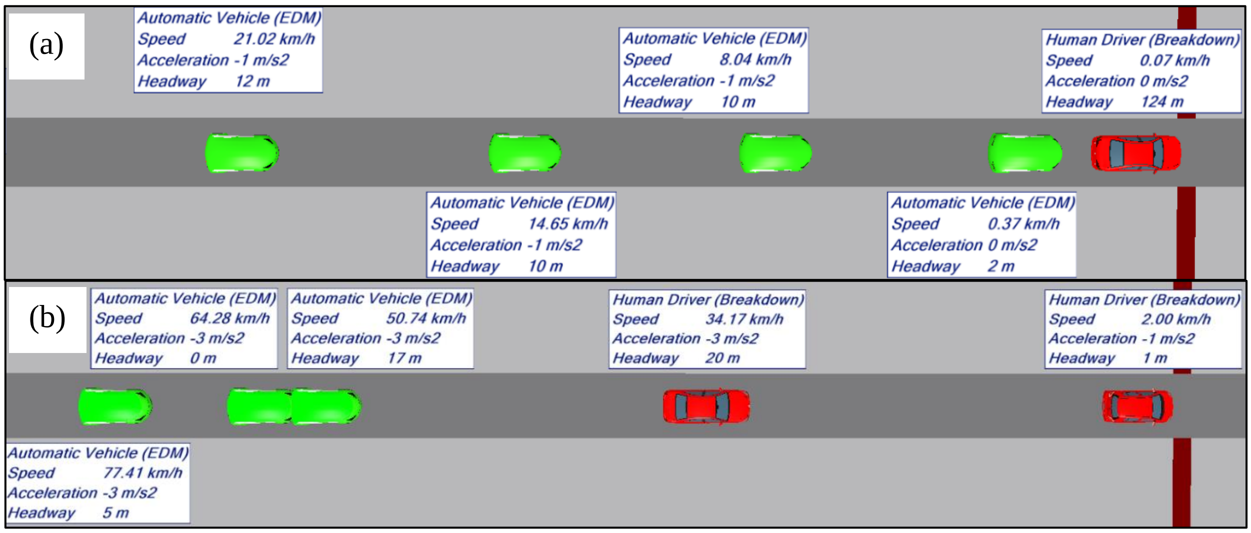

Figure 3-4. Performance of externally control vehicles for a crash scenario (a) CACF model and (b) CACC model – Zoomed 3D graphics

The vehicle types using VISSIM default driving behaviors (i.e. black and red car) have higher deceleration values as compare to the maximum declaration values of the CACC and CACF models which is restricted to -3 m/s^2. So, when the breakdown vehicle becomes standstill by reducing speed to zero, the following vehicles tend to reduce the speed by applying an aggressive breaking phenomenon. However, if the gap from the leading vehicle is not sufficient, the CACC and CACF car would produce a rear-end conflict by either coming so closer to the breakdown vehicle or crossing it due to limitations of deceleration behavior. The safety analysis is performed through the vehicle trajectory .trj files which are generated for each simulation run as discussed in Chapter-2. For example, for each simulation run, a unique .trj file is generated.

As it's a single-lane network, only rear-end conflicts are reported for corresponding TTC values. The SSAM tool provides a number of conflicts for each trajectory file, hence the reported conflict value is an average of the data from 10 simulation runs. The mobility performance of the CACC and CACF models are analyzed for 65 mph (104.7 kph) with 1680 veh/hr/lane.

3.3.4. Sensitivity test 4 – impacts of acceleration coefficients of the CACF on safety for "with-crash" scenario

Since the CACF model is an extension of the CACC algorithm, it uses the same acceleration coefficients such as "ka" for the acceleration of the preceding vehicle, "kv" for velocity-difference, and "kd" for distance difference respectively. The base-value of acceleration coefficients such as ka = 1.0, kv = 0.58, and kd = 0.1 describes "strong behavior" [65, 149]. Arem et. al, evaluated the performance of the CACC model by varying "kv" and "kd" values and keeping "ka" = 1.0 as constant [65]. The sensitivity test 4 evaluated the performance of the CACF model by applying different sets of acceleration coefficients which are adopted by Arem et al in a CACC traffic-flow characteristics study [65] as listed in Table 3-3.

Table 3-3. Comparison of acceleration coefficients for the CACF model

Coefficient comparison cases	**Values**		
	Ka*	Kv	Kd
Base-case	1.0	0.58	0.1
Case-1	1.0	0.58	0.2
Case-2	1.0	3.0	0.2
Case-3	1.0	3.0	0.1

This sensitivity test uses a similar configuration network as discussed previously in Section 3.3.1. The CACF ExternalDriverModel DLL files were edited with different acceleration coefficients as previously listed in Table 3-3. The mobility performance for each coefficient case is analyzed for 65 mph (104.7 kph) with 1680 veh/hr/lane. Figure 3-5 (a-d) shows simulation snapshots for all the cases of acceleration coefficient comparisons at 50% market penetration rate respectively. The snapshot is taken at the same simulation timestep for all four models to compare the behavioral difference visually.

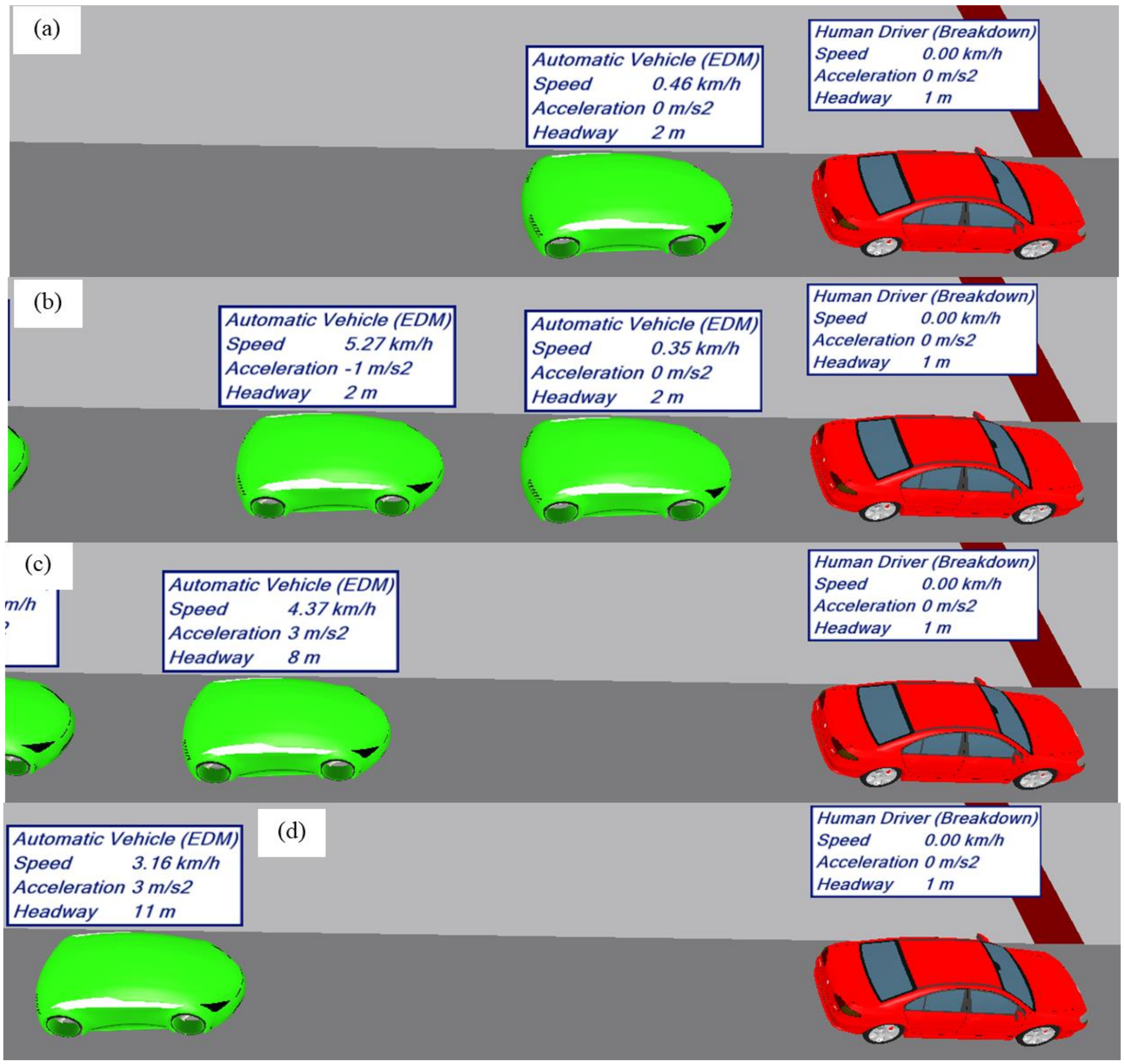

Figure 3-5. Impacts of acceleration coefficients for CACF model (a) Base-case, (b) Case-1, (c) Case-2, (d) Case-3

3.3.5. Sensitivity test 5 – impacts of V2I communication range on safety for "with-crash" scenario

The AVs and CAVs use different types of communication channels such as V2V, V2I, and V2X to communicate with the surrounding environment as previously discussed in Chapter

1. The vehicles equipped with V2V technology can communicate with other vehicles in the operational range of 300 meters using various ADAS technologies [150]. This study has used a base value of 300 meters for the V2I communication range. Additionally, the data of 10 cars within the communication range can be recorded. The sensitivity test 5 investigated the impact of communication range (in meters) on the safety and mobility of the vehicles. Four different communication ranges have been implemented in the CACF code as shown in Table 3-4. In addition to that, the capability of recording the data from the 'n' number of vehicles ahead is also inspected.

Table 3-4. Comparison of different V2I communication ranges and capability of communication

Cases for different communication ranges	Values (meters)	Capability for communication with 'n' number of cars*	No. of cars (#)
Base Case	300	**Base Case**	10
Case-1	150	**Case-1**	5
Case-2	200	**Case-2**	15
Case-3	250		
Case-4	400		

*Note: The default communication range for each case is 300 meters.

3.3.6. Sensitivity test 6 – impacts of communication signal response delay on safety and mobility for "with-crash" scenario

The vehicles communicate with the surrounding environment (i.e. V2I communication) using the data transferred from the sensors embedded on the roadways. It is expected that the network transmission would have delays at some point e.g. poor internet signals, low 4G/5G coverage, equipment malfunction, etc. Thus, it is important to investigate the impact of communication signal response delay on the safety and mobility of vehicles. The response delay is considered by increasing the time-gap i.e. "t_{system}" value. The default value of the time-gap is 0.5 sec where the response delay is zero seconds. This sensitivity test uses a similar configuration network as discussed previously in section 3.3.1 but this sensitivity test 6, three signal response delay cases are considered as mentioned below:

- Case-1 for 0.1 sec delay = t_{system} = 0.6 sec;
- Case-2 for 0.2 sec delay = t_{system} = 0.7 sec;
- Case-3 for 0.3 sec delay = t_{system} = 0.8 sec.

