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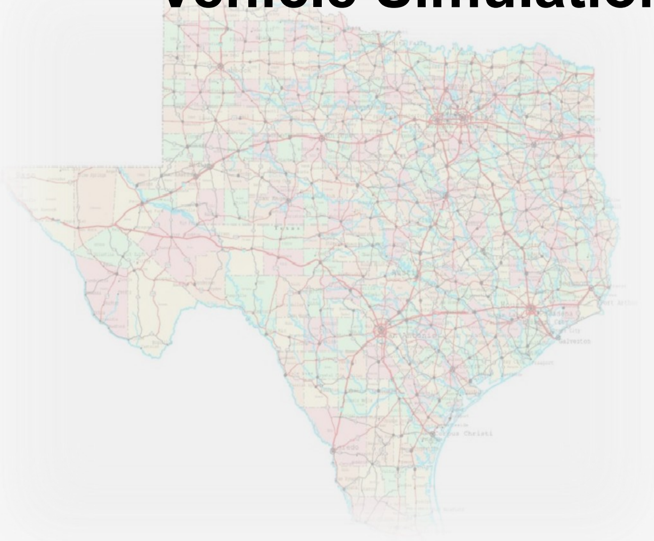
Incorporating Driver Behaviors into Connected and Automated Vehicle Simulation



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DISCLAIMER

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16. Abstract

The adoption of connected vehicle (CV) technology is anticipated at various levels of development and deployment over the next decade. One primary challenge with these new technologies is the lack of platform to enable a robust and reliable evaluation of their benefits given the complexity of interactions among wireless communications, algorithms, and human behaviors. Underlying driver behavior models in microscopic simulation are not always well-suited for modern applications using CV and automated vehicle (AV) technology.

This study proposed a framework for incorporating realistic driver behaviors into a microscopic traffic simulation for AV/CV applications using VISSIM microscopic simulation software. The framework consists of three levels of driver behavior adjustment: event-based, continuous, and semi-automated/automated driver behavior adjustment. The framework provides several examples and details on how various applications can be properly modeled in a traffic simulation environment.

To demonstrate the framework, researchers conducted a case study of a simulation evaluation of cooperative adaptive cruise control (CACC). CACC enables the vehicles to follow each other in a very tight spacing (also known as platooning) using wireless connectivity and automated longitudinal control. The case study shows that a modified driver model can be successfully used in the simulation to evaluate the benefits of AV/CV applications such as CACC with respect to their mobility, safety, and environmental performance.

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EXECUTIVE SUMMARY

The adoption of connected vehicle (CV) technology is anticipated at various levels of development and deployment over the next decade. One primary challenge with these new technologies is the lack of platform to enable a robust and reliable evaluation of their safety and mobility benefits given the complexity of wireless communications, algorithms, and range of human behaviors that will interact with and impact upon the system. A simulation technology is commonly accepted as a tool for providing transportation professionals with impact assessment of various operation and control strategies. Simulation models rely on algorithms for microscopic driver behaviors such as car-following and lane-changing models. While these algorithms are sufficient for traditional operation evaluation, they are not always well-suited for modern applications using CV technology.

This study describes a framework for incorporating realistic driver behavior into a microscopic traffic simulation for CV applications. Researchers used VISSIM traffic simulation as a primary tool in this study as it possesses many advanced features for modeling driver behaviors and it is currently one of the most commonly used software for traffic simulation in the transportation industry. The proposed framework comprises three levels of driver behavior adjustment: event-based, continuous, and semi-automated/automated driver behavior adjustment. The framework provides several examples and details on how various applications can be properly modeled in a traffic simulation environment.

To illustrate the use of proposed framework, researchers conducted a simulation using cooperative adaptive cruise control (CACC) as a case study. The CACC (also known as platooning) application enables the vehicles to follow each other in a very tight formation using wireless connectivity and automated longitudinal control. In this manner, CACC application serves as an ideal application to evaluate both connected and automated vehicle (CV/AV) functionality in a simulation.

The CACC modeling requires the use of customized driver model during platooning to supplement the default driver behavior model in the simulation. The case study demonstrates the successful use of the proposed framework and also provides a platform for examining operational performance, platooning characteristics, environment, and safety performance with respect to wireless communication quality and dedicated platooning lane on a multilane freeway facility. The simulation study showed that the lane control policies for directing all CVs in one lane helped in increasing the flow rate for that lane. This strategy also helped in the formation of longer platoons. Good quality of wireless transmission helps increase the stability and platoon length size of CVs. Aggressive gap distribution for platoon is favorable for reducing emissions. The results also show higher emission rate reductions when there is a dedicated lane for CVs.

1. INTRODUCTION

CV technology enables vehicles to communicate with each other (vehicle-to-vehicle [V2V]) and with the infrastructure (vehicle-to-infrastructure [V2I]) wirelessly. The information from surrounding vehicles or/and the infrastructure can be used for various applications such as safety, control, or traffic routing. This technology has the potential to drastically change the way people travel. CV platform enables automakers, software developers, and traffic engineers to come up with unprecedented solutions that enhance mobility, safety, and environment of our transportation system.

1.1. Overview

To keep pace with times, there is a need to modify the current traffic engineering tools so that they can better predict the impact of CV technology on our roadways. Microscopic traffic simulation tools today are not equipped with features to simulate the effects of CV/AVs. One of the core problems with simulating CVs is that the driver behavior under the new circumstances would be different from what it is at present. Existing driver behavior models in traffic simulation do not account for potential changes in driving behaviors as a result of CV applications. These behaviors can range from simple adjustment of driving speed to fully automated control of the vehicles. The impact of this driver behavior changes can be substantial and needs to be appropriately accounted for. For instance, automated driving can potentially increase the roadway capacity significantly, but it is not fully understood how the traffic stability will be under different compositions of regular versus equipped vehicles. These types of impacts cannot be quantified using standard traffic simulation software. Therefore, this study aims to develop a framework to properly account CV behavior in a simulation environment.

1.2. Research Objectives

The first objective of this research was to identify a framework for modifying driving behavior in a simulation platform so that it can be used to account for appropriate changes as a result of CV applications. The study aims to identify methods to incorporate changes needed for a driver behavior in a traffic simulation, specifically car-following and lane-changing models for CV/AVs.

The second objective was to demonstrate the use of the proposed framework for modeling CV/AV applications. Through this study, researchers modeled a CACC application, which shares both CV and AV functionalities. This model examines various CACC performance and operating characteristics under various traffic and policy scenarios that have not been examined in previous studies.

1.3. Scope of Study

There are various simulation packages available in the market. To develop a framework, researchers specifically selected VISSIM as it is commonly used in North America and possesses many advanced features applicable for CV simulation. The framework will likely apply for other simulation packages as well, but the exact implementation, details, and feature availability will likely be different.

Numerous CV applications require changes in driver behaviors for proper modeling. Some can be as simple as speed adjustments and some can be fairly involved and may require a new driver model. CACC is one application that will require a change in driving model when the vehicle is in platooning mode.

CACC is a component that takes over the control task from the driver. Vehicles with CACC have a dedicated short-range communication (DSRC) device that receives information from surrounding vehicles. The ideal range is 1000 m but the effective communication range can vary greatly depending the environmental condition, obstructions, and network topology. In addition to this, CACC-equipped vehicles are fitted with sensors that collect the control related information from surrounding vehicles. The CACC control uses this information to take over the control task. Since CACC-equipped vehicles can get precise information about parameters such as speed, location, and acceleration of nearby vehicles, they have the ability to maintain smaller gaps.

Various government and research agencies are focused on getting CACC-equipped vehicles in the market in the next few years. A huge amount of money has been spent to develop state of the art facilities to carry out testing on CVs by various agencies such as the U.S. Department of Transportation (DOT). Many successful initiatives have been carried out and are underway by different state DOTs and research institutes like California PATH program and the Texas A&M Transportation Institute to improve upon the CV technologies and to get it ready for the market.

This technology offers great hope for the future of traffic operations. A lot of work has been done on evaluating this technology but most of it is undertaken as research initiatives. When the market penetration of this technology increases and a significant number of vehicles on the road are equipped with it, traffic engineers would need new tools to investigate its impact on the roadways.

This study does not involve any data collection. In this study, the researchers only collect driver behavior and related models from existing studies and propose a simulation platform for driver behavior modeling in CV application evaluation.

1.4. Report Organization

The report consists of seven chapters as follows:

- Chapter 1 is composed of a brief background of CVs and an overview of the limitations of current simulation software, research objective, and the scope of this study.
- Chapter 2 provides a literature review of various CV applications and how the drivers behave in response to these applications. It also describes how the driver behaviors were modeled for CV applications in various studies.

- Chapter 3 presents the features and options available for driver behavior modeling in VISSIM. These range from simple calibration and/or parameter adjustments to the use of customized programming via Component Object Model (COM) and Application Programming Interface (API).
- Chapter 4 proposes the framework for modeling driver behavior for CV applications. It provides a mapping of driver behavior adjustment types and modeling techniques required. It also provides examples using CV applications and discusses necessary implementation details. It demonstrates how different options such as COM and driver model API can be used to model different CVs applications.
- Chapter 5 describes the simulation conducted as a proof-of-concept in this study. The case study focuses on the use of API for modeling CACC application. Researchers examined various CACC scenarios that can play a key role in freeway performance and also quantified the emissions and fuel consumption benefits derived from the CACC operation.
- Chapter 6 documents the analysis of the case study and the findings. The analysis focuses on four aspects of CACC: traffic flow performance, safety performance, platooning characteristics, and environmental performance.
- Chapter 7 summarizes the research conducted and identifies opportunity areas for future research.

2. LITERATURE REVIEW

Since the introduction of CV technology, various applications of CV for safety, mobility, and environment are proposed. Driver behavior in the emerging CV environment can be very different from traditional traffic environment. Several research studies focused on developing alternative driver models to reflect driving behavior changes. This chapter provides an overview of studies on driving behavior changes in CV environment and their proposed models to capture these changes.

2.1. Connected Vehicle Technology

Information about vehicles, infrastructure, and the environment can be relayed to individual entities such as drivers, vehicles, or transportation agencies through wireless communication. CV technology comprises different wireless communication methods of sharing data and innovative ways to use these data to improve safety, mobility, and environment. CVs are equipped with communication devices for facilitating V2V and V2I communication. In addition to data sharing, some applications such as CACC have the automation capability, which directly uses the data to take over the control and guidance task from the driver. Due to CV technology's immense potential for solving various transportation problems, U.S. DOT has significantly invested in research in this area. For the past few years, it has been funding the development of CVs prototypes and test bed facilities. Now, it is starting to deploy CV technology in real world. It would be granting $42 million to New York City, Tampa, Florida, and Wyoming to deploy CVs on roads (*1*). Moreover, the GSM Association predicts that by 2020, nearly every vehicle assembled in United States will have an embedded cellular-based telematics system (*2*). These startling figures indicated that it would not be long before majority of the vehicles on U.S. roadways would be equipped with CV technology.

Various wireless technologies such as DSRC, Bluetooth, long-term evolution, and cellular can provide connectivity for V2V and V2I communications. DSRC is generally used for local area connectivity as it has several advantages over the other communication methods. It has a designated licensed bandwidth, fast network acquisition, low communication latency and high reliability, interoperability, and security (*3*). It works on a 5.9 GHz spectrum, which is a radio communication technology similar to Wi-Fi. DSRC can provide connectivity for time-critical applications such as V2V collision avoidance system as it has low latency of 200 microseconds and an ideal range of 1000 m (*3*). Stable connectivity relies on the cooperation of three components:

- On-Board Unit (OBU) is the embedded equipment on CVs to exchange information.
- Road-Side Unit (RSU) is a roadside information broadcaster and receiver. RSU can only communicate with the vehicles within its range.
- Back-office server connects to the Road-Side Equipment (RSEs) and monitors the entire traffic network. Relative information can be sent to certain Road-Side Equipment (RSE) (*4*).

In general, CV applications can be classified into three categories: safety, mobility, and environmental applications (*3*). SAE J2735 provides standard message sets for CV technology so as to maintain uniformity between differences DSRC enabled devices.

Safety applications of CV are designed to reduce the chance of accident by performing hazard assessment, user advisories, user warnings, and control takeovers. Most of the Advanced Driving Assistance Systems falls in this category. Examples include collision avoidance system, curve speed warning system, lane changing warning, and left-turn gap assistant system.

Mobility applications collect real-time mass traffic data through real time data capture applications (*3*), and the mass data are used for dynamic traffic management systems to improve mobility. CACC and real time intelligent signal timing optimization fall into this category.

Environmental applications capture vehicle real time environment performance data like fuel consumption and emission measures. Then they give out speed and route suggestions or modify signal control strategy to minimize the environmental impact of the traffic flow.

2.1.1. Test Beds for Connected Vehicle Applications

CV test beds are used to evaluate various CV applications. CV test beds include prototype test bed and simulation test bed. Prototype test beds are limited by high cost and small scale. Most CV application algorithms are tested and evaluated in simulation test beds. Only when the CV application development is in the real-world implementation phase, their feasibility and functionality will be tested in the prototype test beds. However, due to the limited scale of the prototype test beds, it cannot be used to study CV applications' impact on large scale traffic flow. Large-scale CV application evaluation still relies heavily on simulation test beds. But researchers often question the reliability of simulation test beds.

In the studies about driver behavior in a CV environment, both simulation test beds and prototype test beds are used. If the prototype vehicles with the tested CV application are available, participants' reactions when using the application can be recorded in a prototype test bed. Driver behavior recorded in a field tests is very reliable. However, due to the limitation of scale in the prototype test beds, the situations that can be tested out are limited. On the other hand, in a simulation driver behavior study, driving simulators are used to imitate the real-world driving experience for participants. More situations can be tested out in a driving simulator study.

Currently, there are seven CV prototype test beds in the United States. These test beds are located in Arizona, Michigan, California, Florida, New York, Tennessee, and Virginia. These sites specialize in specific testing capabilities like traffic and mobility, commercial vehicles, and other functions (*5*). The current test beds include a number of features (*6*):

- OBUs that store messages to be displayed and tracks vehicle's position.
- RSUs that broadcast vehicle-messaging data to vehicles and OBUs.
- Back-office servers that receive requests to post in-vehicle messages.

2.2. DRIVER BEHAVIOR IN CONNECTED VEHICLE APPLICATIONS

CV applications can be classified into three major categories by how they adjust drivers' behavior:

- **Event-based Driver Behavior Adjustment.** This type of CV applications gives drivers one-time visual or audio warnings or instructions about an upcoming event. They only take actions when a potential hazardous event such as a crash, an upcoming amber signal or a stationary queue, is detected. Examples of this category include collision warning, queue warning, lane keeping, and curve warning systems. Most of the applications in this category are safety applications.
- **Continuous Driver Behavior Adjustment (CDBA).** This type of application gives drivers continuous instructions to adjust their behavior for a goal during the whole driving procedure or for a period of time. The goals can be less fuel consumption, more efficient traffic, or safer lane changing, etc. Eco driving systems, lane changing assistant systems, and variable speed limit (VSL) systems are examples of this category. The effectiveness of the applications depends on how well the drivers adhere to these recommendations.
- **Semi-Automated/Automated Driving.** Though AV and CV are two very different concepts, they can be combined together and produce a more efficient traffic system. These applications can take over some part of control of the vehicle but require drivers to set up control parameters. Also, drivers have an option to take back control if necessary. CACC is a perfect representative of this category.