3.3.7. Sensitivity test 7 – the behavior of the multi-lane CACF model for safety

The CACF model for a single lane network only controls the longitudinal behavior of vehicles in a simulation network while the lateral control i.e. lane-change is still controlled by the VISSIM. Thus, the single-lane CACF model is expanded to communicate laterally with the multi-lane traffic. Section 2.4 presents a graphical description of the two-stages while conducting a successful lane-change maneuver. The proposed lane-change logic activates only when the preceding vehicle in the range of communication drops the acceleration value equal to or below -3m/s^2, otherwise, the lane-change logic is control by VISSIM. In the next step, the ego vehicle equipped with Multi-Lane CACF model search for a safe distance in the adjacent lane. Figure 3-6 shows an implementation of a multi-lane CACF logic where the ego vehicle (green color) initiates a safe lane-change because of a vehicle breakdown (red color) in the current lane. Since adequate space is available in the adjacent lane, the vehicle maneuver is accomplished.

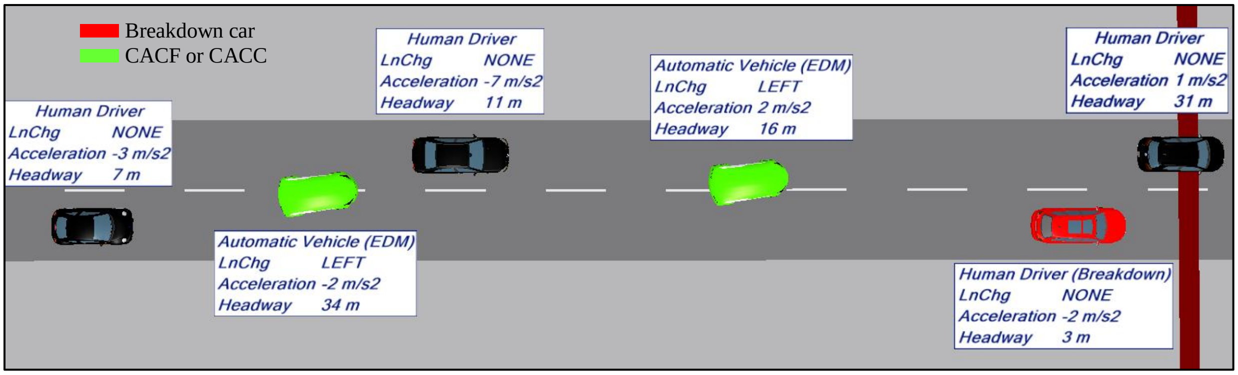

Figure 3-6. Implementation of multi-lane logic for CACF model

The VISSIM simulation network consists of a two-lane basic freeway segment with a vehicle input of 3360 veh/hr and 65 mph (104.7 kph) traffic speed performing at “LOS C”. A “stop sign” with a dwell time of 0.2 sec is located near 3870 meters position which only activates for a “breakdown-vehicle”. The percentage of “breakdown-vehicle” is kept at 1% for all the market penetrations. For example, at 70% market penetration, 29% is a manual car (with no breakdown function) and 1% is manual cars (with breakdown function). The reason to introduce an accident spot is to evaluate the safety implications of multi-lane CACF logic. The sensitivity test 7 for the Multi-Lane CACF model is conducted for three cases as listed below:

- Base Case: Using a Single Lane CACF model where the lateral behavior is controlled through VISSIM default driving logic;
- Case-1 (Cautious Behavior): Front gap = 60 meters, and Back gap = 60 meters [131];
- Case-2 (Aggressive Behavior): Front gap = 10.32 meter, and Back gap = 15.32 meters [132].

3.4. Summary

This chapter briefly defines the simulation setups for performing various sensitivity tests on a single-lane network, and multi-lane network for different car-following models. Accordingly, for each sensitivity study, VISSIM simulation parameters such as network configurations and market penetration rates are defined. The sensitivity tests are evaluated for mobility and safety performances for Wiedemann-99, CACC, and CACF car-following models respectively.

4. EVALUATING SAFETY AND MOBILITY OF THE CACF MODEL

This chapter evaluates the simulation results from each sensitivity test setup based on the mobility and safety performances as was discussed in Table 3-1. Initially, three different car-following models including Wiedemann 99, CACC, and CACF model are compared for their performances under various sensitivity scenarios. Later, a detailed investigation of the recent CACF model is conducted for single-lane and multi-lane networks respectively. The mobility evaluation is recorded through the network performance results provided by VISSIM while the safety performance is estimated through the SSAM tool using the vehicle trajectory file generated by VISSIM.

4.1. Simulation results of VISSIM default driving behavior for AVs

The simulation results of the VISSIM default driving behavior following the test setup in Chapter 3.2 are detailed in this section. Simulation results have been recorded for 10 simulation runs with 4 intervals period of 15 minutes for varying random seeds. VISSIM provides several mobility parameters after each successive simulation runs for evaluating the performance of a network. A total of 160 simulation runs were conducted using a different set of driving behavior and market penetration parameter. This sensitivity test reports maximum throughput, average travel time, average speed, and average delays as shown in Table 4-1.

Table 4-1. Simulation output for VISSIM driving behaviors

Driving behavior	0%	20%	40%	60%	80%	100%
Maximum throughput (veh/hr)						
W99	4691.9	-	-	-	-	-
AV cautious	-	4559.2	4222.1	3934.1	3362.1	2552.0
AV normal	-	4863.3	5009.3	5149.6	5263.6	6690.7
AV aggressive	-	5036.3	5361.8	5734.6	6192.6	9460.2
Average travel time (sec)						
W99	102.9	-	-	-	-	-
AV cautious	-	105.8	108.1	113.2	108.7	90.0
AV normal	-	102.5	102.1	101.5	99.7	90.0
AV aggressive	-	102.9	101.6	100.6	99.2	90.0
Average delay (sec)						
W99	26.2	-	-	-	-	-
AV cautious	-	28.7	30.0	35.1	27.0	0.0
AV normal	-	25.6	24.8	22.8	20.6	0.0
AV aggressive	-	25.9	24.0	22.0	21.3	0.0
Average speed (km/hr)						
W99	100	-	-	-	-	-
AV cautious	-	98.2	97.1	93.8	98.9	120.0
AV normal	-	100.2	100.6	101.7	103.2	120.0
AV aggressive	-	100.0	101.0	102.3	102.8	120.0

From Table 4-1, it can be seen that the overall network mobility performance improve after the introduction of AVs using the AV-normal and AV-aggressive driving behaviors accordingly. The AV-cautious driving behavior is conservative as compared to the W99 model, hence the network performance deteriorates for the increasing market penetration rates. This is because the AV-cautious maintains a larger (cautious) gap as compared to the conventional human drivers. So, when the penetration progresses, the desired safety gap between vehicles creates a significant reduction in the network capacity. At 100% market penetration, AV-cautious observes a 59% reduction in the network throughput., however, due to a stable flow (or platooning behavior), the average speed, delay, and travel times are improved accordingly. Similarly, until 80% of the market penetration rate, AV-cautious shows poor mobility performance as compare to the default driving behavior due to a conservative safety approach.

Since, the network is operating at the LOS E (unstable flow), the conventional vehicles using the W99 model do not succeed in achieving the desired speed of 120 kph. The maximum achievable capacity of default driving behavior is 4691.9 veh/hr/ln with an average speed of 100 kph only. On the other hand, the vehicle’s throughput increases for the aggressive and normal behavior of autonomous vehicles as cars follow each other with closer safety gaps as well as deterministic driving behaviors as shown in Figure 4-1. At a 20% market penetration rate, the increment in the throughput is improved by 3.58% and 7.08% for AV-normal and AV-aggressive driving behaviors respectively, however, average travel time and speed observe minimal improvements due to lower AV penetration rate. Later, the mobility performance for 40% or more penetration rate shows promising mobility improvements.

The AVs performs better as compared to the traditional car-following behavior in terms of average speed, average delay, and average travel time when using AV-normal and AV-aggressive driving behaviors. It is important to note that, at a 100% market penetration rate, the 3 types of AVs behavior achieve the desired speed of 75 mph (120 kph) and shows the behavior of platoon formation. It is also noticeable that the parameter CC1 becomes highly significant for higher speeds. The minimum CC1 value is for AV aggressive behavior which produces the maximum mobility benefits as compare to other driving behaviors.

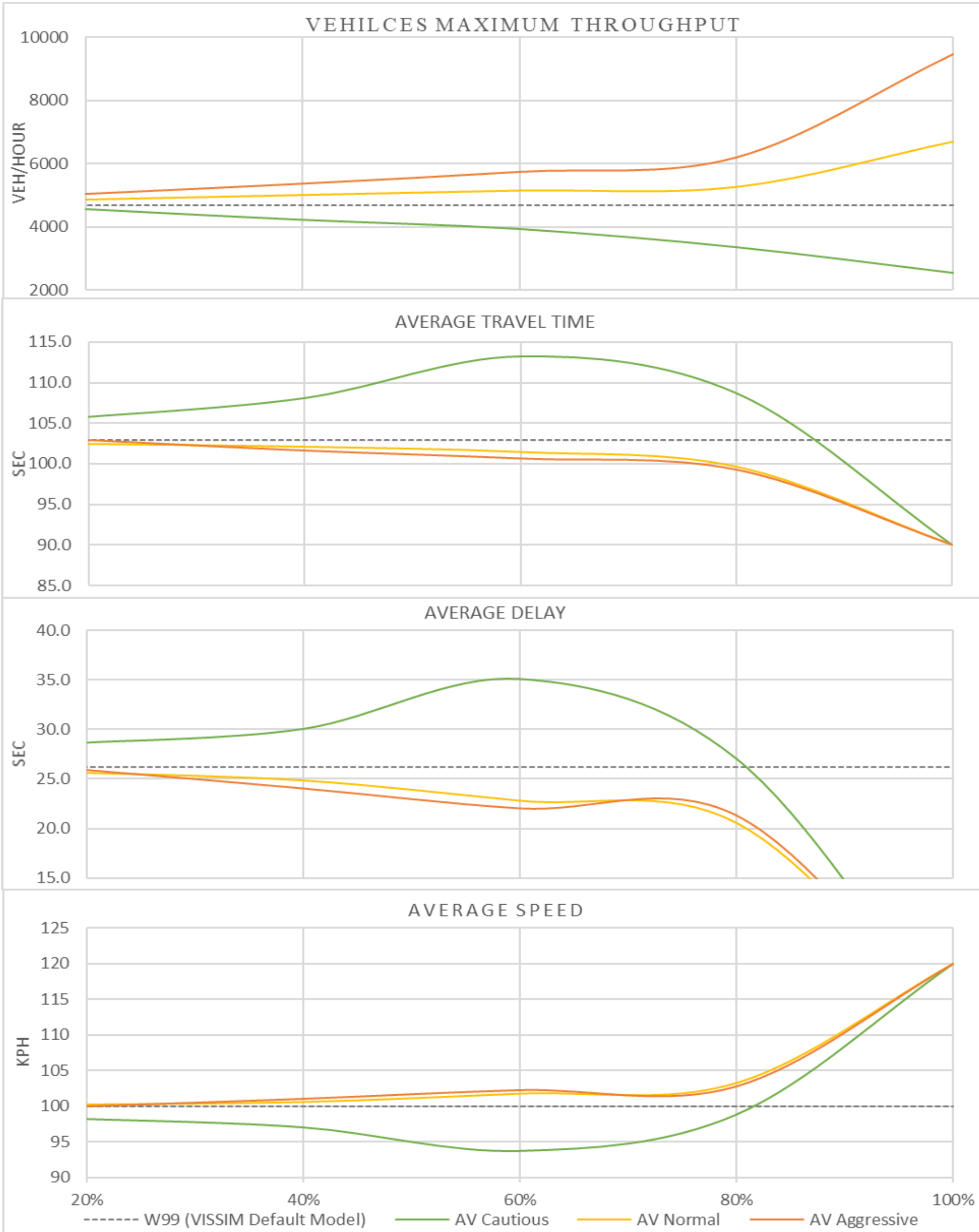

Figure 4-1. Sensitivity results of VISSIM default driving behavior for AVs

4.2. Simulation results for sensitivity tests of the CACC and CACF models

4.2.1. Maximum throughput for CACF model (Test 1)

The sensitivity test 1 evaluated the maximum mobility benefits expected from the CACF model. Simulation results have been recorded for a total of 100 simulation runs i.e. 10

simulations for each consecutive market penetration rate with 4 intervals period of 15 minutes and varying random seeds. Results of maximum throughput, average travel time, average speed, and average delays are shown in Table 4-2.

Table 4-2. Results for mobility performance of CACF model – maximum throughput

0%	**10%**	**20%**	**30%**	**40%**	**50%**	**60%**	**70%**	**80%**	**90%**
Maximum throughput (veh/hr)									
2350.0	-	-	-	-	-	-	-	-	-
-	2598.5	2878.7	3073.1	3217.7	3271.0	3293.9	3308.6	3327.7	3349.0
Average travel time (sec)									
155.8	-	-	-	-	-	-	-	-	-
-	158.4	168.3	176.9	163.8	157.8	155.1	152.1	148.7	144.4
Average delay (sec)									
40.6	-	-	-	-	-	-	-	-	-
-	43.1	50.8	58.9	45.5	38.9	35.9	32.8	29.2	24.9
Average speed (kph)									
90.9	-	-	-	-	-	-	-	-	-
-	89.5	85.3	81.3	88.1	91.8	93.6	95.6	97.8	100.8

The maximum throughput for a single lane network at a 0% market penetration rate is about 2,350 veh/hr/lane which is close to the maximum capacity at “LOS E” of the basic freeway segment as per HCM. The CACF model increases the overall road capacity by 35% for a 90% market penetration. The CACF maximum throughput of approx. 3350 veh/hr/lane is close to the CACC model performance [96] as was discussed in Chapter 1. The average travel time and average speed are slightly improved with increasing rates of the CACF cars. Additionally, the average delay is significantly reduced by 47.9% at a 90% penetration rate. The graphical representation is provided in Figure 4-2.

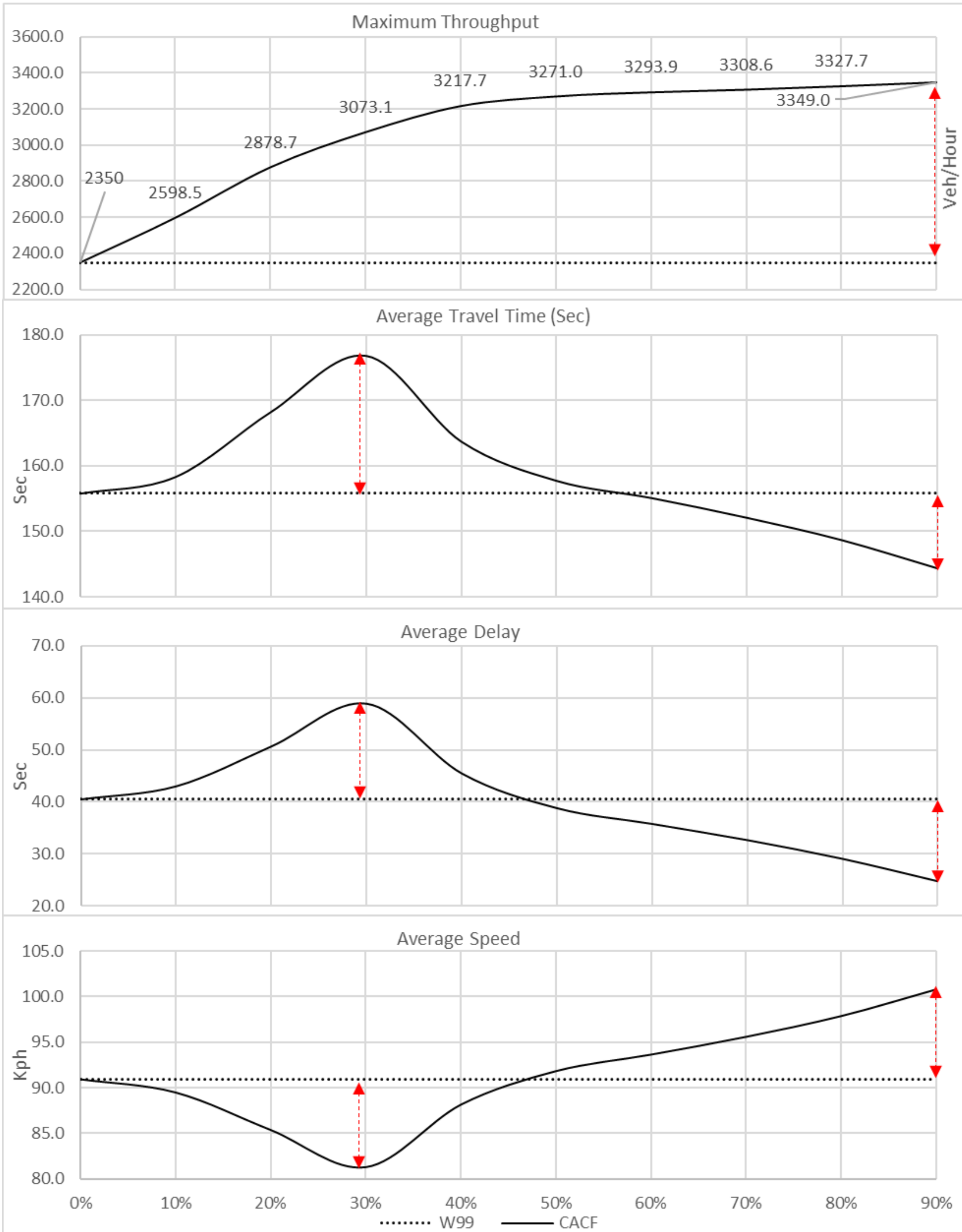

Figure 4-2. Sensitivity results of the CACF maximum throughput

4.2.2. Mobility performances of CACF and CACC models for "no-crash" scenario (Test 2)

A total of 10 simulations for VISSIM default driving behavior and 90 simulation runs for the CACC and CACF models are performed for 10% to 90% market penetration respectively. As the simulation performs smooth operations due to moderate traffic input values, hence, the output shows no significance towards capacity values for each model and is not discussed here. Further, the safety analysis using SSAM tools for the “no-crash” scenario doesn’t generate potential conflict for the CACC and CACF models. On the other hand, VISSIM default driving behavior performs safe operations throughout for any aggressive scenarios and avoids potential rear-end crashes. Results of average travel time, average speed, and average delays are shown in Table 4-3.

Table 4-3. Results for mobility performance of CACF and CACC model – “no-crash” scenario

Driving behavior	**0%**	**10%**	**20%**	**30%**	**40%**	**50%**	**60%**	**70%**	**80%**	**90%**
Average travel time (sec)										
W99	148.9	-	-	-	-	-	-	-	-	-
CACF	-	148.2	147.4	146.7	146.0	145.0	143.9	142.4	140.3	135.9
CACC	-	148.4	147.9	147.2	146.4	145.3	144.0	142.5	140.9	139.4
Average delay (sec)										
W99	13.9	-	-	-	-	-	-	-	-	-
CACF	-	12.7	11.4	10.2	8.8	7.3	5.5	3.3	0.2	-5.3*
CACC	-	12.3	10.5	8.8	7.2	5.6	4.1	2.7	1.6	0.6
Average speed (kph)										
W99	97.6	-	-	-	-	-	-	-	-	-
CACF	-	98.1	98.7	99.2	99.8	100.6	101.6	102.9	104.9	108.9
CACC	-	97.8	98.2	98.6	99.1	99.8	100.7	101.7	102.8	103.9

*Note: the negative delay is when the desired speed is lower than the actual speed of vehicles. A negative value is considered as “zero delays” in the analyses.

The mobility performance of the CACC and CACF models produces less significant results for average travel time and speed, however, the average delays are improved significantly for both the external models as compared to the VISSIM default driving behavior as shown in

Figure 4-3. The average travel time starts to improve from 10% market penetration and is improved by 6.6% for CACC and 9.1% for the CACF model at a 90% market penetration rate as shown in Table 4-3. Similarly, the CACF average speed is improved more as compare to the CACC at higher penetration rates. Finally, the average delay is drastically reduced to ”0 sec” for CACF at 80% penetration and 0.6 sec for CACC at 90% penetration respectively. This test shows that the efficiency of mobility parameters is enhanced for both car-following logics.