The behavior change in vehicles equipped with CV applications can sometimes affect the behaviors of human driven vehicles around them (*7*). Gouy et al. investigated how small headway (0.3 s) automated platoons influence the human drivers around them by conducting a driving simulator experiment. They found participants spend more time driving with headway under 1 s when near a 0.3-s automated platoon. The average headway human drivers maintain when driving next to a 0.3-s headway automated platoon is 0.12 s less than that when they are next to a 1.4 s headway automated platoon.

This section presents the past studies of human factors in various CV applications. First, researchers provided an overview of drivers' acceptance of CV information and then presented the driver behavior studies within CV environment by the three categories mentioned above.

2.2.1. Drivers' Acceptance of Connected Vehicle Information

Compliance Rate

Drivers are loaded with a lot of information in a CV environment. It is important to incorporate drivers' acceptance of the information into the evaluation of CV applications.

Most CV simulation studies assume that all drivers will act as instructed by the applications. No inter driver variation or intra driver variation is integrated in the simulation. As the human factor is one of the most important components of transportation system, humans should not act like robots in the simulation. Current simulation models can handle variation in traditional traffic flow pretty well, but they are not prepared for handling the human factor in the emerging CV environment.

A major concern of drivers' acceptance of CV information is compliance rate, which can most significantly impact the evaluation results of CV applications.

Here some of the factors that can affect drivers' compliance behavior are concluded from literature:

- Traffic condition.
- Advisory type.
- Drivers' familiarity of the road.
- Leading vehicles' behavior.
- Drivers' trust in the CV application.
- Drivers' distraction level due to CV applications.

Drivers' Adaption to New Applications

Other than drivers' compliance, an adaption period exists when a new application is introduced. In this period, drivers are not familiar with the application, so some of them might act different than expected.

Naujoks and Ingo (*8*) looked into the behavioral adaption of a freeway congestion tail warning system. Both younger and older drivers are recruited to conduct a driving simulator experiment. They found there is no change in medium speed, brake readiness, minimum time headway caused by the display of the congestion tail warning. However, they found the maximum speed increased by 7 km/h and the minimum time-to-collision among older participants decreased by about 4.5 s (still higher than the critical value of 1 s). Also, younger drivers are more likely to engage in a secondary task (40 percent more).

There is not yet a unanimous result about whether there is a negative behavioral adaption when driving with adaptive cruise control (ACC) system activated. Some researchers claim that drivers traveled faster during the rides with ACC comparing to manual driving. Piccinini et al. (*9*) pointed out that in the previous studies, the time headway was not adjustable by the drivers during the trials and drivers' experience of ACC should also be taken into consideration. They compared the behavior of drivers familiar and unfamiliar with ACC and found there is no evidence that using ACC can cause negative behavioral adaption on speed and time headway.

Connected Vehicle Distraction

CV information might be distractive or overwhelming to the drivers. Though a lot of CV applications aim to reduce drivers' reaction time but some argue that CV applications could distract drivers and lead to a longer reaction time.

Holmes et al. conducted an experiment to assess the effectiveness of the presentation of CV applications on different interfaces: integrated in the vehicle center console, fixed to windshield, and on a mobile phone (*10*). They tested various types of applications including red light running alert, in-vehicle signage, mobility, and rerouting across the three presentation tools. The way of presentation is mostly speech plus visual. They recorded drivers' compliance rate to alerts, and they also recorded the Time Eyes on Display and Maximum Glance on Display to measure distraction. They found the internet social network and environmental applications have the longest glance time. Also, they found the glance duration at the mobile devices were shorter than others. But as a result, drivers may not be able to process the contents effectively. They concluded that the fixed devices functioned effectively when running simple CV applications. Unfixed devices such as mobile phone may result in decreased compliance performance.

2.2.2. Event-Based Driver Behavior Adjustment

Event-based driver behavior adjustment applications aim to improve drivers' perception and preparation of hazardous situations. They can give out warnings in a visual or vocal way to inform drivers of potential safety hazards and prevent accidents or even secondary accidents from happening. They are usually time critical, so they rely on fast and stable connections between vehicles. Researchers have been using driving simulators or CV test beds to investigate how the alert-based applications influence drivers' perceptions.

Perception Improvement

A lot of the event-based driver behavior adjustment applications provide auditory warnings against stationery obstacles such as an end of queue, a work zone, or an accident scene. Researchers have been studying how these warnings can affect drivers' perception and their deceleration behavior. Chang et al. (*11*) found such warning systems can shorten perception-reaction time significantly from 0.77 s to 0.63 s using driving simulator experiments. However, deceleration rate did not decrease because of the warnings according to them. They also found out the best warning time is when the range between the leading and following car is 50 m–60 m.

Nowakowski et al. (*12*) conducted a field test for a real-time freeway end-of queue alerting system that can announce "slow traffic ahead, XX mph" when it detects slow speed ahead. They only found little difference between situations with the alert system and the baseline situation. However, they did find an overall reduction in mean peak deceleration in morning commute and off-peak hours. They concluded that drivers' familiarity to the route they are driving can affect the impact of such an alert system.

2.2.2.2 Hazardous Behavior Adjustment

Other than improve drivers' perception of the surrounding traffic situation, an event-based driver behavior application can also detect drivers' mistakes that can potentially cause an accident. Once the potential hazardous driving behavior is detected, a warning will be given to the driver so the driver can take mitigation strategies. Examples of these applications include collision avoidance systems and curve-speed warning systems.

A curve-warning system can detect the speed and location of the vehicle. If the vehicle is going faster than the advised speed before it enters the curve, the system will give out alerts and the advisory speed (*13*). Drivers using this system may either slow down their speed toward the advisory speed or keep going at their own speed depending on the willingness to comply.

2.2.3. Continuous Driver Behavior Adjustment

CDBA works under situations that are not very time critical. The adjustments usually aim to improve the efficiency and safety of surrounding traffic flow. This type of CV application does not improve drivers' perception but induces changes in drivers' behavior during a certain driving process. The instruction given allows drivers more time to react and to make decisions. Compliance rate has a significant impact on the effect of this type of application.

Freeway Merging Assistance

Hayat et al. (*14*) carried out field tests for a freeway merging assistance system that can give instructions to both merging vehicles and vehicles on the freeway. The system can detect available gaps on the freeway right lane and tell the merging vehicles when to accelerate to certain speed and when to change lane. It will give out lane changing advisory to selected vehicles on the right lane to create bigger gaps for merging vehicles. As an incentive, inside lanes have a higher VSL.

Participants are most likely to comply at medium traffic condition, followed by free flow condition then heavy traffic condition (*14*). They also found that the lane changing advisories has a higher compliance rate than the merging control advisories while the speed limit advisory has the highest non-compliance rate of 44 percent. Familiarity of the road can also affect drivers' compliance. Seventy percent of the participants agreed they will comply when they are driving on an unfamiliar road. Also, they found that leading vehicles' compliance will also affect drivers' choices. Most drivers claim they will comply when they see a vehicle in the merging area.

In 2015, Hayat et al. conducted a field test of the above freeway merging assistant system in the Smart Road facility in Virginia (*15*). They measured the compliance rate for the three parts of the system: VSL, lane change advisory, and merging control algorithm. Figure 1 shows the results. Also, by comparing the compliance rate across different gap sizes, they found in large and medium size gap conditions, drivers have an average compliance rate around 90 percent. If compared across different advisory types, they found the merging control algorithm and lane change advisory have better compliance rates than VSL.

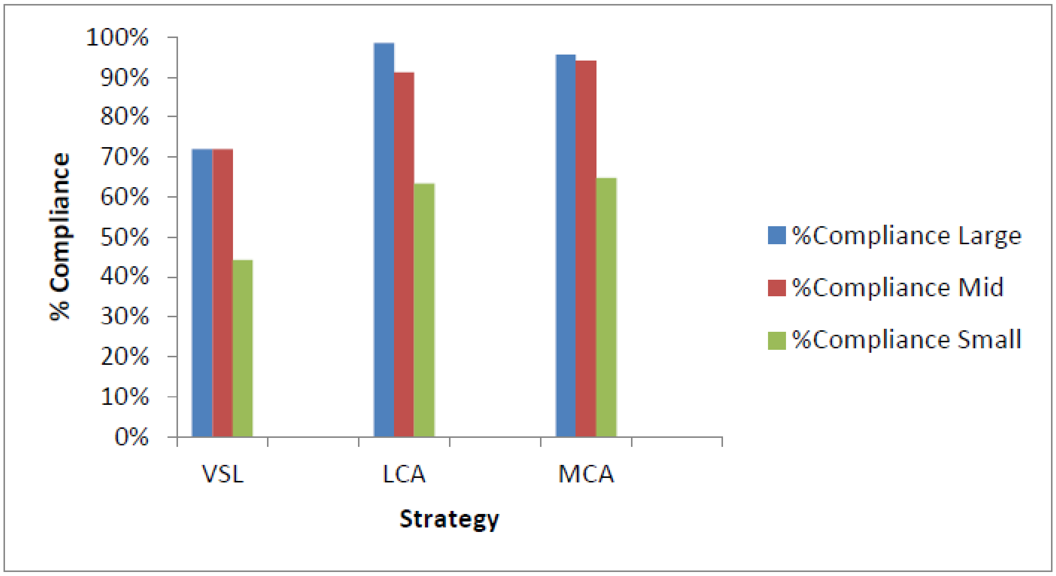


Figure 1: Compliance Rate of Merging Assistant Systems (*15*).

2.2.3.2 Variable Speed Limit

VSL or speed harmonization system is another typical CDBA CV application. VSLs have two major approaches, one is to stabilize or harmonize traffic flow, and the other is to prevent or resolve a traffic jam created by a bottleneck. The goal of traffic flow stabilization is to maintain a desired density and flow in traffic (*16*). In contrast, the traffic jam resolve approach aims to control the inflow to a high density jammed area and prevent the propagation of the congested front (*17*).

Researchers have proposed several methodologies to decide the optimal speed limit, such as linear control (*18*), multilayer control (*16*), model predictive control (*19*), and shockwave based control (*17,20*). Hegyi et al. combined the traditional VSL systems with CV data and found even a penetration rate of 1 percent can provide an observable improvement (*20*). Grumert et al. proposed a VSL system for CV environment. In this VSL system, in which the speed limits are sent directly into individual vehicles through V2I communication (*21*). In their VSL system for CV environment, speed limit given to an individual vehicle is decided by its distance from the new speed limit suggestion point, its current speed, and the suggested speed. Before the vehicle reaches the next speed limit suggestion point, it can adjust its speed to have a smooth deceleration/acceleration toward the next speed limit suggestion. Speed limit suggestion points still have the traditional VSL sign.

Studies of VSL also adopt various performance measures for VSL systems. Grumert et al. investigated the acceleration/deceleration distribution to evaluate the smoothness in vehicles' speed change (*21*). In traditional sign-based VSL system field test studies, researchers often investigate the impact of VSL on speed and headway distribution, increase in safety, and capacity (*22*). Lee and Park investigated the impact of VSL system under CVs by looking into the reduction in travel time (*23*). Nissan and Koutsopoulosb proposed a statistical model to evaluate the impact of VSL (*22*). They used the data before and after the implementation of VSL systems to calibrate a traffic stream model and use the difference in the Sum of Square Residuals and parameter values in each calibration to evaluate how much difference can the VSL make. Zhang et al. examined the impact of VSL by plotting out the discharge flow rate at bottleneck with and without VSL (*24*). The diagram can show how much VSL can increase the discharge flow rate and how much less time it takes the VSL to resolve the jam.

In general, the most common performance measures used in past studies are mobility benefit and safety benefit measures. Mobility benefit measures include travel time, average speed, throughput of bottleneck, and density. Safety measures include collision potential or probability and speed differences (*25,26*).

Though VSLs on CVs have not been implemented yet, a lot of studies have been carried out for existing traditional sign-based VSL systems, especially in Europe. In the M25 motorway in UK, drivers are found to keep more uniform headways with VSL. Also accidents with injuries were reduced by 10 percent. Even the traffic noise, fuel consumption, and emissions demonstrated a decrease (*22*).

Driver compliance situation can influence the effect of VSL systems. Several studies assumed full speed limit compliance or did not include compliance issue in the simulation evaluation (*18,24*). Some others used fixed compliance rates(*23,27*).

Hellinga and Mandelzys evaluated the impacts of drivers' compliance on VSL systems using simulation (*25*). In their study, drivers' reactions to VSLs from existing literature are summarized. They investigated drivers' compliance behavior to static speed limits. They decided that the compliance behavior of static speed limits is insufficient for predicting drivers' responses to VSL. Four compliance levels for VSL are defined: low, moderate, high, and very high. The results show that as the compliance level increases, the safety performance improves and the mobility benefit decreases. They also found selection of operating strategy and parameter settings should take compliance into consideration.

Hadiuzzaman et al. proposed a method to model driver compliance behavior for VSL (*26*). They defined compliance with the speed limit as the speed of the vehicle within ±5 percent of the speed limit. Non-compliant vehicles are classified into defensive and aggressive drivers. Defensive drivers are those who drive at a speed 5 percent under the posted speed limit while aggressive drivers drive at a speed 5 percent over the posted speed limit. They set three compliance levels: low, moderate, high with compliance rates of 20 percent, 45 percent, and 80 percent, respectively. Under each compliance level, different percentages of defensive and aggressive drivers are assumed for different posted speed limits. The percentage of aggressive driver will increase as the posted speed limit lowers. A speed distribution according to drivers' compliance to VSL can be worked out. They found both mobility and safety benefits are positively correlated with increasing compliance levels.