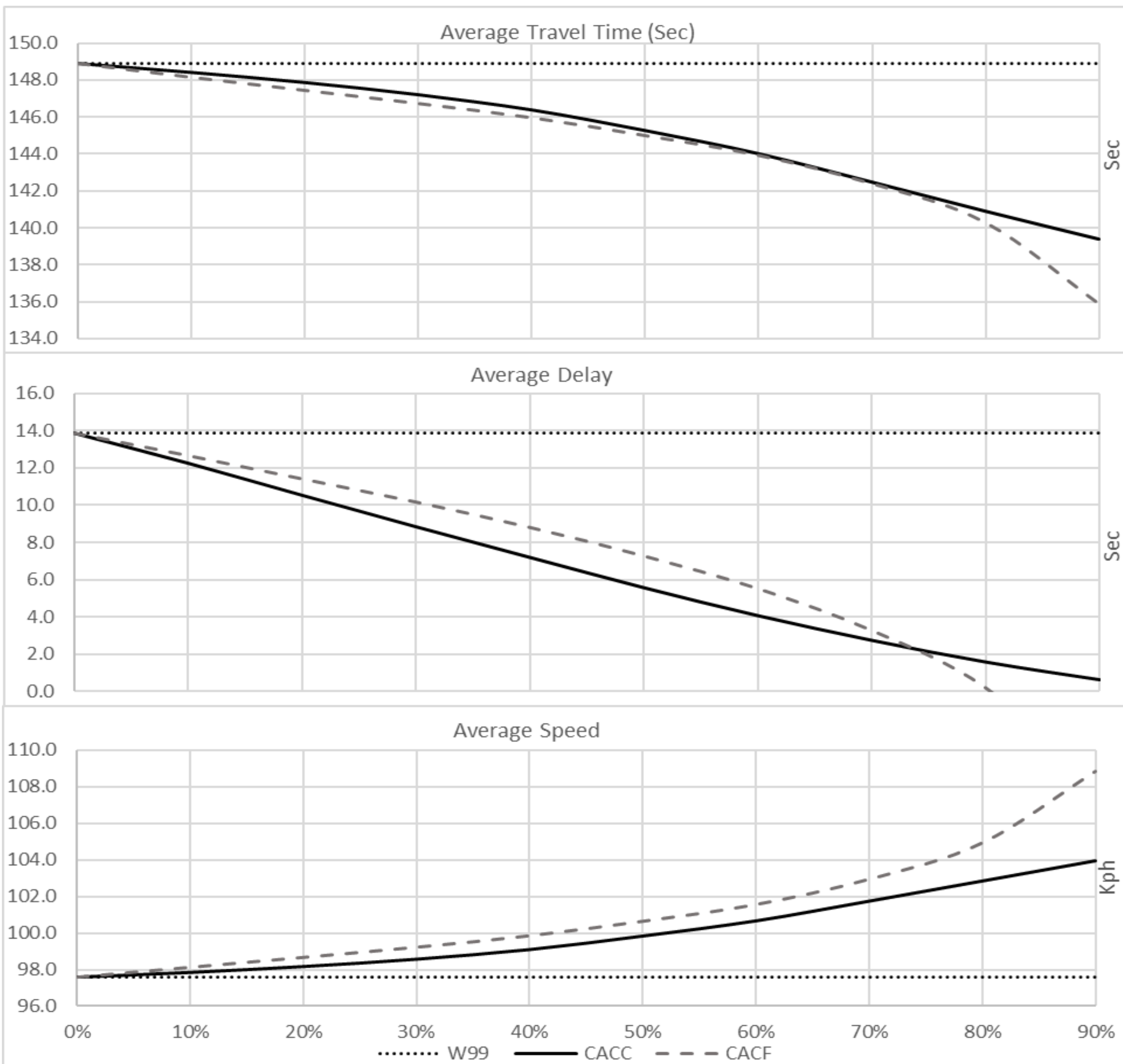

Figure 4-3. Sensitivity results of the CACC and CACF models for mobility performance for “no-crash” scenario

4.2.3. Mobility and safety performances of the CACF and CACC models for “with-crash” scenario (Test 3)

The sensitivity test 3 investigated the safety performance of the CACC and CACF models and compared for varying market penetration i.e. 0% to 90%. Results are reported from the evaluation results of 190 VISSIM simulation runs and 420 SSAM runs. The number of conflicts is reported using TTC values ranging from 1.0 sec until 3.0 sec with an interval of 0.1 sec respectively. Table 4-4 and 4-5 shows the average number of rear-end conflicts resulted from the CACC and CACF models, respectively. Accordingly, the mobility performance is reported through average travel time (sec), average speed (kph), and average delays (sec) as shown in Table 4-6.

Table 4-4. Number of rear-end conflicts from the CACF model for “with-crash” scenario

TTC	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%
≤1.0	1	5	7	7	10	13	13	15	16	13
≤1.1	3	8	10	9	12	15	15	16	17	14
≤1.2	4	12	11	11	15	17	16	17	18	15
≤1.3	9	17	15	16	18	21	21	20	23	18
≤1.4	21	24	20	21	22	25	24	24	27	21
≤1.5	38	40	32	30	31	32	33	30	34	27
≤1.6	48	50	40	35	38	39	40	41	48	44
≤1.7	56	60	45	41	43	44	43	44	50	45
≤1.8	70	75	52	49	49	48	47	48	55	48
≤1.9	81	85	57	54	53	53	51	50	58	51
≤2.0	90	98	65	59	58	57	53	53	62	55
≤2.1	95	108	69	64	62	61	57	56	64	58
≤2.2	98	117	72	69	66	65	60	59	66	60
≤2.3	105	127	77	76	69	68	62	61	69	62
≤2.4	117	140	83	84	76	71	65	65	72	63
≤2.5	128	157	91	93	83	78	74	72	79	68
≤2.6	147	175	102	101	92	86	82	80	87	79
≤2.7	168	195	111	111	100	92	88	85	93	82
≤2.8	185	212	120	121	105	102	95	92	99	86
≤2.9	200	230	128	129	112	107	98	97	104	91
≤3.0	207	244	135	135	120	116	106	107	116	106

Table 4-5. Number of rear-end conflicts from the CACC model for “with-crash” scenario

TTC	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%
≤1.0	1	16	55	108	183	305	376	518	667	877
≤1.1	3	17	57	110	185	309	380	523	673	883
≤1.2	4	19	59	114	188	313	384	528	680	890
≤1.3	9	24	64	119	195	322	392	533	687	898
≤1.4	21	31	71	125	201	329	401	541	695	906
≤1.5	38	45	84	135	211	339	412	550	705	915
≤1.6	48	55	94	144	219	346	420	559	715	922
≤1.7	56	62	104	154	227	353	427	568	725	932
≤1.8	70	73	117	168	238	364	440	580	737	943
≤1.9	81	84	127	178	248	375	451	590	750	955
≤2.0	90	95	139	192	257	384	461	600	760	964
≤2.1	95	103	151	203	266	394	469	610	770	975
≤2.2	98	111	160	214	276	404	480	621	781	987
≤2.3	105	119	171	225	286	414	490	629	793	994
≤2.4	117	129	183	239	297	425	500	638	802	1002
≤2.5	128	140	196	250	308	436	508	649	810	1009
≤2.6	147	153	209	267	321	451	523	659	821	1022
≤2.7	168	169	221	281	336	465	536	674	842	1040
≤2.8	185	178	235	295	346	481	549	687	859	1056
≤2.9	200	190	247	309	360	497	565	702	877	1075
≤3.0	207	196	257	323	374	512	579	718	894	1090

Table 4-6. Results for mobility performance of the CACC and CACF models – “with-crash” scenario

Driving behavior	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%
					Average travel time (sec)					
W99	150.2	-	-	-	-	-	-	-	-	-
CACF	-	149.2	148.3	147.6	146.8	146.2	144.9	143.7	142.1	138.4
CACC	-	149.7	149.3	148.8	147.9	147.5	145.9	144.7	143.0	141.3
					Average delay (sec)					
W99	14.9	-	-	-	-	-	-	-	-	-
CACF	-	13.5	12.2	10.9	9.5	8.3	6.4	4.4	1.7	-3.2*
CACC	-	13.3	11.5	8.0	7.8	5.7	4.5	3.5	2.2	1.1
					Average speed (km/hr)					
W99	96.9	-	-	-	-	-	-	-	-	-
CACF	-	97.6	98.2	98.7	99.4	100.0	101.0	102.2	103.9	107.2
CACC	-	97.1	97.4	97.7	98.3	98.6	99.6	100.5	101.6	102.8

*Note: the negative delay is when the desired speed is lower than the actual speed of vehicles. A negative value is considered as “zero delays” in the analyses.

The performance of the CACC and CACF models varies significantly through the course of different market penetration rates. The mobility performance of the CACC and CACF models have low-significance behavior as shown in Figure 4-4 which is similar to the sensitivity test 2 mobility results for the “no-crash scenario”. The CACF model has slight mobility improvements over the CACC model for increasing market penetration rates. However, the safety performance is improved significantly for the CACF model as it proceeds with the penetration rates, unlike the CACC model where the safety analysis has resulted in poor performance for the increasing rate of penetrations. Figure 4-5 shows the safety performance of the CACF and CACC model at 10%, 30%, 50%, and 70% market penetration rates, respectively.

The primary reason for such behavior of the CACC model is because of the logic implications i.e. the vehicles equipped with the CACC model tend to follow other CACC cars with closer gaps which is the reason for high rear-end conflict values for 20% or greater market penetrations. Hence, in the event of a break-down situation, the CACC vehicles creates a “congestion behavior”. On the other hand, vehicles equipped with the CACF model communicate with the “n” number of vehicles ahead (depending upon the communication range e.g. 300 meters) and are ready to react in advance to avoid conflicts. Further, it is also noticed that the CACF model maintains a larger gap as compared to the CACC model for mild shockwaves, leading to lesser conflicts. For the TTC value of ≤3.0 sec, the number of conflicts is reduced by 64.5% for a 90% market penetration rate using the CACF model.

Additionally, in the events of a vehicle breakdown accident in downstream traffic, the CACC cars decelerate aggressively up to a maximum limit of -3 m/s^2, however, the acceleration is not sufficient for shorter gaps between the ego-CACC vehicle and the preceding vehicle. It is important to note that, even the CACF model has a maximum deceleration limit of -3m/s^2, yet the acceleration control avoids reaching the maximum limit and maintains smooth operations of acceleration and decelerations by not creating a shockwave or traffic bottlenecks. The CACF model indicated that the overall safety of a freeway facility can be improved by incorporating effective V2I communication where an ego-vehicle communicates with the preceding vehicle, records the cumulative influence of surrounding vehicles, and takes a safe decision in advance to avoid unusual conditions such as vehicle breakdown in downstream traffic. Recommendations for the improvements in the safety of CACC models are discussed in Chapter 5.

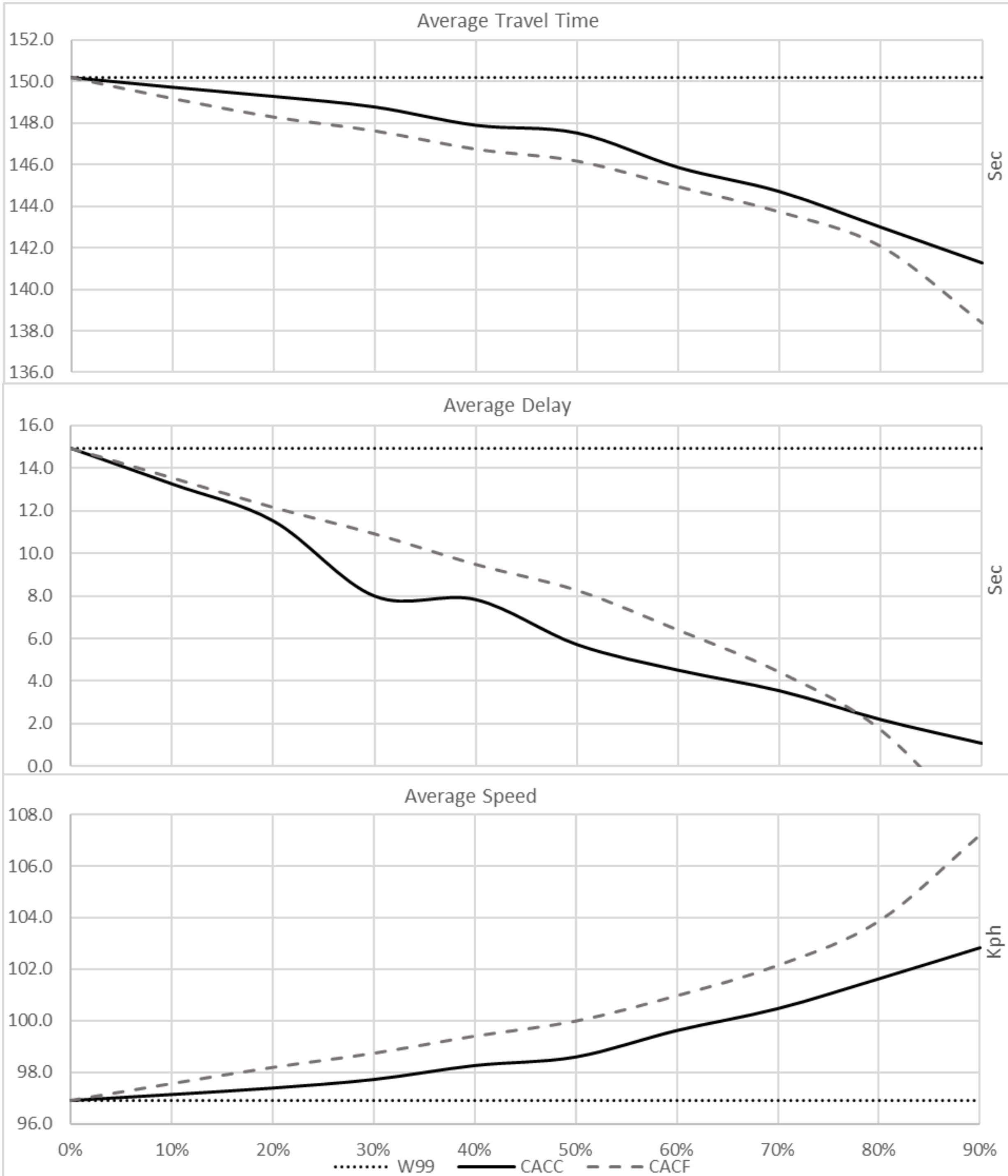

Figure 4-4. Sensitivity results of the CACC and CACF models for mobility performance for "with-crash" scenario

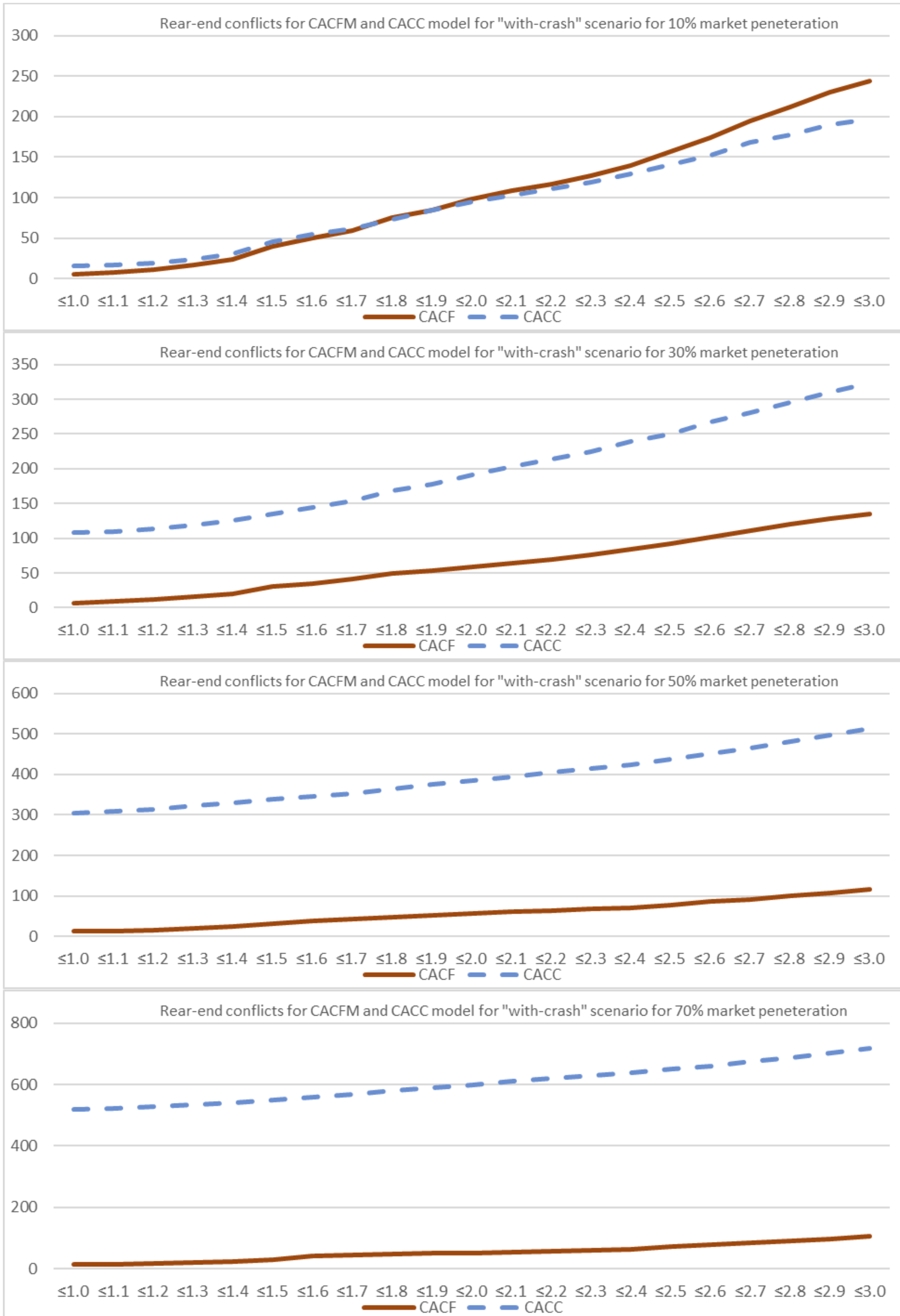

Figure 4-5. The safety performance of the CACC and CACF models for the "with-crash" scenario at 10%, 30%, 50%, 70% market penetration rates

4.2.4. Impacts of acceleration coefficients of the CACF model on safety for "with-crash" scenario (Test 4)

For sensitivity test 4, the simulation for three additional cases of acceleration coefficients are conducted for 20%, 50%, and 70% market penetration rates only. The mobility performance is insignificant and hence not reported here. The number of rear-end conflicts are calculated for TTC values of ≤1.0 sec, ≤1.5 sec, ≤2.0 sec, ≤2.5 sec, and ≤3.0 sec. The safety performance results of the base-case are used from the sensitivity test 3 as was discussed in section 4.2.3.

The sensitivity test for "kv" and "kd" shows that the most significant parameter is "kd" for the distance difference. The "Case-1" produces the highest number of conflicts while comparing it with the base-case. The only difference in "Case-1" is the value of distance difference "kd" which is changed from 0.1 to 0.2. Similarly, the safety analysis of "Case-2" also shows a high number of conflicts. The "Case-3" has the same "kd" value as the base-case, whereas the "kv" value is increased which creates more rear-end conflicts as shown in Table 4-7. Thus, this sensitivity test indicated that the base-case of the acceleration coefficient has the least number of conflicts as compared to the considered cases. Figure 4-6 plots rear-end conflicts for each case recorded at a 70% market penetration rate.