2.2.3.3 Eco-Driving Assistant System

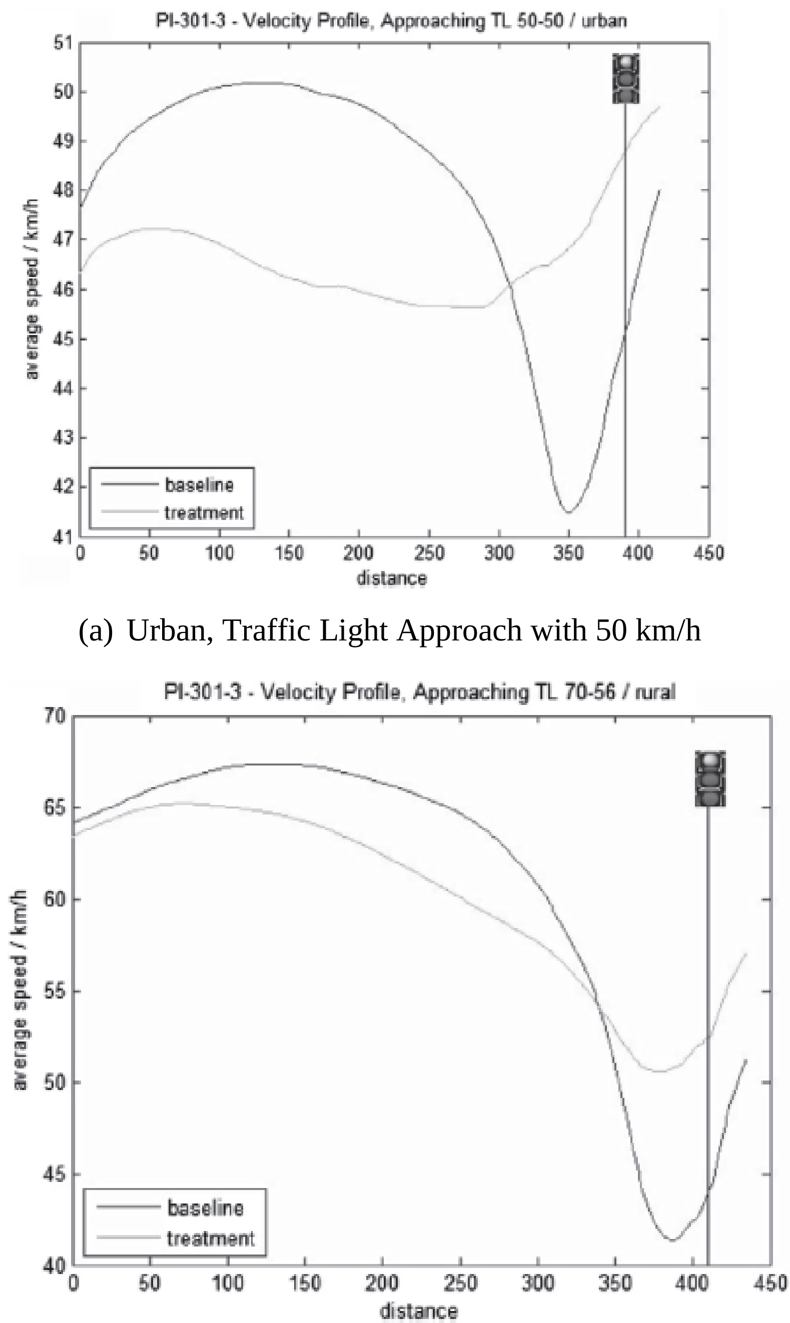
Environmental CV applications aim to improve fuel efficiency and reduce emission by changing the driving style of the vehicles. Eco driving applications can work both on freeways and on urban signalized roadways. On a signalized urban roadway, the major impact factor of fuel efficiency and emission is vehicle acceleration and deceleration behavior. Eco-driving assistant systems can communicate with traffic control devices such as traffic signs and traffic lights and recommend to the drivers how and when to accelerate and decelerate fuel-efficiently. Ideally, a smoother driving style with more constant velocities and less deceleration or acceleration maneuvers can lead to less fuel consumption and emission (*28*). With the know-ahead information and throttle control advisories provided by eco-driving assistant systems, drivers can take actions ahead of time and adopt smaller deceleration and accelerations as shown in Figure 2. Performance indicators of eco-driving assistant systems include fuel reduction potential, its impact on travel time, speed standard deviation, gear shifting behavior, and time to collision (*28*).

Like other CV applications in this category, driver compliance to advisory has a great impact on the effect of the application. The closest research about driver behaviors in an eco-driving assistant system is a driver simulator study carried out by Staubach (*28*). The eco-driving assistant system they evaluated presents advisories visually via an onboard display. They did not measure the compliance behavior of drivers to the advisory. But they did a gaze analysis to measure distraction of the system. They found drivers looked away from street for more than 2 s at first, but the gaze away time became shorter as the experiment continues. The gaze away time dropped to around 1.7 s when the experiment continues for 40 minutes. This result indicates that distraction can be a problem of these types of advisory assistant systems but as drivers get more familiar with it, the distraction can decrease and drivers can possibly adapt to the new technology.

2.2.4. Semi-Automated/Automated Driving

Semi-automated or automated driving means drivers can hand over some part of vehicle control or even full vehicle control to the embedded controller of the vehicle. Sensing the surrounding objects can be achieved by sensors or by CV technology.

Drivers' choices of control parameters such as desired gap in CACC have a great impact on how this type of applications performs. The choices of parameters should differ across driver population instead of universally identical.



(a) Urban, Traffic Light Approach with 50 km/h

(b) Rural, Traffic Light Approach with 56 km/h

Figure 2: Speed Profile Change using Eco-Driving Assistant Systems (*28*).

Nowakowski et al. (*29*) investigated drivers' choices of CACC control parameters by giving out prototype vehicles for participants daily use. They recorded the duration of CACC activations, actual speed and gap conditions at the onset and deactivation of CACC, and participants' desired speed and gap setting behavior; they made comparisons between actual gaps and set gaps during the CACC activations. Table 1 summarizes the results.

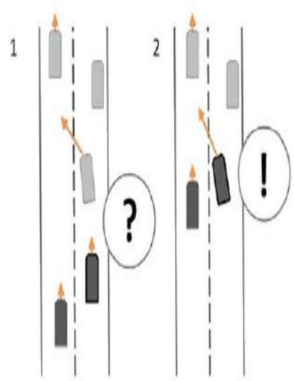
Table 1: Drivers' Choices of CACC Control Parameters.

Choices	At Activation	At Deactivation
Duration of CACC Activation	Average of 3 minutes and standard deviation of 4.1 minutes.	
	Minimum 1 s and maximum 25 minutes.	
Actual Speed	Mostly within 3 mph of the set desired speed.	Lower than actual speed. Higher than 20 mph. Indicates most vehicles are in gap regulated mode at deactivation.
Number of Activation	Mode is 3 times per trip. But some drivers have more than 13 activations.	
Time Gap Setting	If the driver has activated CACC several times that trip, they tend to choose smaller gaps. If it is their first or second activation during the trip, they will start with larger gap 1.1 s first.	Drivers change the time gap setting toward lower gaps during the activation. This finding also applies to first time activation.
Actual Time Gap	Most actual gaps are larger than desired gaps. Drivers let the system close up the gap instead of doing it manually.	Most actual gaps are identical with desired gaps. This indicates, at deactivation, most vehicles are in gap regulated mode.

The available automation technology cannot handle all driving situations. This requires users to monitor and take actions when necessary. When a driver takes back control from automation system, the automation system is deactivated. The deactivation process can be hazardous depending on drivers' distraction and trust in the system. Kircher et al. (*30*) investigated the tactical driving behavior of currently available automated driving systems: ACC, assisted steering (lateral positioning assistance), and collision avoidance systems. The actions drivers can take include braking, manually switching off the automation system, taking foot off the throttle, steering and changing lanes, or do nothing when encountering a situation that the automated system cannot handle.

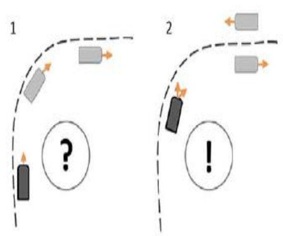
Kircher et al. (*30*) established three events that cannot be handled by the automated systems as described in Table 2. The number of drivers taking different actions is recorded. They found out that the type of automation does affect tactical behavior. In addition, trust in the automation system does vary in drivers and affects their choice of when to reclaim control.

Table 2: Events to Reclaim Control from Automated Driving (*30*).

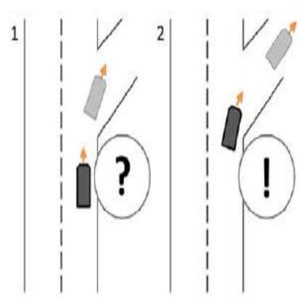


Broken Down Car Event. The participant drives in dense traffic in the right lane on a single carriageway. A vehicle is parked/ stopped in the right lane, forcing traffic to merge to the left. The vehicles ahead of the ego vehicle merge left. Another vehicle travels in the left lane next to the ego vehicle, preventing the ego vehicle from merging. If the driver brakes to let the vehicle in the left lane pass, this vehicle brakes as well and lets the driver merge to prevent crashes. The driver can also accelerate and merge before the vehicle in the left lane.

In the ACC condition, the ego vehicle loses contact with the lead vehicle when the lead vehicle merges left, causing acceleration toward the set speed (75 km/h). The driver needs to steer or brake. In the ACC-AS condition, the ego vehicle follows the lead vehicle, just making it past the vehicle in the left lane if the driver does not intervene. The “broken down car” event is defined to begin when the car in front of the lead vehicle starts to indicate a merge to the left and ends when the ego vehicle is passing the stopped vehicle.



Curve Event. The participant drives through a sharp turn. In the ACC condition, the ego vehicle may lose contact to the vehicle ahead, depending on lateral position and headway of the ego vehicle. If that happens, the ego vehicle accelerates to the set speed (75 km/h). In the ACC-AS condition, the function loses contact to the lead vehicle at a specific location and issues a warning, if the driver has not reclaimed control beforehand. If the driver does not steer, the ego vehicle enters the oncoming lane. The curve event is defined to begin when the curve sign is first visible and ends when the road is straight again.



Exit Event. The exit event always occurs a while after a new vehicle has merged into the gap between the ego vehicle and the lead vehicle. The cars drive along the road on a single carriageway. The new vehicle in front of the ego vehicle turns on its right indicators and leaves the main road via an exit. In the ACC condition, the ego vehicle continues to go straight. In the ACC-AS condition, the ego vehicle would follow the exiting vehicle without driver intervention, so the driver is forced to steer actively in order to stay on the main road. The exit event is defined to start when the lead car turns on its indicator and ends when the ego vehicle has passed the exit.

Apart from CACC, there is also an eco-cruise control system. Eco-cruise control systems can control the vehicle speed in order to maximize fuel efficiency and reduce emission. Unlike eco-driving assistant systems mentioned in Section 2.2.3, eco-cruise control systems are used on freeways. On freeways, most vehicles do not brake under regular traffic conditions. So the main influence factor of emission and fuel consumption on freeway is the roadway grade. A 6 percent increase in a roadway grade can increase the vehicle fuel consumption levels by 40 percent to 94 percent (*31*). However, sometimes eco-cruise control may lead to larger headways and impair mobility. Also, traditional eco-cruise control systems do not include interactions between vehicles like regular ACC does. Ahn et al. integrated the eco-cruise control system with regular car-following cruise control systems (*31*). Their eco-cruise control system can generate optimal vehicle speed profiles according to changes in roadway grades. Their proposed system can switch between eco-cruise control mode and car-following control mode to avoid significantly increased headways. They also integrated a collision avoidance model into the control algorithm.

In addition to the situations mentioned, drivers may also want to resume manual control when the traffic is congested or before they want to perform maneuvers like lane changing. Varotto et al. did a driving simulator experiment on this transition period for ACC (*32*). Three situations were set in the experiment. Manual driving is the control condition, the second condition involves a sensor failure after which the drivers need to resume control, and in the third condition, drivers can switch on and off the ACC whenever they want. They found after the sensor failure event, there would be a significant speed drop and an increase in speed standard deviation. Also, a similar speed drop is observed before the voluntary switch on of the ACC system. The medium time to resume control after the sensor failure is 3.85 s, and the medium time before voluntary switching ACC on after sensor failure is 5.8 s. Control transitions can result in higher time headways.

2.2.4.1 CACC Impact on Freeway Operations

During the past few decades, several researchers have worked on CACC technology and tried to quantify the effect of CACC vehicles on freeway performance measures such as capacity, emissions, and traffic stability. Many of the studies are promising and show that at high market penetration rates, CACC-equipped vehicles can have a positive effect on freeway performance.

Increase in traffic has put immense pressure on the existing infrastructure. There is need for roadway widening at many corridors in the United States but not enough resources. To address this situation, researchers developed CACC. CACC technology has the potential to drastically increase freeway capacity and traffic stability.

Vanderwerf et al. (*33*), after developing a car-following model for the ACC and CACC, equipped vehicles performed Monte Carlo simulation to estimate the effect of different vehicle types on the freeway capacity. For 100 percent Market Penetration Rate (MPR), the authors found that the freeway capacity was 2050, 2200, and 4500 vehicles/hours for manual driving, ACC, and CACC, respectively. CACC significantly increases the capacity as compared to other two. ACC-equipped vehicles make decisions based on sensor data, which is error prone, so a platoon of ACC vehicles is not string stable and has to maintain a longer distance as compared to CACC platoons that are string stable. Thus the capacity increase for ACC was less than CACC.

Milanes et al. (*34*) got similar results as Vanderwerf et al. (*33*). After running the simulation for varying market penetration rates for different vehicle types, the authors found that when only ACC-equipped vehicles and manual vehicles were simulated, the increase in MPR of ACC-equipped vehicles had a very little effect on the capacity. For CACC vehicles, as the MPR rate increased, the capacity also increased. The maximum capacity obtained was around 4000 vehicles/hour. It was also found that Here I am vehicles help in further increasing the capacity of highways at lower MPR of CACC vehicles.

Van Arem et al. (*35*) checked the impact of CACC-equipped vehicles on stability by considering a platoon of four vehicles approaching a predecessor vehicle. Different market penetration rates were tested. CACC at 100 percent MPR was able to maintain a smaller gap, and the platoon acceleration and deceleration was smoother as compared to the reference case with only manual driver vehicles. The authors then evaluated the impact of CACC on traffic flow at different MPR. They found that throughput does not change much at MPR less than 40 percent. To have benefits on traffic stability and throughput, MPR should be greater than 60 percent.

Kesting et al. (*36*) found a linear increase in capacity as the percent of ACC increased by 1 percent. These results, according to Milanes et al. (*34*), might not be representative of real world scenarios; in actual field tests, there was a capacity reduction when ACC-equipped vehicles are tested.

There is a body of literature that shows CACC would increase the freeway traffic capacity and stability. Conflict of opinions comes when evaluating the impact of ACC vehicles on freeway capacity. Some studies have shown ACC-equipped vehicles will improve capacity, whereas others have shown it to be no better than manual driving. However, as more and field tests are being conducted, it is becoming evident that ACC would have little or no impact on capacity.

2.2.4.2 CACC Impact on Fuel Consumption and Emissions

CACC-equipped vehicles can maintain smaller gaps as compared to manual driving. So when CACC-equipped heavy vehicles move in a platoon, they experience wind drag reduction, which translates to reduction in overall power that a vehicle has to exert to maintain the same speed or accelerate. This reduces the fuel consumption and the tailpipe emissions.

Alam et al. (*37*) evaluated platoons formed by Heavy Goods Vehicle (HGV) equipped with ACC. They added a feature to allow the following vehicle to obtain the information of traffic conditions ahead of lead vehicle. This feature is similar to the CACC framework, so the experimental results can be extrapolated for CACC-equipped vehicles. The authors showed that due to close following and reduction in wind drag, a reduction in fuel consumption between 4.7 to 7.7 percent can be obtained. Also the authors found that reduction in fuel consumption is affected by the weight of the leading truck. A heavier lead truck will result in lower fuel consumption as compared to lighter truck. The authors also found that a smaller gap results in lower fuel consumption, because the wind drag reduces as the clearance between the vehicles in a platoon reduces.

Bonnet et al. (*38*) used an electronic tow bar to allow two heavy vehicles to move at a close spacing. The lead vehicle was driven manually, and the following vehicle had a controller to follow the leader automatically. The author ran a series of experiments at different speed and spacing combinations with the highest spacing being 16 m. The authors found a reduction in fuel consumption at all the levels. The reduction in fuel saving reduces with decreases in clearance but reduction reaches a plateau at a clearance of 10 m, so 10 m clearance is optimal for fuel savings. A fuel saving of 5 to 10 percent was observed in this study.