Table 4-7. The safety performance of different acceleration coefficient cases for the CACF model

	Base-Case				**Case-1**		
TTC	20%	50%	70%	TTC	20%	50%	70%
≤1.0	7	13	15	≤1.0	10	44	168
≤1.5	32	32	30	≤1.5	45	79	217
≤2.0	65	57	53	≤2.0	95	138	309
≤2.5	91	78	72	≤2.5	131	212	428
≤3.0	135	116	107	≤3.0	230	376	651
	Case-2				**Case-3**		
TTC	20%	50%	70%	TTC	20%	50%	70%
≤1.0	11	24	28	≤1.0	10	21	18
≤1.5	36	41	44	≤1.5	34	40	31
≤2.0	73	74	77	≤2.0	71	74	58
≤2.5	104	112	128	≤2.5	101	118	113
≤3.0	155	166	189	≤3.0	144	156	146

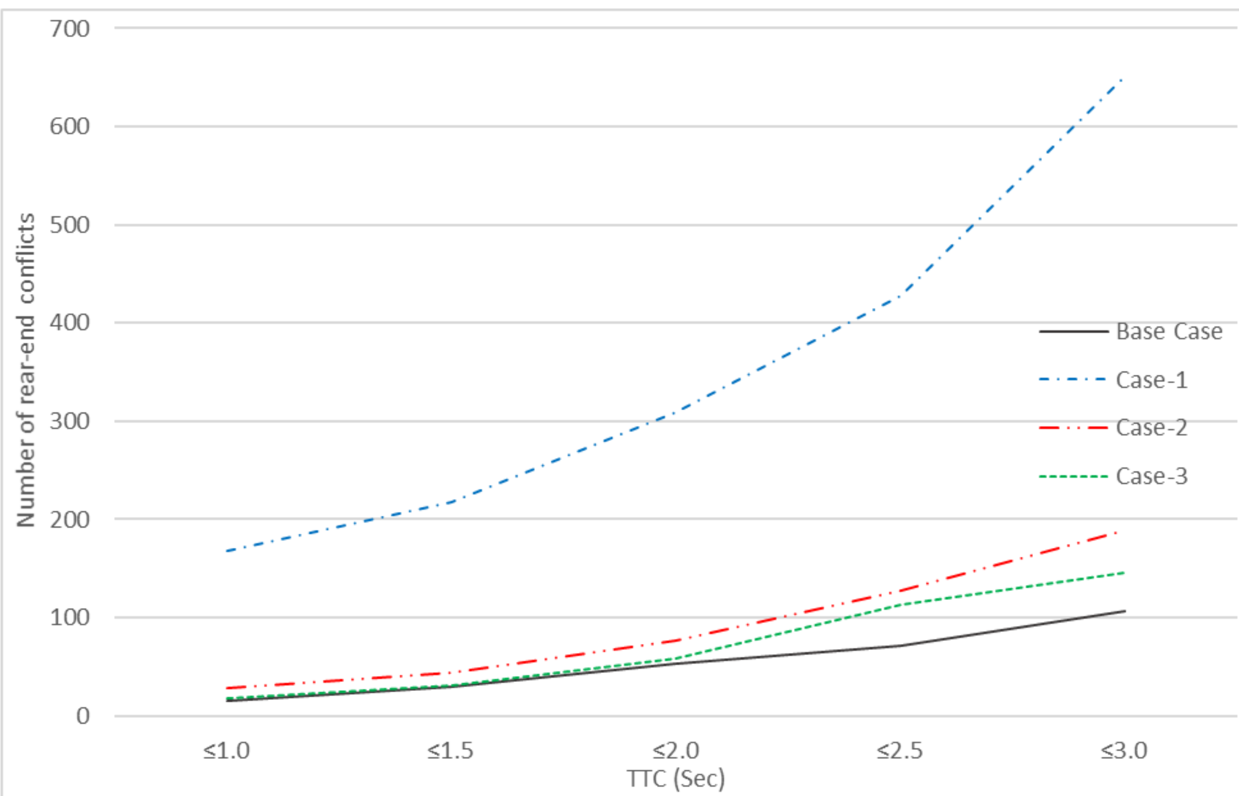

Figure 4-6. Safety performance of the CACF model for different acceleration coefficients at 70% market penetration rate

4.2.5. Impact of V2I communication range on safety for "with-crash scenario" (Test 5)

For the sensitivity test 5, the simulations are conducted for 10%, 30%, 50%, and 70% market penetrations using the CACF models for varying communication range as well as varying capability of communicating with 'n' number of cars. The mobility performance is insignificant and hence not reported here. The number of rear-end conflicts are calculated for TTC values of ≤1.0 sec, ≤1.5 sec, ≤2.0 sec, ≤2.5 sec, and ≤3.0 sec respectively.

The communication ranges such as 200-250 meters generate minimal average rear-end conflicts for lower and higher market penetration rates. However, case-1 with 150 meters showed a slight increase in conflicts for a 10-30% market penetration rate. The higher communication range i.e. 400 meters showed somewhat equal results with the base case of 300 meters. Table 5-8 presents average rear-end conflicts and percentage differences of each case against the base case. The results indicated that the CACF model has low significance for operation range greater than 300 meters. Thus, a communication range between 200 to 250 meters is suitable for the CACF model for a single lane-network. Figure 5-7 plots rear-end conflicts for each case recorded at a 70% market penetration rate.

The sensitivity test for the capability of communicating with 'n' number of cars such as 5 cars ahead, 10 cars ahead, and 15 cars ahead shows no significance for safety and mobility results. Even if the CACF car communicates with 5 vehicles ahead, it will maintain a safe behavior because of the nature of the proposed model implementation. Hence, it indicates that the CACF model is sensitive to the range of communication (in meter) rather than the number of cars ahead. On the other hand, even only 5 cars enough to produce safe behavior for an accident scenario.

Table 4-8. The safety performance for different communication range cases for the CACF model

	Base case (300 m)				Percentage Difference Case-1			
TTC	10%	30%	50%	70%	10%	30%	50%	70%
≤1.0	5.1	6.8	12.8	14.9	15.7	2.9	-5.5	2.0
≤1.5	40.0	30.0	32.1	29.5	9.5	-0.3	-5.0	0.7
≤2.0	98.0	59.2	56.6	52.8	4.2	3.5	-5.3	-7.4
≤2.5	157.0	92.6	78.4	71.7	3.6	1.1	-4.5	-10.2
≤3.0	243.9	135.0	116.4	106.9	0.5	-0.2	-6.0	-11.2
	Case-1 (150 m)				**Percentage Difference Case-2**			
≤1.0	5.9	7.0	12.1	15.2	-27.5	-4.4	5.5	-5.4
≤1.5	43.8	29.9	30.5	29.7	-15.0	1.7	3.1	6.8
≤2.0	102.1	61.3	53.6	48.9	-15.6	1.7	0.2	-3.8
≤2.5	162.6	93.6	74.9	64.4	-15.0	0.0	0.0	-5.9
≤3.0	245.0	134.7	109.4	94.9	-10.8	1.5	-1.3	-5.1
	Case-2 (200 m)				**Percentage Difference Case-3**			
≤1.0	3.7	6.5	13.5	14.1	-2.0	1.5	0.0	-45.0
≤1.5	34.0	30.5	33.1	31.5	1.3	-0.3	1.9	-28.8
≤2.0	82.7	60.2	56.7	50.8	0.4	0.8	-0.2	-31.3
≤2.5	133.4	92.6	78.4	67.5	0.1	-0.6	1.5	-30.3
≤3.0	217.5	137.0	114.9	101.5	-0.4	-0.5	-0.5	-29.7
	Case-3 (250 m)				**Percentage Difference Case-4**			
≤1.0	5.0	6.9	12.8	8.2	39.2	0.0	1.6	0.0
≤1.5	40.5	29.9	32.7	21.0	7.0	0.3	0.0	0.3
≤2.0	98.4	59.7	56.5	36.3	2.1	0.2	-0.4	0.6
≤2.5	157.2	92.0	79.6	50.0	-0.6	0.0	0.0	0.4
≤3.0	243.0	134.3	115.8	75.1	-0.5	0.1	-0.3	-0.1
	Case-4 (400 m)							
≤1.0	7.1	6.8	13.0	14.9				
≤1.5	42.8	30.1	32.1	29.6				
≤2.0	100.1	59.3	56.4	53.1				
≤2.5	156.1	92.6	78.4	72.0				
≤3.0	242.8	135.2	116.1	106.8				

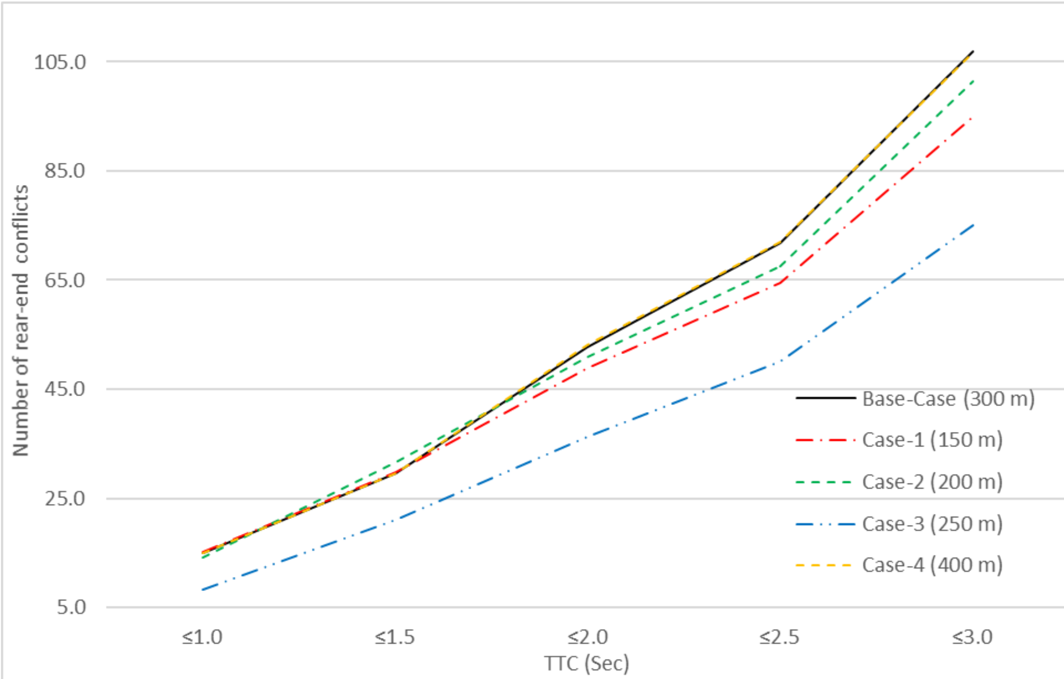

Figure 4-7. Safety performance of the CACF model for varying communication ranges at 70% market penetration rate

4.2.6. Impacts of communication signal response delay on safety and mobility of the CACF model for "with-crash" scenario (Test 6)

The CACF code is edited for each case of signal response delay i.e. 0.1 sec, 0.2 sec, and 0.3 sec respectively. A total of 40 simulation runs have been performed for each case while the base-case results are taken from the previous sensitivity test as discussed in previous sections. The mobility performance is evaluated through VISSIM while safety is reported as the number of conflicts computed by the SSAM tool. The number of rear-end conflicts are calculated for TTC values of ≤1.0 sec, ≤1.5 sec, ≤2.0 sec, ≤2.5 sec, and ≤3.0 sec, respectively. Since the simulation input volume is low to moderate, average travel time, average speed, etc. does not demonstrate a high significance for different cases. Thus, the average delay is reported here only in the mobility performance results.

The inclusion of signal response delay negatively impacted the acceleration of automatic vehicles. When the vehicles receive a signal response with a delay (e.g. 0.1-sec), the acceleration of the vehicle is reduced and vehicles maintain a “careful” behavior. Thus, the number of conflicts is reduced when the response delay is increased as shown in Table 4-9. For TTC≤3.0 at a 50% market penetration rate, the average conflicts are reduced by approximately 11% for case-1,20% for case-2, and 21% for case-3 respectively. Figure 4-8 plots the average number of rear-end conflicts produced at 70% market penetration. Although, it shows a positive trend for safety performance, yet the mobility performance is impacted to some extent as shown in Table 4-10. Since the vehicle starts to move with slower acceleration, the average delay starts to increase. The maximum average delay difference is recorded to 0.9 sec for case-3 at a 70% market penetration rate.

Table 4-9. The average number of rear-end conflicts for each case of communication delay

	Base Case (no delay)				**Case-1 (Delay 0.1 sec)**			
TTC	10%	30%	50%	70%	10%	30%	50%	70%
≤1.0	5.1	6.8	12.8	14.9	4.7	5.6	12.3	14.0
≤1.5	40.0	30.0	32.1	29.5	42.5	28.0	30.7	27.2
≤2.0	98.0	59.2	56.6	52.8	111.7	56.8	53.1	50.0
≤2.5	157.0	92.6	78.4	71.7	181.8	86.6	73.2	63.7
≤3.0	243.9	135.0	116.4	106.9	272.1	125.5	104.1	93.0
	Case-2 (Delay 0.2 sec)				**Case-3 (Delay 0.3 sec)**			
TTC	10%	30%	50%	70%	10%	30%	50%	70%
≤1.0	3.9	6.0	10.1	12.7	3.5	5.7	8.4	12.3
≤1.5	26.2	28.2	26.3	25.5	35.3	26.1	25.2	22.5
≤2.0	57.7	55.9	48.3	47.1	87.1	55.6	46.1	41.8
≤2.5	80.2	84.0	69.8	60.1	140.9	84.1	68.0	60.2
≤3.0	116.3	119.0	95.2	84.8	210.8	116.1	94.1	80.8

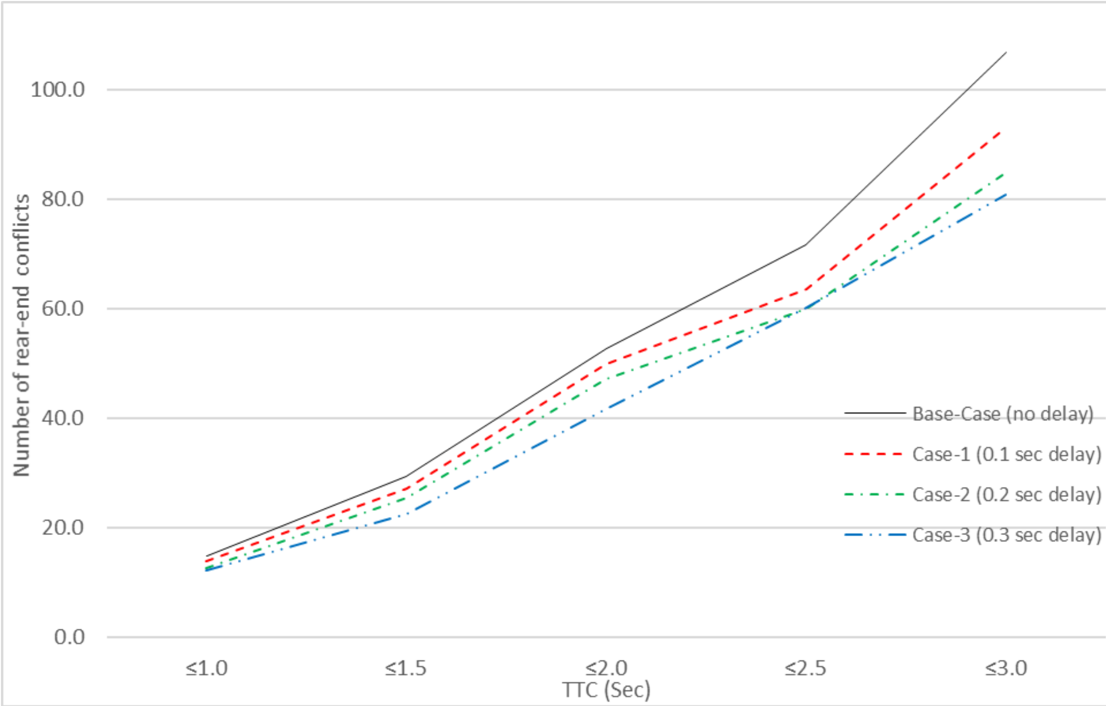

Figure 4-8. The safety performance of the CACF model for varying communication response delay at 70% market penetration rate

Table 4-10. The average delay safety performance of different communication signal response delay cases for the CACF model

Market Penetration	**Base Case**	**Case- 0.1 sec delay**	**Case- 0.2 sec delay**	**Case- 0.3 sec delay**
10%	13.5	13.6	13.6	13.7
30%	10.9	11.1	11.1	11.3
50%	8.3	8.4	8.6	8.9
70%	4.4	4.7	5.0	5.3

4.2.7. The behavior for multi-lane CACF model for safety (Test 7)

The multi-lane CACF model is tested for 10%, 30%, 50%, and 70% market penetrations using the CACF model added with the capability of controlling both longitudinal and lateral behaviors. The SSAM tool classifies the conflict type as rear-end, lane-change, and crossing as previously discussed in Chapter 1. This sensitivity test reports the lane-change conflicts for each considered cases in Chapter 3. The number of lane-change conflicts is calculated for TTC values of ≤1.0 sec, ≤1.5 sec, ≤2.0 sec, ≤2.5 sec, and ≤3.0 sec, respectively.

The safety performance of the base case (i.e. using a single-lane CACF model) and cautious behavior (i.e. using a multi-lane CACF model with 60 meters safe gap) produces lesser lane-change conflicts as compare to aggressive behavior as shown in Table 4-11. Since the safe distance for aggressive behavior is between 10 m to 15 m, the ego vehicle doesn't get enough space for a safe maneuver. The lane-change conflicts for aggressive behavior are more severe for higher TTC values. The mobility benefits such as average travel time, average delay, and others have less significance for different "back" and "front" distance values. Figure 4-9 shows the safety performance of different lane-change logics at 70% market penetration rates. Hence, cautious behavior is suitable for the Multilane CACF model. However, additional sensitivity tests are required to inspect the behavior of multilane. Chapter 5 recommends certain improvement and expansion for the multi-lane logics.

Table 4-11. Average lane-change conflicts for multi-lane logics

TTC	Base Case				Case-1 (Cautious)				Case-2 (Aggressive)			
	10%	30%	50%	70%	10%	30%	50%	70%	10%	30%	50%	70%
≤1.0	12.3	11.9	15.0	25.7	11.6	12.1	16.4	21.4	13.1	14.9	27.2	55.8
≤1.5	21.3	22.5	25.6	43.0	20.5	23.1	26.2	37.8	22.7	26.9	41.8	87.4
≤2.0	42.5	35.9	44.6	68.8	41.3	36.1	43.3	63.8	44.0	40.1	65.1	126.7
≤2.5	56.8	51.8	64.2	95.8	55.9	53.3	62.8	91.4	59.4	59.4	88.2	165.2
≤3.0	71.3	64.5	80.4	122.4	69.8	64.8	77.0	115.1	73.0	72.8	105.9	194.6

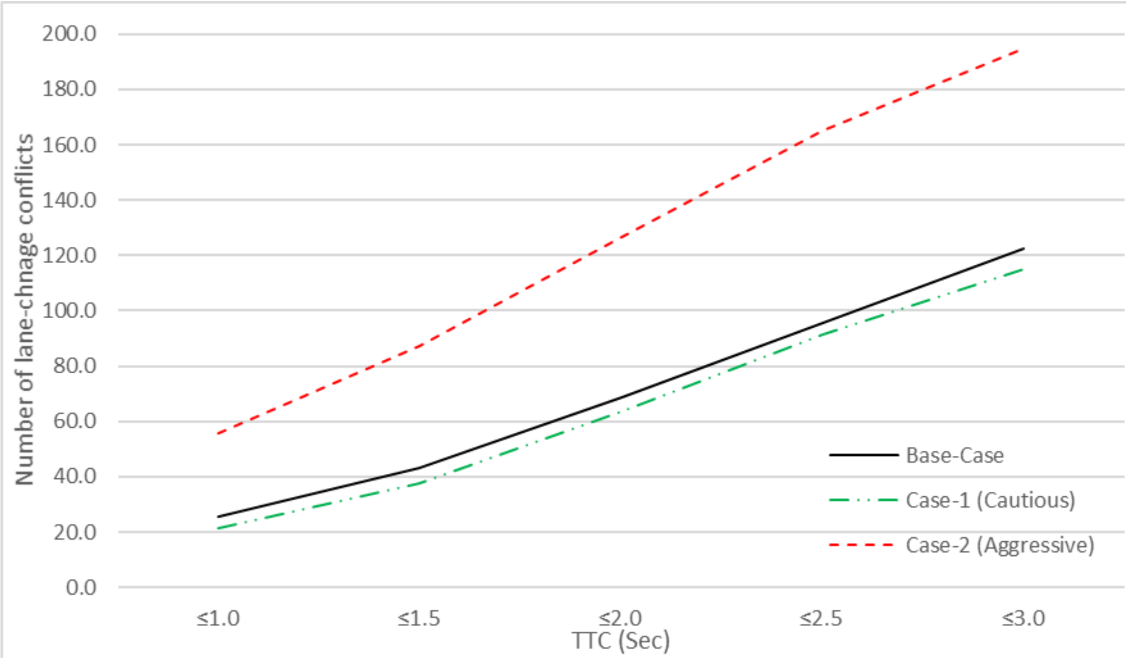

Figure 4-9. The safety performance of Multi-lane logic CACF model at 70% market penetration rate

4.3. Safety and mobility evaluation of the CACF model based on the sensitivity tests

Table 4-12 presents the highlights of safety and mobility results for each sensitivity test. From Table 4-12, it can be seen clearly that the recent CACF model performs similar on mobility as compared to the CACC model, but drastically improves network safety for increasing market penetration rates of the CAVs in mixed traffic. The safety improvement starts to show significance compared to the CACC model even at low penetration rate of 30% or lower. More detailed conclusions will be summarized in next Chapter.