Tsugawa et al. (*39*) conducted a study to evaluate platooning with respect to three CACC-equipped heavy vehicles and found similar results. The authors focused on the impact on emission and energy consumption due to close following and found a 2.1 percent reduction in CO_2 at a spacing of 10 m and 40 percent market penetration rate.

There have been a lot of studies similar to the above mentioned studies and almost all have shown CACC will have a positive impact on fuel consumption and emissions. A common conclusion that can be made from the above studies is that with closer spacing, there would be an increase in fuel consumption reduction and emission reduction.

2.3. Driver Behavior Modeling in Connected Vehicle Applications

Traditional car-following or lane changing models are unable to capture all possible driver behaviors in a CV environment. This section introduces the existing driver models developed for modeling driver's behavior using CV applications.

2.3.1. Overview of Car-Following and Lane Changing Models

Most driving models describe the car-following behavior of a driver (*40*). Car-following models can be further divided into three types (*41*):

1. Stimulus based models: Drivers make braking or accelerating decisions based on stimulus (speed change) from the preceding vehicle (GM model).
2. Safety distance models: Drivers change speed in order to maintain a safe distance from the preceding vehicle.
3. Psychophysical or Action Point (AP) Models: AP models focus on human driving decision-making mechanisms.

To build an AP model, relative distance and relative speed between preceding and following cars are collected. Then they are plotted on a dv (relative speed) versus dx (relative space) plane (see Figure 3). Other measures such as acceleration, pressure, and time to collision are also collected and plotted against relative speed. Patterns of the plots are recognized and turning points of the plots are identified as action points. The identified turning points are used to calibrate a curve function where the drivers make a decision to accelerate or brake. Those calibrated curves are used to model drivers' decisions (see Figure 4). Other driving models include merging situations, lane keeping, and steering control (*40*).

The most common lane-changing model is the gap acceptance model. A lane change can be categorized into mandatory lane changing (MLC) and discretionary lane change (DLC). MLC happens when drivers have to change lanes to stay on their route. DLC happens when drivers think the traffic condition in the target lane is better. A risk factor that is acceptable to a driver is introduced to model the necessity and desirability of lane changing (*25*). In a rule-based lane changing model, the decision regarding DLC can be probabilistic (*27*). When the speed of the preceding vehicle is lower than a driver's desired speed, he/she is going to consider a DLC. The probability a driver decides to go for a DLC depends on his/her impatience level and perception of speed difference (*27*). Gap acceptance model is used to model drivers' choices in lane changing. The gap acceptance model should be able to capture the fact that DLC critical gap is higher than a MLC critical gap. Various gap acceptance models based on different distribution assumptions are developed.

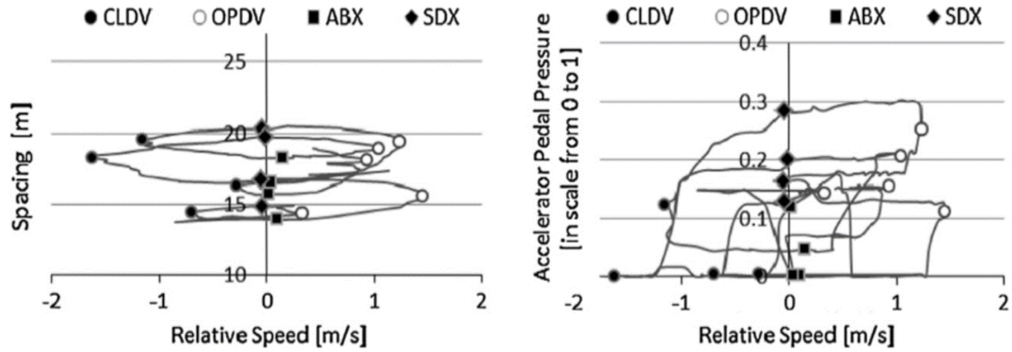


Figure 3: Driving Decision Plot (*41*).

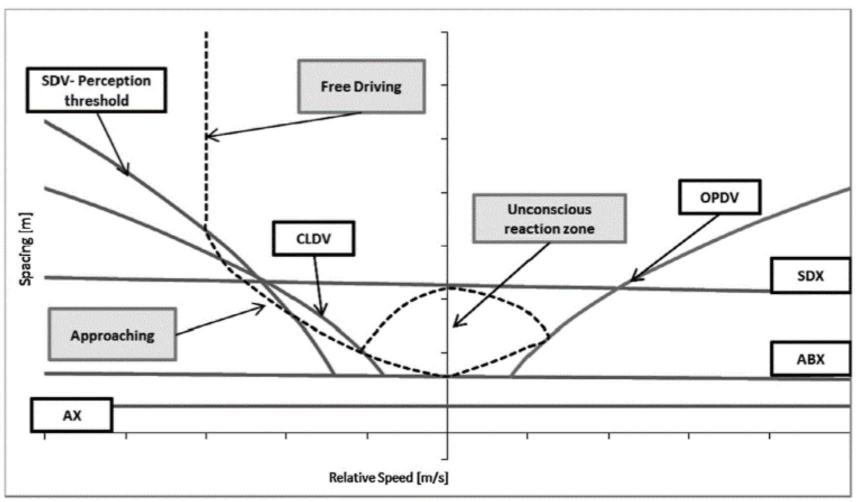


Figure 4: An Example of AP Modeling Scheme (*41*).

2.3.2. Driver Models for Driver Behavior Adjustment in CV Applications

Researchers have been trying to find a way to account for driver behaviors in the evaluation of CV applications. In a realistic driver model for CV environment, the drivers should not follow CV application advisory like robots. Tampere et al. concluded that the models of future traffic flow should account for driver, vehicle assistant systems, vehicle capability, additional information through communication, and roadside traffic control systems (*42*). Future traffic flow models should be able to capture drivers' interaction with CV driving assistant applications.

Tampere et al. proposed continuous traffic flow modeling approach for Advanced Driving Assistant Systems that can give out warnings (*42*). The model uses the activation level of drivers to model drivers' active or passive driving behavior in reaction to CV information. The activation level is constrained in a range [a_{normal}, a_{max}] indicating the excess of activation. Three main macroscopic traffic flow variables regarding space *x* and time *t* are involved in the model:

- Vehicular density *k*.
- Expected or average velocity *V*.
- Expected or average activation level of the drivers *A*.

Their relationships are described in three differential equations:

$$\frac{\partial k}{\partial t}+\frac{\partial kV}{\partial x}=\left(\frac{dk}{dt}\right)_{\text{discrete}} \tag{2-1}$$

Equation (2-1) means that the total number of vehicles cannot change unless at some discrete locations (on- or off- ramps) the inflow is $\left(\frac{dk}{dt}\right)_{\text{discrete}}$ per unit of time and ramp length:

$$\frac{\partial kV}{\partial t}+\underbrace{\frac{\partial k\left(V^2+\Theta^e\left(k\right)\right)}{\partial x}}_{\text{Convection}}=\underbrace{k\left\langle \dot{v}\right\rangle_{v,a}}_{\text{Continuous Behavior}}+\underbrace{\int_a\int_v v\left(\frac{d\rho}{dt}\right)_{\text{discrete}}dvda}_{\text{Discontinuous Behavior}} \tag{2-2}$$

Equation (2-2) states that the change per unit of time of the product of density and speed at location x and time t is caused by the following three processes:

1. Convection: change of average speed at location x because the traffic currently occupying this location is replaced by immediately upstream traffic. In the expression of convection, $\Theta^e\left(k\right)$ represents the speed variance.
2. Continuous behavior: change in the average speed due to the net result of individual drivers accelerating or decelerating. The net result is indicated by $\left\langle \dot{v}\right\rangle_{v,a}$.
3. Discontinuous behavior: change in the average speed due to net effect of discrete changes. Discrete changes include change in average speed caused by traffic entering or leaving the highway through on- or off- ramps. ρ indicates the generalized density:

$$\underbrace{\frac{\partial kA}{\partial t}+\frac{\partial kAV}{\partial x}}_{\text{convection}}=\underbrace{k\left\langle \dot{a}\right\rangle_{v,a}}_{\text{continuous behavior}}+\underbrace{\int_a\int_v a\left(\frac{d\rho}{dt}\right)_{\text{discrete}}dvda}_{\text{discontinuous behavior}} \tag{2-3}$$

Equation (2-3) also has the same structure as Equation (2-2). But Equation (2-3) measures the change per unit of time of the product of density and activation level. There are also the same three processes as in Equation (2-2). But the change in average speed is replaced by change in activation level.

The acceleration term $\left\langle \dot{v}\right\rangle_{v,a}$ can be obtained by integrating a car-following relationship:

$$\left\langle \dot{v}\right\rangle_{v,a}=\int_{a_j}p_a\int_{v_j}p_{v_j}\int_{s_j}p_s\int_{v_{j-1}}p_{v_{j-1}}\dot{v}_j dv_{j-1}ds_j dv_j da_j \tag{2-4}$$

Equation (2-4) calculates the expected value of a microscopic car-following function type. $\dot{v}_j$ is the individual acceleration of car *j* as a function of its own speed, activation level a_j of the driver, speed of the predecessor v_{j-1}, and the gap s_j between the vehicles as in Equation (2-5):

$$\dot{v}_j = f_{CF}\left(v_j, a_j, s_j, v_{j-1}\right) \tag{2-5}$$

$$\begin{aligned} p_a &= p_a\left(a_j \mid t, x\right) \\ pv_j &= p_v\left(v_j \mid t, x\right) \\ p_s &= p_s\left(s_j \mid t, x, v_j\right) \\ p_{v_{j-1}} &= p_v\left(v_{j-1} \mid t, x + s_j, v_j, s_j\right) \end{aligned} \tag{2-6}$$

Equation (2-6) stands for the probability distribution functions of each variable.

A well designed warning-based CV application can increase drivers' activation level. When messages are received, a driver's activation level a_0 will be increased by factor *f*:

$$a_1 = f a_0 \tag{2-7}$$

Tampere et al. assumed that each vehicle can receive $n_{\text{received}}(t, x)$ warnings at time t and location. The probability that warnings are sent at location x and time t by vehicles of class c is $p_{send}^{c}\left(t, x'\right)$. Also, there is a maximum number $n_{\max}$ of warnings a driver can receive. The activation increase factor is determined by drivers' current activation level, warning messages received, and current activation level:

$$f = 1 + \left(\frac{a_{\max}}{a_0} - 1\right)\frac{n_{\text{received}}}{n_{\max}} \tag{2-8}$$

The net increase in activation level is expressed as:

$$\underbrace{\int_a \int_v a\left(\frac{d\rho}{dt}\right)_{\text{discrete}} dv da}_{\text{discontinuous behavior}} = k \frac{a_{\max} - A}{\tau_{ADA} \dfrac{n_{\max}}{n_{\text{received}}}} \tag{2-9}$$

where τ_{ADA} and *A* are parameters.

The more warnings are received, the faster the maximum activation level will be reached. When no warnings are received, drivers tend to drive at a normal activation level a_{normal}. After the sudden increase in activation level, the activation level will relax with time constant τ_a. In this case, the continuous behavior term in Equation (2-3) becomes:

$$k\left\langle \dot{a}\right\rangle_{v,a} = k\,\frac{a_{normal} - A}{\tau_a} \tag{2-10}$$

Equation (2-3) becomes:

$$\frac{\partial kA}{\partial t} + \underbrace{\frac{\partial kAV}{\partial x}}_{\text{convection}} = \underbrace{A\left(\frac{dk}{dt}\right)_{\text{inflow}}}_{\text{merging}} + k\left(\underbrace{\frac{a_{normal} - A}{\tau_a}}_{\text{relaxation}} + \underbrace{\frac{a_{\max} - A}{\tau_{ADA}\,\frac{n_{\max}}{n_{\text{received}}}}}_{ADA}\right) \tag{2-11}$$

In general, this model proposed by Tempere et al. (*42*) introduced the concept of activation level to describe the effect of warnings from CV applications. They modeled the change of activation level over time and incorporated the activation level into the modeling of traffic flow.

Kesting et al. described vehicular traffic as a typical multi-agent system (*43*). A driver-vehicle unit is a discrete agent of this system. Figure 5 shows the characteristics of an agent. They incorporate inter-driver variability and intra-driver variability into their simulation model. Inter-driver variability means different drivers behave differently in the same situation. Intra-driver variability means that the same driver changes his/her driving behavior overtime in similar traffic situations.

Kesting et al. used Intelligent Driver Model (IDM) (*43*) to model the behavior of each driver-vehicle agent. Inter-driver variability is simulated by setting different model parameters for different drivers. A memory effect is mentioned for intra-driver variability. The idea of memory effect is that the actual driving style of a driver depends on the traffic conditions of the last few minutes. Kesting et al. introduced a time dependent model of IDM parameters to describe drivers' frustration in a jam:

$$\frac{d\lambda}{dt} = \frac{\lambda_0(v) - \lambda}{\tau} \tag{2-12}$$

where:

$\lambda(t)$ is the subjective level of service of a driver at time *t*.

$\lambda(t)$ ranges from 0 (in a standstill) to 1 (free flow).

Equation (2-12) represents the process that the subjective LOS $\lambda(t)$ relaxes to the instantaneous LOS $\lambda_0(v)$ with a relaxation time τ. The value of relaxation time is typically 5 minutes. The subjective LOS can affect the desired time gap T in IDM. In Kesting's model, the desired time gap is varied between T_0 and $T_{jam} = \beta_T T_0$:

$$T(\lambda) = \lambda T_0 + (1-\lambda)T_{jam} = T_0\left[\beta_T + \lambda(1-\beta_T)\right] \tag{2-13}$$

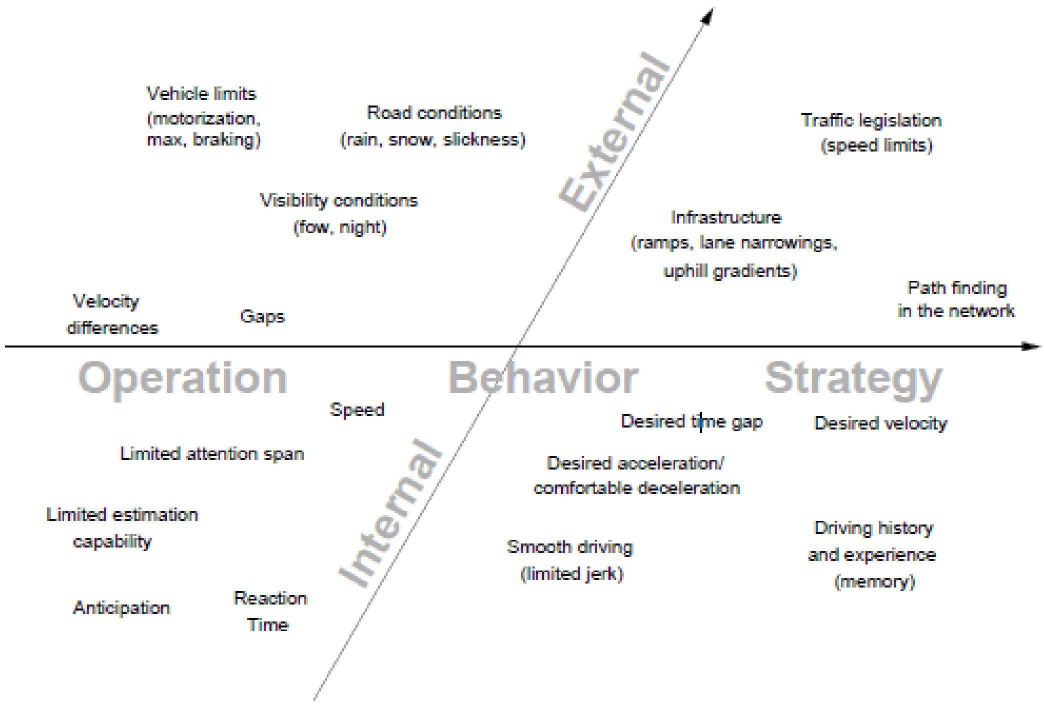


Figure 5: Characteristics of a Driver-Vehicle Agent (*43*).