Table 4-12. Summary of safety and mobility evaluation of the CACF model

Sensitivity test	Mobility	Safety
Test 1 - Maximum CACF Throughput	The road capacity for the CACF model increases by 35% for a 90% market penetration as compared to the VISSIM default Wiedemann 99 car-following model.	-
Test 2 - Mobility performance of CACC and CACF models	The average delay of the Wiedemann 99 model is 13.9 sec. However, the delay is drastically reduced to 0.2 sec and 1.6 sec for CACF and CACF models at 80% market penetration rate respectively.	
Test 3 - Mobility and safety performance of CACC and CACF models	The mobility performance of both models has low significance.	The CACC model only performs better at 10% market penetration rate. The CACF model drastically improves network safety for increasing market penetration rates.
Test 4 - Impact of acceleration coefficients on safety	-	The acceleration coefficient of distance "kd" is most influential to network safety. Number of conflicts are increased for higher "kd" values.
Test 5 - Impact of V2I communication range on safety		A communication range between 200 to 250 meters is suitable for the CACF model.
Test 6 - Impact of communication signal response delay on safety and mobility	Since the vehicle starts to move with slower acceleration, the average delay starts to increase. The maximum average delay difference is recorded to 0.9 sec for case-3 at a 70% market penetration rate.	The inclusion of signal response delay negatively impacted the acceleration of automatic vehicles and vehicle maintains a "careful" behavior. For TTC≤3.0 at a 50% market penetration rate, the average conflicts are reduced by approximately 11% for 0.1 sec delay,20% for 0.2 sec delay, and 21% for 0.3 sec delay.
Test 7 - Safety performance of CACF model for multi-lane logic	-	The CACF cautious lane-change and VISSIM default lane-change performs safer as compare to CACF aggressive model.

Note: The blank fields show insignificance either for mobility or safety analysis. Hence, no analyses are performed accordingly

5. CONCLUSIONS AND RECOMMENDATIONS

The automation industry is progressively improving nowadays to provide benefits for the end-users in terms of traffic congestion reduction, safety enhancements, fuel cost savings, and reduction in driver's fatigue levels. The autonomous vehicles (AVs) and connected autonomous vehicles (CAVs) are expected to improve various mobility parameters of traffic flow and overall road safety issues. Additionally, self-driving cars would require several years to completely penetrate the local traffic market. Therefore, it is important to investigate the impacts of AVs and CAVs in a mixed traffic stream.

5.1. Conclusions

This study evaluated the safety and mobility benefits of the recent CACF car-following logic for connected automatic cars using the data collected from V2X using V2I as an example which considering the data obtained from the sensors embedded in roadways using V2I technology. The benefit of using an application of Intelligent Transportation System (ITS) such as V2I instead of V2V (vehicle-to-vehicle) communication is because for the near future, not all the vehicles would be connected autonomous cars and hence it would be a difficult task to gather the vehicular characteristics such as; speed, acceleration, vehicle's length, and headway of preceding vehicles or data from vehicles in the adjacent left/right lanes.

Apart from it, the use of V2I communication would also enable the automatic car to foresee far apart traffic conditions. It would enable the ego vehicle (equipped with proposed car-following logic) to gather the data from "n number of vehicles" from downstream and react in advance for any emergency scenarios. For example, a vehicle got an accident in the traffic downstream so the ego vehicle either slows down or changes a lane to avoid any crash or delays.

Additionally, the CACF logic is compared with already established cooperative adaptive cruise control (CACC) car-following logics using a microsimulation tool PTV VISSIM.

The existing and CACF logics are simulated using the VISSIM API interface knows as External Driver Model-DLL. The longitudinal (acceleration control) and lateral (lane change control) are coded in VISSIM External Driver Model DLL using the C++ language. Several sensitivity tests are conducted to analyze the performance of the proposed logic. The sensitivity tests are evaluated for two types of benefits including mobility e.g. average travel time, average throughput (capacity), average speed, average delay, and safety i.e. rear-end conflicts (for single lane network), lane-change conflicts (for multi-lane network). VISSIM provides a detailed report of network mobility performance after each successful simulation run. Similarly, the safety parameter is measured through a surrogate safety assessment modeling tool (SSAM) which is developed by the FHWA. The SSAM tool computes the vehicle trajectory file (.trj) which is extracted from VISSIM after each simulation run.

The simulation consists of two types of network configuration including the single-lane and multi-lane networks. For each configuration, the simulation network consists of a 5 kilometers basic freeway road segment. The sensitivity tests performed for “maximum throughput” of any logic uses an ideal maximum vehicle input. Thus, VISSIM would generate as many cars as possible in a given simulation period. Similarly, for the rest of the sensitivity tests, a vehicle input of 1680 veh/hour/lane for 65 mph (104.7 kph) network speed is assigned accordingly. For some sensitivity tests, a “with-crash” scenario was developed to analyze the critical safety assessment of the developed logic Hence, a slow-moving vehicle-type (known as “breakdown-vehicle”) was introduced into a traffic simulation that stops in midway traffic (at stop sign) and therefore generating a hypothetical incident or more likely a shockwave in a traffic stream. The stop sign was placed at a 4000-meter position which only activates for a specific "breakdown vehicle".

Since the behavior of the traffic stream is random, a total of 10 simulation runs with varying random seeds are used for each set of the sensitivity parameters. The simulation period is 5400 sec (1.5 hours), in which 900-4500 sec (1 hour) is used for a mobility evaluation whereas safety evaluation is performed for a complete simulation period i.e. 5400 seconds. The AVs market penetration such as 0%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, and 90% are modeled through VISSIM vehicle traffic composition. For example, at 0% market penetration, no external logic is implemented during a simulation. Similarly, at 90% AVs market penetration, the rest 10% are manual cars using the VISSIM default driving behaviors. The safety evaluation is performed for a range of TTC values (time-to-collision) such as 1.0 sec, 1.1 sec,1.2 sec to 3.0 sec using the SSAM tool.

The conclusions drawn from various sensitivity test are summarized as follows;

1. The sensitivity test of VISSIM default driving behavior shows an overall increment in the capacity for AV aggressive and AV normal behaviors as compared to conventional vehicles i.e. W99 model. For example, at 80% market penetration for AV aggressive, the capacity is increased by 27.5% approximately, average travel time is reduced by 3.6%, and the average delay is reduced by 20.6% respectively. It also indicated that the CC1 driving behavior parameter is highly significant for higher speeds.
2. The maximum throughput for CACF models shows a maximum capacity increase of 42% at a 90% market penetration rate. The average delay starts to improve after a 50% market penetration rate while comparing with the default VISSIM model. A

maximum average delay reduction of 15.7 sec is recorded for 90% market CACF market penetration accordingly.

3. The mobility performance of the CACC and CACF models shows the average travel time is improved by 6.8% for CACC and 9.5% for CACF at a 90% market penetration rate accordingly. Also, the average delay reduced drastically for a higher market penetration rate for both the models. Nevertheless, both logics have performed well, however, CACF mobility benefits are further enhanced as compared to the CACC model.
4. The CACF model avoids aggressive breaking through cumulative-anticipative communication with the preceding vehicles. Since the CACF model communicates in advance with each vehicle i.e. either automatic or conventions, it avoids the traffic shockwaves and bottlenecks created by a breakdown vehicle.
5. The safety analysis indicated that “kd” is the most influential acceleration coefficient. When the “kd” value is changed from 0.1 (base case) to 0.2 (case-1), the number of rear-end conflicts are increased up to 167.2% approximately at TTC $\leq$1.0 and 70% market penetration rate.
6. The significance is lost for higher communication ranges and a 300 meter is sufficient for communication range of connected autonomous vehicle and no significance is recorded for safety and mobility results with different in car numbers to be communicated if more than 5.
7. The time delay has a negative impact on the acceleration of a vehicle. After the inclusion of a delay i.e. acceleration is reduced and vehicles start to maintain a “careful” behavior. Therefore, the number of conflicts is reduced accordingly, thus,

safety performance is improved. But mobility is impacted to some extent such as a maximum average delay difference of 0.9-sec is recorded for 0.3-sec delay at 70% market penetration rate.

8. The CACF multi-lane logic improves network safety because it considers both lateral and longitudinal communication for connected vehicles. However, it is only possible when an adequate distance is available on the adjacent lane for example a gap of 60 meters for front and back distances. The lane-change conflicts would increase if a narrow gap window is available during a lane-change maneuver.

The overall results from each sensitivity test showed promising improvements in the network capacity and roadway safety using the recent CACF car-following logic with consideration of inputs from V2X, especially V2I. This study is a potential contribution towards the existing knowledge of vehicle and highway automation where it uses the application of Intelligent Transportation Systems (ITS) and implements it in a simulation platform. The effective communication between vehicles using the sensors embedded in the road infrastructure will ensure the safety of drivers by reducing the number of conflicts and crashes, improve travel times for different routes, and provide a tool for managing traffic congestion and traffic flows.

5.2. Recommendations, limitations, and future work

This study recommends the use of cumulative-anticipative car-following techniques for future autonomous and connected cars using V2I technology. This approach is a potential tool for solving the existing problems of road safety, traffic delays, driver’s stresses, travel costs, and others. The benefits of using V2V technology are possible when higher market penetration of AVs and CAVs are available. Hence, early investing in V2I technology would enable safe and convenient mobility options. The simulation platform provides an opportunity for researchers and technology developers to implement and assess the idea before launching it to the actual ground. Therefore, the use of a simulation platform such as VISSIM is highly recommended at the initial stage where the concept is in the evaluation stage.

The poor safety performance of CACC logic in the event of an accident can be improved by enhancing the communication capability of the ego car such that it can communicate effectively with the surrounding environment (i.e. multi-anticipative technique) and takes a decision accordingly. In addition to that, it is expected that CACC performance would have a positive impact on road safety when the platoons are formed accordingly. Finally, defining criteria for “emergency braking” where an aggressive deceleration value e.g. -9.9 m/s^2 can be implemented would also reduce the rear-end conflicts.

This study has implemented the CACF logic for a basic freeway segment. However, other control conditions such as merge, diverge, weaving, signalized urban intersection, all-way stop, ramp control, etc. are not considered. The implementation of the proposed CACF logic requires another sensitivity study to investigate the different controls of the freeway, multi-lane highway, arterial and other sections accordingly. Similarly, the multi-lane logic needs to be expanded so that the lane-change maneuver produces lesser conflicts, considers different weight factors for the order of the cars in front, a sensitivity test for defining various scenarios for the initiation of a lane-change logic, and the consideration of a freeway network consisting of more than two lanes. Additionally, the traffic is composed of private cars only with no heavy vehicles. The inclusion of trucks and other heavy good vehicles in the freeway network would have an impact on the safety and mobility performance of the proposed logic. The logic requires an additional sensitivity study to inspect the role of different vehicle types.

In the future, the methodology of collecting the vehicular data from the sensors embedded on the roadways and importing it into the VISSIM software would be established. Further, the proposed logic would expand to consider the functions of arterials, urban intersections network i.e. ego vehicle communicates with signalized junctions using V2I technology, etc. Finally, the impacts of fuel efficiency and weather conditions on network optimization and safety would also be considered.

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