In Zhu and Ukkusuri's mixed CV environment simulation model, they classified the drivers into timid, neutral, aggressive, and CV drivers (*44*). Each class of driver has a different time space profile (Figure 6).

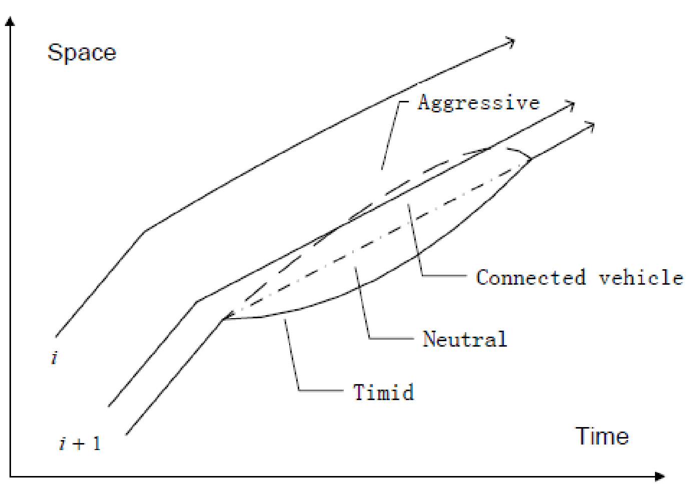


Figure 6: Trajectory of Different Driver Classes (*44*).

Talebpour and Mahmassani believe that CV applications can help drivers make better decisions (*45*). So they modeled the behavior of human drivers by a probabilistic driving behavior model in which drivers will sometimes make bad decisions that can lead to a crash. The probabilistic behavior is due to drivers' wrong perception of the surrounding traffic conditions. For CVs, they used a deterministic IDM model because drivers can make better decisions with the information provided by CV applications.

In general, to account for the effect of CV information, some researchers choose to introduce a variable indicating drivers' acceptance or perception of the information (*42,43*), while others induce uncertainty into traditional car-following models (*45*).

2.3.3. Car-Following Models for Semi-Automated/Automated CV Applications

Some CV applications can take over part of vehicle control from driver, such as CACC and eco-cruise control systems. Modeling of these applications require a different car-following model to replace the traditional car-following models.

Vanderwerf et al. set the foundation of CACC modeling in 2001 (*33*). They proposed a set of mathematical models to predict the effects of ACC and CACC with 100 percent penetration in a platoon. The following describes several driving conditions defined in their model.

Free Driving: When a vehicle has no vehicle ahead of it or has at least 100 m of clearance to the preceding vehicle, the controller attempts to maintain a desired velocity with its acceleration limited to ±2 m/s^2. The acceleration of free driving state is modeled by the following equation:

$$u_2(t) = -k_f\left[\dot{x}_2(t) - v_{2d}(t)\right] \tag{2-14}$$

where:

$k_f = 0.4$.

$\dot{x}_2(t) =$ Speed of the following vehicle.

$u_2(t) =$ Acceleration of the following vehicle.

$v_{2d}(t) =$ Desired speed of second vehicle.

Human Driving: Modeled by traditional car-following models.

Autonomous CACC Driving:

$$\begin{aligned} &u_2(t) = k_0\ddot{x}_1(t) + k_1\left[\dot{x}_1(t) - \dot{x}_2(t)\right] + k_2\left[r(t) - r_d(t)\right] \\ &u_2(t) \le a_{\max} \\ &u_2(t) \ge d_2 \end{aligned} \tag{2-15}$$

where:

$r_d(t) =$ Desired distance between vehicles.

$r(t) =$ Current distance between vehicles.

$\ddot{x}_1(t) =$ Acceleration of preceding vehicles.

$\dot{x}_1(t) =$ Speed of preceding vehicle.

$\dot{x}_2(t) =$ Speed of following vehicle.

$a_{\max} =$ Maximum allowed acceleration.

$d_2 =$ Maximum allowed deceleration.

$k_0 = 1, k_1 > 0, k_2 > 0 =$ Gains.

Desired safe range, $f_d(t)$, is the maximum among safe following distance, following distance with 0.5 s time gap and a minimum allowed distance chosen to be 2 m:

$$\begin{aligned} r_d(t) &= \max\left[r_{safe}(t), r_{0.5s}(t), r_{\min}\right] \\ r_{safe}(t) &= \frac{\dot{x}_1^2(t)}{2}\left(\frac{1}{d_2} - \frac{1}{d_1}\right) + \delta \dot{x}_1^2(t) \\ r_{0.5s}(t) &= 0.5\dot{x}_2(t) \\ r_{\min} &= 2 \end{aligned} \tag{2-16}$$

where:

$\delta =$ 20 ms = communication delay.

$d_1 =$ Braking capability of preceding vehicle.

$d_2 =$ Braking capability of following vehicle.

ACC system's response time can be around 0.1–0.2 s, which can be neglected compared to human response time 1 s. Kesting et al. (*46*) summarized the criteria of ACC simulation models:

- Must be collision free.
- The dynamics should correspond to a natural and smooth manner of driving.
- Adaptions to new traffic situations, such as the leading vehicle brakes or another vehicle cuts in, should be performed without any oscillations.
- The model should have only a few parameters. Different driving behaviors should be able to be represented by different parameters.
- Calibration should be as easy as possible.

One of the common models that are currently used is the IDM:

Acceleration:

$$\dot{v}(s, v, \Delta \mathrm{v}) = a\left[1 - \left(\frac{v}{v_0}\right)^4 - \left(\frac{s \times (v, \Delta \mathrm{v})}{s}\right)^2\right] \tag{2-17}$$

$$s^*(v, \Delta v) = s_0 + vT + \frac{v\Delta v}{2\sqrt{ab}} \tag{2-18}$$

where:

s = Net gap distance between consecutive vehicles (m).

v = speed of object vehicle (km/h).

Δv = approaching rate to leading vehicle (km/h).

a = Maximum acceleration.

b = Braking decelerations to the comfortable deceleration.

T = Following the leading vehicle with a constant safe time gap T.

s_0 = Minimum distance in congested traffic (km/h).

v_0 = Desired speed (km/h).

The IDM model is suited for ACC controlled vehicles; its difference from human driving style includes:

- Human has a reaction time.
- Limited attention spans and imperfect judgments.
- Humans can scan several vehicles ahead; ACC can only react to the vehicle immediately ahead.
- Human can anticipate the future traffic situations.

Milanes et al. (*47*) used four production cars by Infinity equipped with ACC controller, CACC controller, and a IDM model controller in a field experiment. These controllers were tested to find out the actual response of the vehicles. They found that the original IDM produced an unrealistic behavior, so they updated the equation so that the last term in the equation can avoid negative values:

$$a_{IDM} = a\left[1-\left(\frac{v}{v_0}\right)^{\delta}-\left(\frac{s_0+\max\left[0, vT+\frac{v\Delta v}{2\sqrt{ab}}\right]}{s}\right)\right] \qquad \text{(2-19)}$$

where:

a, b =Maximum acceleration and deceleration = 1 m/s^2 and 2 m/s^2.

v = Current vehicle speed (m/s).

v_0 = Desired speed in free-flow traffic =120 (km/h).

s = Bumper-to-bumper inter-vehicle clearance (m).

s_0 = Vehicle -vehicle clearance in stand-still situations, set to 0 m because these tests were carried out on highways at speeds higher than 25 (m/s).

T = Minimum steady state time gap = 1.1 (s).

Speed responses, acceleration response, time gap error, and following distance overtime are plotted against time as performance measurements of each controller. They found:

- IDM has significant delay in the response to speed changes of the leading car.
- ACC and IDM controllers are braking harder than the leading vehicle; CACC controller is breaking more gently than the leading vehicle with an excellent time gap error.
- IDM's time gap error is 0.4 to 0.7 s and never goes to zero. ACC time gap error fluctuates around 0.1 s and that of CACC stabilizes around 0.
- Preset time gap of ACC and IDM is 1.1 s and for CACC 0.6 s.

They concluded that IDM is not good enough for simulating ACC and CACC controllers realistically. They proposed CACC and ACC models based on the data they collected from the field experiment. The CACC model introduced gap error e_k and its derivative as a factor in deciding vehicle speed for each control cycle:

$$e_k = x_{k-1} - x_k - t_{hw} v_k \tag{2-20}$$

where:

x_{k-1}, x_k = Current position of the preceding vehicle and the following vehicle.

v_k = Current speed of the subject vehicle.

t_{hw} = Current time-gap setting.

The error and its derivative are used for determining vehicle speed on each control cycle:

$$v_k = v_{kprev} + k_p e_k + k_d \dot{e}_k \tag{2-21}$$

where:

$\dot{e}_k$ = Derivative of e_k.

v_{kprev} = The speed of the subject vehicle in the previous iteration.

k_p = 0.45, k_d = 0.25.

RMSE = 0.1046 m/s for the second vehicle, 0.2034 for the second vehicle and 0.2567 for the fourth vehicle.

The model can simulate the real CACC speed and following distance profile accurately and without delay. They modeled the ACC acceleration by:

$$a_k = k_1 \left(x_{k-1} - x_k - t_{hw} v_k \right) + k_2 \left(v_{k-1} - v_k \right) \tag{2-22}$$

where:

a_k = Acceleration of the kth vehicle.

x_{k-1}, x_k = Current position of the preceding and the subject vehicle.

v_{k-1}, v_k = Current speed of the preceding and the subject vehicle.

k_1, k_2 =Gain values on the both positioning and speed errors, respectively.

Integral absolute error (IAE) is used to determine the gain values:

$$IAE = \int_0^T \left(\left| v_{real} - v_{simulated} \right| \right) dt \tag{2-23}$$

k_1 = 0.23s^{-2}, k_2 = 0.07s^{-1}

This model also worked accurately and smoothly regarding their field experiment data.

3. DRIVER BEHAVIOR MODELING IN MICROSCOPIC SIMULATION

There are many microscopic simulation packages today. PTV VISSIM is one of the most widely used microscopic simulation packages for traffic engineering studies in North America. It contains several features that can be customized for CV applications. These include custom driver models and capability to access simulation object data during run time. Therefore, this study adopted VISSIM as a simulation package for comprehensive review of its capabilities and features in driver behavior modeling. The review is based on VISSIM version 7 but the concepts should apply to other versions as well.

3.1. VISSIM Overview

In VISSIM, users can enter customized distributions for driving behaviors and vehicle attributes such as desired speed, vehicle weight, dwell time, and occupancy. VISSIM uses a psycho-physical car-following model for longitudinal driver behavior and a rule-based lane changing model. Parameters of each driver behavior model can be set before starting the simulation run. Additionally, VISSIM provides various add-on API, which allows users to integrate their own applications into VISSIM. There are two major programming interfaces that are pertinent to this study: COM and External Driver Model Dynamic Linked Library (DLL) interfaces. Through COM, users can start VISSIM from other applications and access attributes of features such as vehicles and signal controllers in the VISSIM network. While COM allows external programs to access simulation objects, External Driver Model DLL interfaces can replace the internal driving behavior by a user-defined behavior for some or all of the vehicles. COM can be written in different programming languages such as VB, C#, C++, JavaScript, and Python. External Driver Model DLL interface can only be implemented in C++. The various options to modify driving behaviors make VISSIM a go-to choice for CV application simulation.

The following sections introduce techniques and options for changing driving behavior and their potential use in simulating CV applications.

3.2. Longitudinal Driving Behavior

The longitudinal driving behavior model of VISSIM is based on the extensive work of Wiedemann. Users can define several different driving behaviors and assign them to different types of vehicles.

3.2.1. Acceleration and Deceleration Behavior

Acceleration and deceleration are functions of the current speed. So VISSIM defines functions to define acceleration and deceleration. Four acceleration and deceleration parameter functions are defined; they are:

- **Maximum acceleration** is used to keep the acceleration on slopes in a technically possible value. The maximum acceleration is automatically adjusted for up and down gradients of links.
- **Desired acceleration** is used in all situations. A maximum desired acceleration is not required.
- **Maximum deceleration** is the smallest negative acceleration technically possible. The maximum deceleration is also automatically adjusted for gradients of the link.
- **Desired deceleration** is used as the upper bound of deceleration in non-emergency cases. The desired deceleration should not exceed the maximum deceleration.

The change of acceleration with respect to time is called jerk. It is limited by the share that corresponds with twice the duration of time step. For example, if the time step is 0.1 s, then the limit of jerk is 0.2 (20 percent) of the intended change in acceleration per time step.

The functions of the four acceleration and deceleration functions can be adjusted in the Base Data tab of VISSIM user interface. Acceleration and deceleration are function of current speed of the vehicle. When the vehicle is stopped, the acceleration is the largest and it decreases as speed increases. In the case of deceleration, the deceleration is the smallest when the speed of the vehicle is near zero and increases as the speed rises. Acceleration and deceleration are stochastic rather than fixed. A vehicle's acceleration lies within a range. A random value inside this range is generated for each non-HGV vehicle at a certain speed. Random values are not used for HGV vehicles. A power-to-weight ratio is taken into account. For detailed settings of acceleration and deceleration functions, the users can refer to section 5.3.3 of VISSIM 7 User Manual.

3.2.2. Wiedemann's Driving States

VISSIM is a time step based, stochastic, and microscopic model based on Wiedemann's traffic flow model. The basic units in VISSIM are driver-vehicle units. Wiedemann assumes that there are four different driving states for a driver:

- **Free driving:** When no preceding vehicle is observed, drivers try to maintain their desired speeds. Due to imperfect throttle control, his speed will oscillate around the desired speed.
- **Approaching:** The process where the driver approaches a preceding slower vehicle. The approaching driver will decelerate until there is no difference in speed when he reaches the desired safety distance.
- **Following:** The driver follows the preceding vehicle and maintains the safety distance. Due to imperfect throttle control, the following distance oscillates around safety distance.
- **Braking:** When the distance to the preceding vehicle falls below the desired safety distance, the following driver will apply medium to high deceleration rates to increase the distance.

Drivers switch between driving states when they reach certain thresholds. The acceleration of a vehicle is a function of current speed, speed difference, distance to the preceding vehicle, and individual driver characteristics. Each driver has his own perception of safety distance, desired speed, and speed difference. Each vehicle has its own physical characteristics.

3.2.3. Car-Following Model Parameters

Note that in this section, the **bold** phrases represent the parameters in VISSIM.

The VISSIM car-following model defines look-ahead distance and look back distance to imitate how drivers examine the traffic situation during driving. Each distance has a minimum and a maximum value. Table 3 summarizes the use of look-ahead and look-back distance. In the look-ahead situation, **observed vehicle** is also taken into account. The number of observed preceding vehicles affects how well vehicles in the link can predict and react to movements of other vehicles. Vehicles treat some network elements such as reduced speed area, red signal head, and stop sign as preceding vehicles. So when these kinds of network elements are put near each other, the user should increase this observed vehicles value.

Table 3: Forward and Backward Looking Distance.

Car-Following Parameters	Definitions	Notes
Max. Look Ahead Distance	Max. distance a driver can see forward in order to react.	
Min. Look Ahead Distance	Min. distance a driver can see forward, important for lateral vehicle behavior.	When this value is zero, only the number of observed preceding vehicles is applicable.
Max. Look Back Distance	Max. distance a driver can see backward in order to react.	
Min. Look Back Distance	Min. distance a driver can see backward in order to react.	Relevant when accounting for lateral behavior of vehicles

Additionally, VISSIM car-following model can also model drivers' lack of attention while driving by defining its duration and probability. The smooth close up behavior option can vary vehicles' behavior when approaching a stationary obstacle. If the option is checked, vehicles can plan to stop at a stationary obstacle once the obstacle is within its maximum look-ahead distance. Users can also define the **standstill distance for static obstacles**. If not specified, the standstill distance will be normally distributed with mean 0.5 m and a standard deviation of 0.15 m.

Parameters for Wiedemann Models

VISSIM provides two Wiedemann models for the main car-following model. Wiedemann74 model is more suitable for urban traffic and merging areas. Wiedemann 99 can better model freeway traffic with no merging areas. Each car-following model has its own set of parameters.

Wiedemann 74 model only has three parameters. This model controls the distance between consecutive vehicles. The three parameters are shown in Table 4. The safety distance d is calculated by:

$$
\begin{aligned}
&d = ax + bx \\
&bx = \left(bx\_add + bx\_mult \times z\right) \times \sqrt{v}
\end{aligned}
\tag{2-24}
$$

where:

ax = Standstill Distance.

v = Vehicle speed.

z = A value of range [0,1], normally distributed around 0.5 with a standard deviation of 0.15.

Table 4: Wiedemann 74 Model Parameters.

Parameters	Definitions
Average Standstill Distance (ax)	Average Desired Standstill Distance between two cars. The range is [−1, 1] and the value is normally distributed around 0 m with a standard deviation of 0.3 m.
Additive Part of Safety Distance (bx_add)	Value used for computation of the desired safety distance.
Multiplicative Part of Safety Distance (bx_mult)	Value used for computation of the desired safety distance.

Wiedemann 99 Model has nine major parameters. Table 5 shows the parameters.

Table 5: Wiedemann 99 Parameters.

Parameters	Description	Notes
CC0 (Standstill Distance)	The average desired standstill distance between two vehicles.	It has no variation.
CC1 (Headway Time)	The distance in seconds, which a driver wants to maintain at a certain speed. At a given speed v (m/s), the average safety distance is dx_safe = CC0+CC1×v.	The higher the value, the more cautious the driver is. This is the minimum distance a driver will maintain when following another vehicle.
CC2	How much more distance than the desired safety distance a driver allows before he intentionally moves closer to the car in front.	Default value 4 m results in a quite stable following behavior.
CC3	This value controls the start of the deceleration process. The number of seconds before reaching the safety distance.	At this stage, the driver recognizes a preceding slower vehicle.
CC4 CC5	CC4 is the negative speed difference during the following process. CC5 is the positive speed differences during the following process.	Low values result in more sensitive driver reaction to the acceleration or deceleration of the preceding vehicle.
CC6	Influence of distance on speed oscillation while in following process.	When set to zero, the speed oscillation is independent of the distance. When set to large values, there is greater speed oscillation with increasing distance.
CC7	Oscillation during acceleration.	
CC8	Desired acceleration when starting from standstill.	Limited by maximum acceleration defined within the acceleration curves.
CC9	Desired acceleration at 80 km/h.	Limited by maximum acceleration defined within the acceleration curves.

3.2.4. Driving Behavior Parameters for Signal Control

Vehicles' reaction to traffic signals can also be defined through several model parameters. A big part of driving behavior for signal control is how drivers react to amber signals. VISSIM provides two different decision models for amber signal behavior.

The continuous check model reads the amber light at each time step. All the vehicles in this model assume the amber light will only last another two seconds. When an amber signal is presented, the vehicle will decide whether to stop or not. The vehicle will not brake if its max deceleration does not allow it to stop at the stop line. The vehicle will break if it cannot pass the signal head within two seconds at its current speed. The decision of vehicles in dilemma zone will be made using a normally distributed random variable.

The one decision model calculates the probability p of whether a driver stops at amber light. The model is based on a logistic regression function:

$$p = \frac{1}{1 + e^{-a - \beta_1 v - \beta_2 dx}} \tag{2-25}$$

where:

α, β_1, β_2 = model parameters.

dx = distance to stop line.

v = vehicle speed.

If the driver decides to brake at an amber light, it will be assigned a constant deceleration value $b_{applied}$:

$$\begin{aligned} b_{required} &= \frac{v^2}{2dx} \\ b_{applied} &= \min(b_{required}, b_{\max}) \end{aligned} \tag{2-26}$$

where

dx = distance to stop line.

v = vehicle speed.

$b_{required}$= required deceleration.

b_{max} =maximum deceleration according to deceleration function defined for the vehicle.

Apart from drivers’ reaction to amber light, users can also define how drivers approach a stop line. In a car-following model, the vehicles treat a red signal head as a preceding vehicle, so there will be a safety distance between it and the stop line. But in real world, drivers would not keep a safety distance from stop lines, so when the preceding vehicle is a stop line, the safety distance needs to be reduced. Within a distance defined by the **start upstream of stop line** and **end downstream of stop line** values, the original safety distance will be multiplied by a **reduction factor**. Start upstream of stop line, end downstream of stop line, and reduction factor are three parameters of this model.

3.3. LATERAL DRIVING BEHAVIOR

The lateral driving behavior that is relevant to CV applications is lane-changing behavior. VISSIM provides a rule-based lane changing and a lateral behavior model for lane keeping and vehicle angles inside a lane.

3.3.1. Lane Changing Rules

In VISSIM, two lane changing situations are identified. Necessary lane changing is to allow vehicles to reach the next connector on its route. Free lane changing happens when a vehicle wants to reach its desired speed through bypassing slower vehicles.

The deceleration of necessary lane changing depends on the vehicle's distance to the emergency stop position of the next route connector. Each connector will have an emergency stop position before it. If the target lane cannot be reached before this position, the vehicle will stop and wait for a sufficient gap. The minimum length of emergency stop position to the connector is 5 m. The modeling of emergency stop position can be found in VISSIM User Manual Section 6.10.2.

In a free lane change, the desired safety distance to the trailing vehicle on the new lane is checked. Users can adjust the speed dependent safety distance to control drivers' lane changing aggressiveness.

3.3.2. Lane Changing Model Parameters

Parameters of necessary lane changing includes the **maximum deceleration, change of deceleration,** and **accepted deceleration** for both the lane changing vehicle and the trailing vehicle on the new lane. **Maximum deceleration** and **accepted deceleration** defines the range of deceleration for two involved vehicles. The change of deceleration parameter: **−1 m/s^2 per distance** controls the maximum deceleration at different distance to the emergency stop position. The closer the vehicle is to the emergency stop position, the higher its maximum declaration is. When the vehicle is far from the emergency stop position, its maximum deceleration will be reduced down to accepted deceleration. This change of deceleration value specifies how fast the maximum deceleration reduces to the accepted deceleration with increasing distance to the emergency stop position. It is the slope of the two lines in Figure 7.

Figure 7: Change of Deceleration Diagram.

In the driving behavior parameter set, users can also define how much time a vehicle will wait at the emergency stop position. **Waiting time before diffusion** does just that. When the vehicle's waiting time at the emergency stop position is longer than this parameter value, the vehicle will be taken out of the network. Before each lane changing, VISSIM will check if the **minimum front and rear headway** will be available after it happens. If not, the lane changing will not take place. During the lane changing, VISSIM will reduce the lane changer and its trailing vehicle's safety distance by multiplying **safety distance reduction factor.** The **maximum deceleration for cooperative braking** specifies how the trailing vehicles in the new lane brake cooperatively to the lane changing vehicle. If the trailing vehicle finds it has to brake harder than the set value, it will not brake to let the lane change happen. By checking the **overtake reduced speed areas**, users can model the lane dependent speed limits that are considered by vehicles during lane changing. If this option is not selected, vehicles will ignore the reduced speed areas on the new lane, and they will never start a free lane change directly upstream a reduced speed area. The **advanced merging** option enables more vehicles to make their necessary lane change earlier and reduce the probability that vehicles wait at the emergency stop position.

VISSIM also allows the modeling of cooperative lane changing. Cooperative lane changing means that vehicle A in the new lane observes the lane changing vehicle B and changes to the next lane to let B move. Cooperative lane changing behavior has its own set of lane changing parameters such as **maximum speed difference** and **maximum collision time.**

3.4. VISSIM Component Object Model

VISSIM COM interface allows you to start VISSIM from another application. Within this application, COM can be used to:

- Prepare and process traffic data.
- Run different scenarios.
- Integrate user specified control algorithms.
- Access all network object attributes.

VISSIM COM model has a hierarchy structure (see Figure 8). The various objects and attributes can be found in the COM interface reference in the Online Help of VISSIM (see Figure 9.). Examples can be found in VISSIM Example Training Folders.

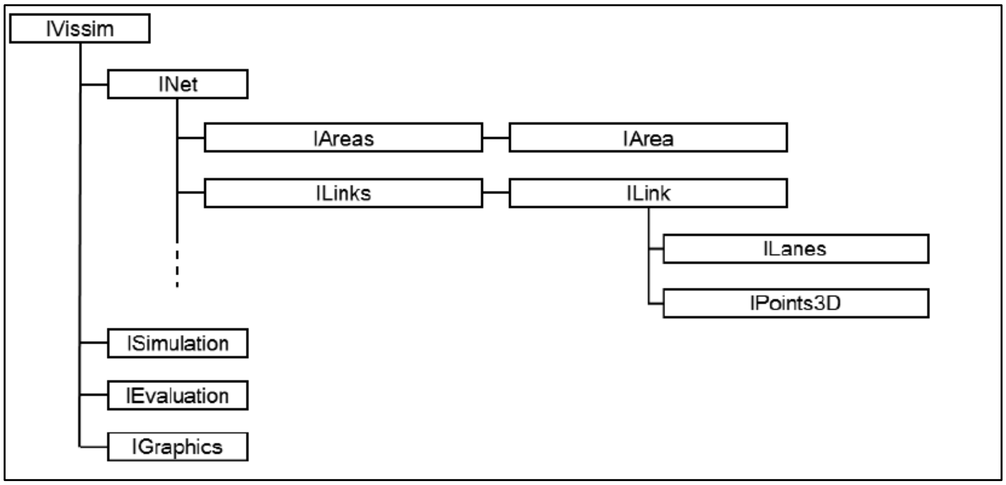


Figure 8: VISSIM COM Model Hierarchy Structure.

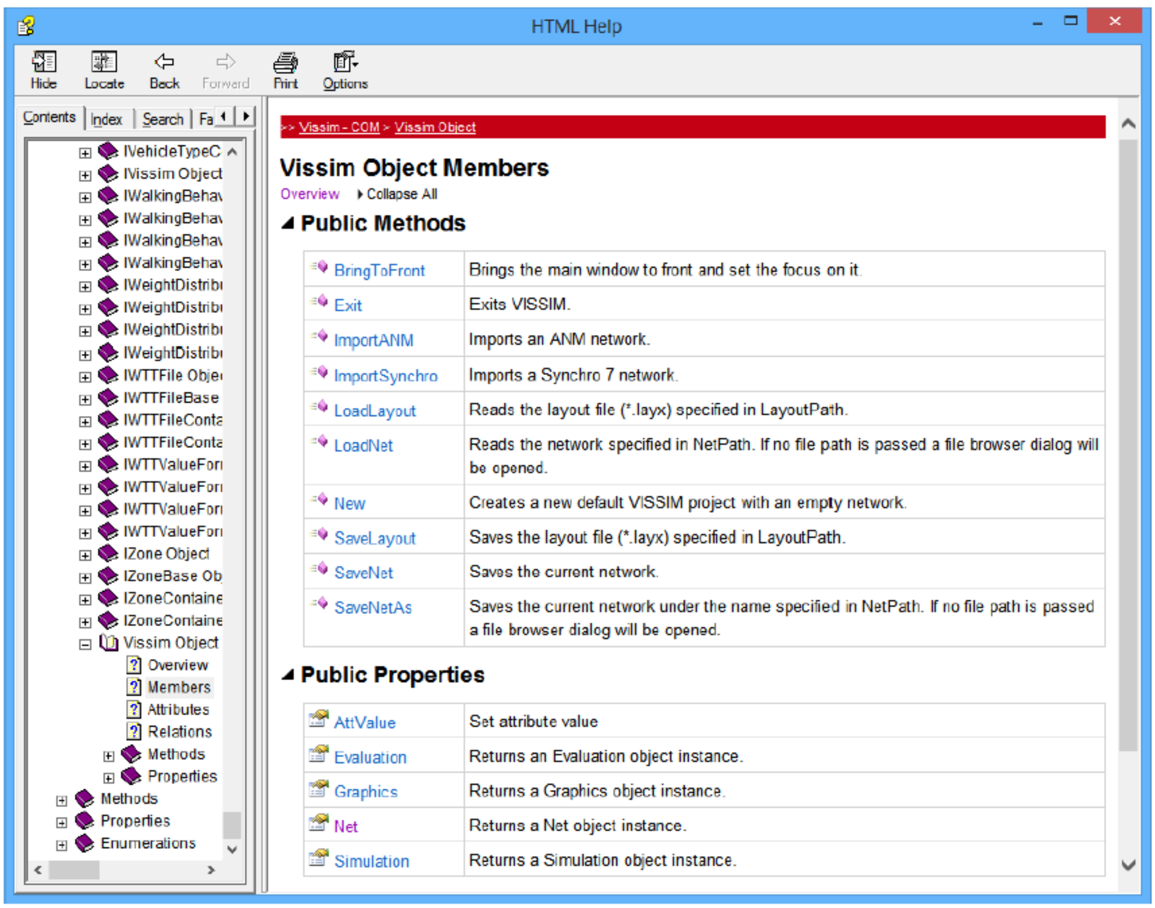


Figure 9: VISSIM COM Reference.

3.5. VISSIM External Driver Model DLL Interface

External Driver Model DLL interface is written in C++. After compile, a DLL file will be generated. For the target vehicle type, users can specify the path and filename of the user defined

DLL file. A folder called DriverModelData must be created in the same directory as the VISSIM.exe folder to avoid run-time error from VISSIM.

Figure 10 shows the mechanism of VISSIM Driver Model DLL. Driver Model DLL retrieves data from VISSIM network in every time step and uses the data to do calculations. Then Driver Model DLL returns the control back to the VISSIM Network. It controls the type of vehicles that are using the External Driver Model DLL. Table 6 shows some of the data items that can be controlled by Driver Model DLL commands.

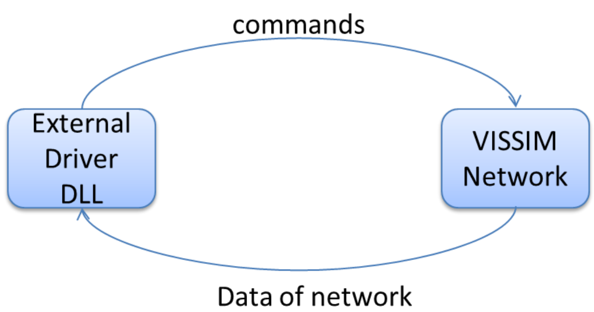


Figure 10: Mechanism of External Driver Model DLL.

Table 6: Data Items in DLL Commands.

Data Item	**Description**
Vehicle Turning Indicator	left=1, right=−1, none=0,both =2
Driver Desired Speed	desired speed in m/s
Vehicle Color	vehicle color (24 bit RGB value)
Driver Desired Acceleration	New acceleration in m/s^2
Driver Desired Lane Angle	Desired angle relative to the middle of the lane in rad. Positive=turning left
Lane Change	Direction of active lane change movement, +1 = to the left, 0 = none, −1 = to the right
Target Lane	Target lane, +1 = next one left, 0=current lane, −1 = next one right

Variables such as desired speed, current speed, current acceleration, spacing from the leader, target lane can be obtained for the ego vehicles. Also, data for two vehicles upstream and downstream and same lane and two lanes on both sides of the ego vehicle can be obtained. The adjacent vehicles have two identifying numbers associated with them. One number helps to find out whether the vehicle is upstream on downstream. The second number is to find out the adjacent vehicle's lane. Different variables can be extracted for the adjacent vehicles. These include speed, lane position, and spacing from the ego vehicle. VISSIM puts a visibility distance after which information regarding other vehicles in the network is not obtained by the ego vehicle. This limit is 800 feet.

The DLL has four commands:

- INIT – The initialization command is called when the simulation run starts. This command is called only once. Objects that need to be created only once and would be used throughout the simulation can be created under this function. This function can also be used to provide path for input and output files.
- CREATE – This command is called when a new vehicle is inserted into the network. This is the location where the piece of code to hold information pertaining to a particular vehicle should be implemented. This command can be called multiple times during a time step.
- MOVE – The command is called at every time step for every vehicle that is present in the network. This command is where different driver models and other relevant factors can be modified. This is the only command that is called at every time step so this is a very powerful command. It can be used to send acceleration values, target lane values, and other values critical for vehicle control to VISSIM. One thing to keep in mind while using this command is that it is called multiple times during every time step depending on number of vehicles in the network. So if a user wants to call a function only once per time step, he/she needs to write the code appropriately. This command is also useful for adding codes for extracting the performance measures.
- KILL – This command is called whenever a vehicles exit a network. This command is also called when the simulation ends in order to remove all the vehicles from the network. This command provides the user with the power to keep track of vehicles in network and of those that have left the network.

Driver model DLL also offers the user two options to carry out the lane change. One is called the simple lane change. In this type of lane change, the user just specifies the target lane of the ego vehicle and VISSIM takes care of the entire lane change process. During this lane change, VISSIM does not take suggestion from the user. The second type of lane change gives more power to the user. In this type of lane change, the user has the ability to control the entire lane change process. This includes specifying the angle at which the ego vehicle should initiate the lane change, the criteria to stop lane change, and other control related parameters. The user needs to specify the target lane.

Detailed VISSIM Driver Model DLL structures can be found in Appendix 1.

4. DRIVER BEHAVIOR MODELING FRAMEWORK FOR CONNECTED VEHICLES

In a CV environment, human drivers can have different reactions to the information and warnings provided. For some applications that provide semi-automated control such as CACC, drivers will still have different choices of control parameters, such as desired speed and gap. In addition, inter-driver and intra-driver behavior variations do exist across all types of drivers and these differences should be carefully accounted for during the model development.

Most simulation evaluation studies of CVs assume all the CVs would act as programmed and ignores the variation in driving behavior.

In VISSIM, there are four major options to incorporate driver behaviors into simulation of CV application:

1. Modify driver behavior parameters before starting the simulation.
2. Use COM to modify driver behaviors during run time.
3. Replace or supplement VISSIM's existing driver models using the Driver Model API.
4. A mixture of all the above options.

In Section 2.2, researchers classified CV applications into three categories for modeling purposes: event-based driver behavior adjustment, CDBA, and semi-automated/automated driving. Table 7 shows the modification options that can be used in each type of CV applications. The filled cells show that the modification option of the column can be used to model the driver behavior of the row.

Table 7: Application Category versus Simulation Modification Type.

CV Application Categories	Parameter Modification	Run-Time Modifications (COM)	Driver Model (DLL)	Mixed Modification
Event-Based Adjustment	x	x		
Continuous Adjustment		x	x	x
Semi-Automated or Automated Driving			x	x

Among the four modification options, the complexity and resources needed increases in the order of the described options. Efficiency can be maximized when the simplest approach is used for the appropriate application. In this section, the modeling of driver behavior in each type of CV application will be explained respectively.

4.1. VOLUNTARY DRIVER BEHAVIOR MODELING

Among the three types of CV applications mentioned in Section 2.2, both event-based driver adjustment and continuous driver adjustment applications give out advisories. Drivers can choose how to react to the advisories. However, advisories in the two types of CV applications are different, event-based adjustments only give out warnings and one-time short advisories while continuous adjustments give out advisories continuously in the driving process. Modeling of the two types of CV applications follow the same general steps as shown in Figure 11.

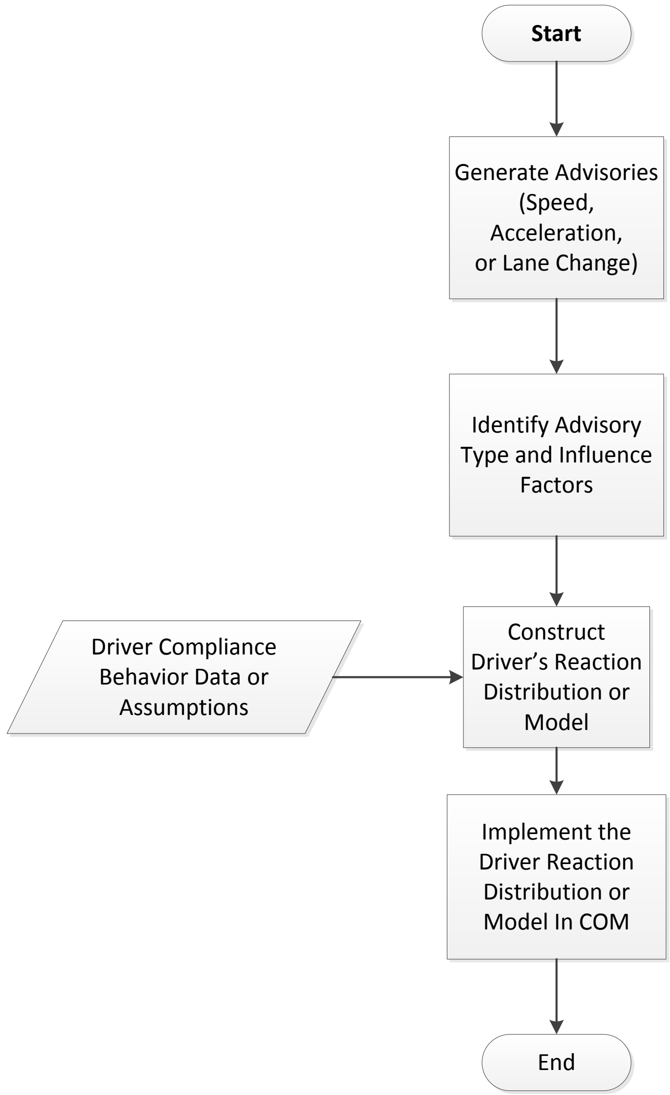


Figure 11: Process for CDBA.

The advisory generation process differs in different applications. Advisory generation for event-based applications is generally simpler than that of continuous based applications. For event-based applications, VISSIM COM is enough to model most of the advisory generation. VISSIM COM requires more complicated calculations to acquire certain attributes of the traffic flow, so the modeling of continuous adjustment applications sometimes require a mixed approach of VISSIM COM and external Driver Model DLL.

Given that continuous advisories are usually more complicated than one-time event-based warnings, the modeling of continuous adjustment compliance behavior will be more complex. The compliance behavior involved in an event-based driver behavior adjustment is mostly just comply or not comply. For example, in a red light warning system, the advisories given to drivers are just “red light ahead, prepare to stop.” The most obvious modeling approach is to assume a compliance rate. On the other hand, when modeling a VSL system that continuously give out speed adjustment advisories, drivers’ reaction will no longer be one compliant decision. Drivers’ may drive with a speed over, around, or below the VSL. The modeling of drivers’ choices of speed is much more complex than assuming a compliance rate.

In this section, modeling approaches of drivers’ voluntary choices in reaction to CV application advisories in event-based and continuous CV applications are described. Drivers’ reactions are mainly modeled by two approaches. First, in CV applications that only give out simple advisories, compliance rate is used to model the diversity in drivers’ choices. Second, for more sophisticated CV applications, drivers’ choices are assumed to follow probability distributions. Compliance rate and distribution are the simplest way to model human factors in CV applications. When more details are expected in the simulation, a discrete choice model or a choice regression model can also be used to capture complex driver decisions as a function of observable driver parameters and operating characteristics.

4.1.1. Event-based Driver Behavior Adjustment Modeling

As described in Section 2.2.2, CV applications that require event-based driver behavior adjustment can either improve drivers’ perception to surrounding traffic conditions or help drivers avoid hazardous maneuvers. The perception improvement applications can detect emergency situations that need immediate attention and action of the driver to prevent an accident from happening. Such situations include freeway end of queue, sudden deceleration of preceding vehicles, work zone, or an accident. On the other hand, the hazardous behavior adjustment applications can detect drivers’ risky maneuvers and then provide appropriate alerts. Hazardous behaviors can be speeding, drifting out of lane, aggressive lane changing, or going through curves with high speed.

The driver behavior associated with this type of application is drivers’ compliance behavior to the warnings issued. Drivers’ compliance rate can be affected by the traffic condition, advisory type, drivers’ familiarity of the road, leading vehicles’ behavior, drivers’ distraction due to CV applications, and so on. Compliance behavior may vary among different drivers and also under different traffic conditions for a driver.

Since VISSIM driving behavior parameter sets are defined based on link rather than vehicle types, only limited CV application associated driving behavior modifications can be done in VISSIM without using VISSIM COM or external driver model DLL interfaces. Also, since VISSIM is based on a psycho-physical car-following model, VISSIM does not provide an adjustable perception reaction time parameter for users. The value of time step is the value of perception reaction time. Based on the above reasons, a one-time parameter adjustment option can only be used to model the situation of 100 percent penetration of CV for only certain CV applications.

COM can model drivers’ compliance behavior by continuously modifying the parameters for selected vehicles. Though there is no perception reaction time parameter to alter, users can still control the actual driver behavior in COM to achieve the effect of certain CV applications. If other factors are to be considered, such as drivers' trust in CV applications, familiarity of the road, and traffic conditions, then continuous parameter modification should be adopted with some models that can relate those factors to corresponding driver behavior variables.

4.1.1.1 Driver Behavior Modeling with One-Time Parameter Modification

Sections 3.2 and 3.3 summarize all the longitudinal and lateral driving behavior parameters that can be adjusted within VISSIM. Because the parameters are link-based, this one-time parameter modification can only model the 100 percent CV scenario. Also, the realism of CV application effects that can be provided with this modeling approach is somewhat limited. For the CV applications that provide alerts for traffic events, a feasible modeling approach is to adjust the look-ahead distance parameter set (see Section 3.2.1). By increasing the observed vehicles parameter in the look-ahead distance parameter set, vehicles can see a maximum of 10 vehicles forward and make decisions accordingly. Increasing the look ahead observed vehicles can result in a much smoother speed profile in the traffic flow.

For the hazardous driving maneuver adjustment such as a curve speed warning system, the effect can be simulated by modifying the distributions. For example, without the curve speed warning system, the percentage of vehicles exceeding the safe curve speed s mph is *a* percent. In VISSIM, there will be a desired speed distribution describing this speed choice situation. After the application of curve speed warning system, this percentage of curve speeding reduces to *b* percent. The distribution of desired speed on the curve reduced speed area should be altered accordingly.

Sections 3.2 and 3.3 list all the car-following and lane changing parameters that can be modified in PTV VISSIM. When modeling the effect of a CV application with 100 percent penetration ratio, those driving behavior parameters can be changed according to the specific function of the application. Table 3, Table 4, and Table 5 are good references of the adjustable parameters.

Due to the structure and limitation of VISSIM driving behavior parameter settings and the complexity of CV applications, the one-time parameter modification is obviously not the most versatile choice for driver behavior modeling within CV applications.

4.1.1.2 Compliance Behavior Modeling with Continuous Modification

Introduced in Section 3.4, VISSIM COM is a powerful tool in CV application evaluation. COM can access and control most of the objects in VISSIM network. The downside is that COM access VISSIM network using specific external interfaces. The more the number of simulation objects that the algorithms need to access; the slower the simulation will run. For the modeling of event-based driver behavior adjustment, COM can control the whole process of the CV application, including the alert algorithm, drivers' reaction to the alert, time step by time step, and vehicle by vehicle.

In COM, the program can run VISSIM simulation time step by time step. In each time step, the program can loop through all the vehicles in the whole network and access the attributes of the vehicle such as type, position, speed, and acceleration.

Let us consider the curve speed warning application as an example. In VISSIM, the curves can be modeled using connectors. CVs can be assigned a unique vehicle type. In this way, the penetration rate of the CV can be modeled in the simulation. This is an important advantage compared to the one-time parameter modification approach. In each time step, the vehicles are looped through and if they belong to the CV type and are currently traveling on a connector, their speed will be compared to the speed limit of the curve. The speed limit of the curve can be stored in a reference database in advance. If a vehicle’s speed is higher than the speed limit of that curve, a warning will be issued.

After the warning is given, the immediate problem is the compliance behavior of the CV drivers. The compliance rate can either be preset or be determined by a model. If it is the preset situation, say the compliance rate is set to 70 percent. Users can generate a random number between zero and one in the COM code every time a driver receives the warning. If the random number is smaller than 0.7, the driver will comply and reduce his/ her speed to the speed limit. Otherwise, the driver will keep his/her current speed and ignore the warnings. Figure 12 shows the entire modeling process in COM using the example of curve speed warning.

For a perception improvement CV application, such as a freeway queue warning system, the modeling process is similar. But first a look-ahead distance, representing the farthest distance a CV application can detect. Inside that detection distance, the system detects the vehicle speeds and compares to a threshold representing the queueing condition. If low speed is detected in an area, an alert will be sent to the approaching vehicles. After receiving the alert, the same compliance rate model can be applied. Or the users can define a deceleration distribution for the deceleration of vehicles after getting the warnings. In the COM program, a random variate can be drawn from the defined deceleration distribution for each CV.

There are some studies on drivers’ reaction to the event-based warnings given by this type of CV applications. In Tampere et al.’s human kinetic models (*42*), activation level is used to model the impact of these alerts upon the drivers. Though human kinetic model is not a microscopic model designed for a microscopic simulation, the idea of activation level can be applied to model drivers’ compliance behavior to warnings in a more sophisticated manner. Also, Kesting et al. used a subjective level of service of each driver to model drivers’ frustration, hence aggressiveness (*43*). In general, activation level can capture drivers’ attention level, and subjective level of service can relate current traffic condition with drivers’ behavior.

The above studies provide another more complex approach to model drivers’ compliance behavior. The compliance behavior is affected by driver’s attention, the more drivers are activated by the alerts, and the more likely they will comply. The more frustrated by the traffic condition, the more they will not comply and take aggressive choices. In the modeling of compliance behavior, users can construct a model that can demonstrate these relations by introducing the activation and frustration variables. These two variables may have a positive or negative impact on the traffic variable that the specific CV application tries to adjust. Since different applications can regulate different traffic variables of the driver such as speed, deceleration, and lane changing behaviors, different models should be introduced on a case-by-case basis.

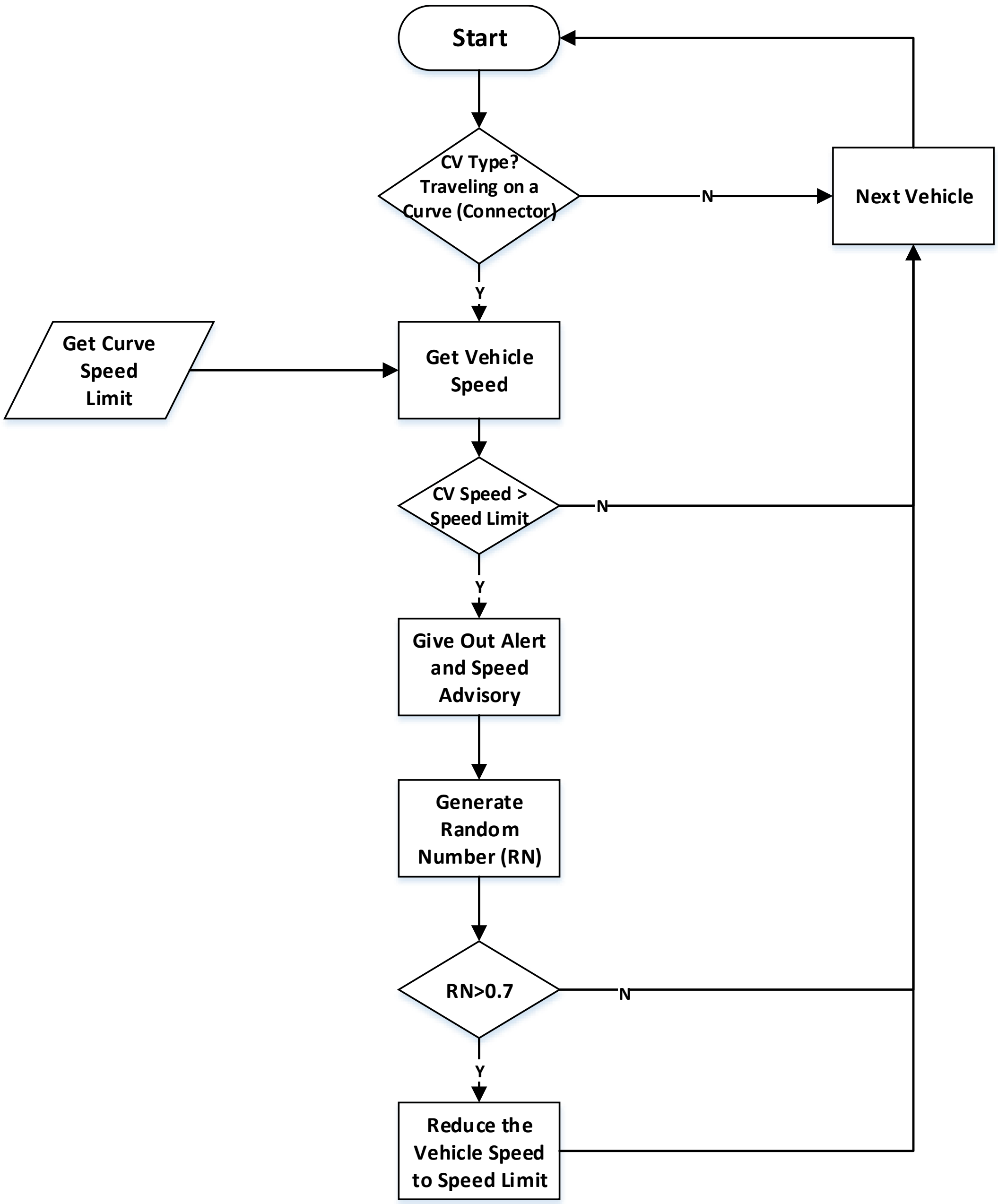


Figure 12: Curve Speed Warning Flow Chart.

The variable affected by activation level and drivers' frustration can be classified into two types:

- Binary Compliance Variable: Suitable for the applications in which the expected reaction of the warnings is just whether to comply or not (e.g., curve speed limit warning, red light warning).

- Numerical Compliance Variable: Suitable for the applications in which the expected reaction of the warning is not just comply or not. An example is a freeway end-of-queue warning. Drivers can choose different decelerations or even accelerations after receiving the warning.

The construction of the activation and frustration models should distinguish between these two types. For the binary compliance variable type applications, a utility function can be proposed as part of a logit model of discrete choices. For the numerical compliance variable type, users can assume a linear model for the value of acceleration (deceleration) choices.

4.1.2. Continuous Driver Behavior Adjustment Modeling

Examples of continuous driving behavior adjustment applications include VSL, eco-driving supporting system, turning assistant system, and freeway merging assistant system. One-time modification of the driving behavior parameters in VISSIM is not enough to model continuous driver behavior. VISSIM COM or a mixed approach of COM and external driver DLL can model CDBA. In this section, researchers describe three examples of CV applications that require CDBA.

Because this type of applications only issues control advices to drivers, the driver behavior adjustments still primarily involve drivers' compliance. Because continuous advisory speed or throttle control is more than a sudden alert, the compliance behavior here is more complex than that in event-based driver behavior adjustment applications. Drivers' compliance behavior will be influenced by more factors.

In the freeway merging assistant system discussed in Section 2.2.3, CVs on the merging lanes receive advisories about when to merge and what speed to accelerate to when a gap on the freeway outside lane is detected. Vehicles traveling on the outside lane will be given advisories about when to switch to its left lane to create gaps for merging vehicles. Different VSLs are assigned for each lane. As an incentive to encourage drivers to stay out of the outside lane, inside lanes have higher speed limits. In this CV application, three advisories are provided and each will have different compliance rate. Also, as shown in Figure 1 gap size detected by the system affects compliance rate.

Since the advisories of the merging assistant system are mostly simple and only involve discrete choices of drivers. Compliance rate will be sufficient for modeling drivers' behavior in this system. The modeling of the advisory generation process is a little tricky for merging assistant systems. COM environment is not ideal for accessing the information of nearby vehicles in adjacent lanes. Driver Model API can implement the entire modeling process easily. In Driver Model API, the vehicle information of up to two vehicles upstream and downstream can be obtained for each individual vehicle. The DLL file can only be assigned to the vehicle type representing CV. Compliance rate can be implemented within the Driver Model DLL.

Another typical example of CDBA is VSL system under CV environment. VSL has been implemented using dynamic VSL signs on some European highways for several years. In a CV environment, electronic VSL signs are still used, but the real-time speed limit information can be broadcast to targeted CVs even before the drivers' visibility range. Additionally, CV-based VSL applications can also suggest speed adjustments to achieve a smooth transition between different speed limits. Detailed literature about VSL can be found in Section 2.2.3. Advisory generation of VSL only requires aggregated traffic flow information such as average speed and density by location. So the advisory generation process can be carried out by using COM interface.

Drivers' compliance behavior of VSL is more complicated than that of freeway merging assistant system. Hadiuzzaman et al. proposed a modeling approach of VSL compliance distribution (*26*). In reference to Hadiuzzaman's approach, compliance to VSL can be defined as when the vehicle speed is ±5 mph or ±5 percent from the posted VSL. Drivers are classified into defensive and aggressive drivers. Aggressive drivers will drive at a speed higher than 5 percent or +5 mph the speed limit and defensive drivers will driver at a speed lower than −5 percent or −5 mph of the speed limit. Also, several driver compliance levels are assumed: low, moderate, high, and ideal. Under each compliance level, the percentage of defensive and aggressive drivers is assumed in each driver compliance level as in Table 8.

Table 8: Non-Compliance Rates under Different Compliance Levels (*26*).

Posted Speed Limit (kph)	Driver Compliance Levels							
	Low (CR=20%)		Moderate (CR=45%)		High (CR=80%)		Ideal (CR=100%)	
	D	A	D	A	D	A	D	A
V_{min}=20	30%	50%	15%	40%	5%	15%	0%	0%
30	30%	50%	15%	40%	5%	15%	0%	0%
40	30%	50%	15%	40%	5%	15%	0%	0%
50	30%	50%	15%	40%	5%	15%	0%	0%
60	40%	40%	20%	35%	10%	10%	0%	0%
70	40%	40%	20%	35%	10%	10%	0%	0%
V_{max}=80	40%	40%	20%	35%	10%	10%	0%	0%

Notes: D=Defensive, A=Aggressive

Figure 13 shows the process of modeling drivers' choices in reaction to VSLs. Here the construction of drivers' desired speed distribution needs detailed descriptions. In a VSL system, each segment of roadway has its own speed limit. CV drivers receive the speed limit once they entered a specific roadway segment. If a driver chooses to comply, his or her desired speed will be in the ±5 percent of the current speed limit in this segment. If the chosen compliance level is moderate for instance, and the VSL is 50 kph for the segment, then there will be 45 percent of the vehicles with a desired speed in (47.5 kph, 52.5 kph). The defensive driver will comprise 15 percent, and the aggressive driver will comprise 40 percent. This means 15 percent of the drivers choose a desired speed that lies in (20 kph, 47.5 kph) and 40 percent of the desired speed lies in (52.5 kph, 80 kph). The 15^{th} to 60^{th} percentile of this desired speed distribution is 47.5 kph and 52.5 kph. The minimum speed is 20 kph and the maximum speed is 80 kph.

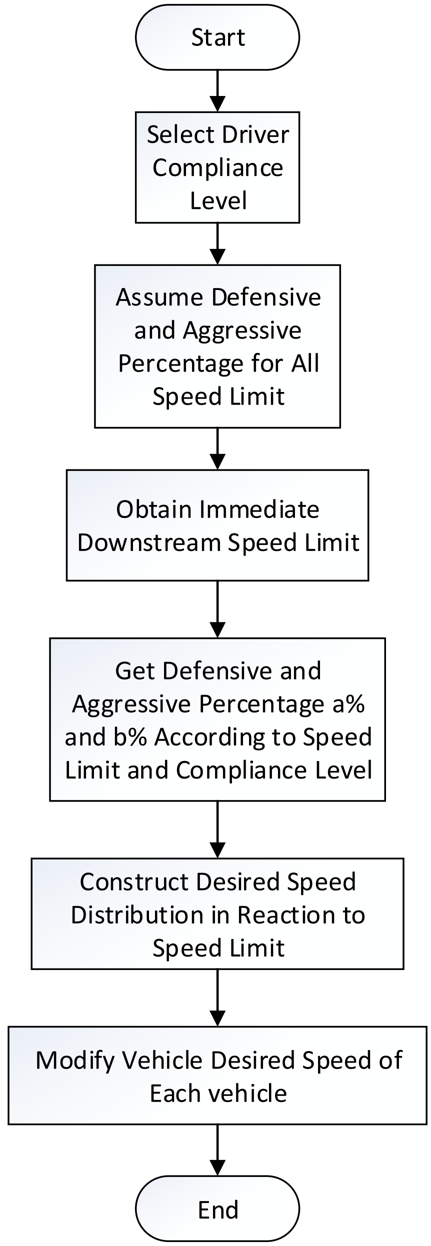


Figure 13: VSL Compliance Modeling Process.

Compared to regular vehicles, CV drivers may have a smoother speed change profile when they receive a new speed limit. Also, their compliance speed distribution will be different. Since the desired speed distribution varies whenever the speed limit changes, it is more convenient to implement these changes through COM. VISSIM user interface speed limit tools cannot support the variation of speed limit. In COM, each vehicle will be assigned a new desired speed limit according to the desired speed distribution generated.

4.2. SEMI-AUTOMATED/AUTOMATED DRIVER BEHAVIOR MODELING

Semi-automated or automated driving assistant systems can change the way vehicles are driven completely. Machines do not have reaction time or temporary lack of attention problems as human drivers do. Driving assistant systems such as CACC can follow preceding vehicle with a time headway as small as 0.6 s (*29*). Modeling of the semi-automated/automated driving assistant systems requires supplementing default driver model or changing the entire driver model in VISSIM using external Driver Model DLL API.

In this approach, at each time step and for every vehicle VISSIM calls the External Driver model DLL. The DLL then calculates various parameters such as acceleration, destination lane, and whether to initiate a lane change or not. One can use the DLL to implement the car-following and the lane changing models to represent the CACC system. The car-following model can calculate acceleration based on various vehicle parameters that it obtains at each time step for each vehicle. DLL can access parameters such as clearance, desired speed, and relative speed difference with the lead vehicle. As discussed in Section 2.3, there are a plethora of models that have been developed for CACC system. External Driver Model DLL can be used to implement a suitable model. Also, lane change behavior can be controlled using proper lane change logics. External Driver Model DLL can access parameters such as current lane of a vehicle and positions of vehicle on adjacent lanes. Lane change behavior can be programmed based on these parameters. There are two types of lane change models that are possible. A simple lane change is when the user specifies the target lane and VISSIM take cares of the lane change. A more comprehensive lane change logic is when the user has to determine various factor such the angle at which the vehicle should change lane, when to stop lane change, etc.

External Driver Model DLL can modify factors such as desired gap and desired speed throughout the course of simulation. This allows modeling the reduction in gap when CACC system is activated. The user can model various modes for the same vehicle. This is convenient when modeling platooning for CACC-equipped vehicles. During platooning, the gap between platoon members is much tighter than the non-platooning mode. Signal drops can also be modeled by using a suitable distribution for signal drop for CVs.

However, it is hard to model freeway merging using External Driver Model DLL alone. A vehicle can only obtain information about the nearby vehicles on the same lane. Modeling freeway merging will need DLL to be used in conjunction with VISSIM COM to obtain information about nearby merging vehicles.

4.3. Proof-of-Concept Simulation

Researchers created a simulation platform to model semi-automated driving scenario. Driver model API was used to carry out the modeling. The next chapter discusses in detail the various models that were coded in the external driver model API to create the simulation platform. To demonstrate the use of the driver modeling framework, researchers designed a CACC - simulation study with two primary objectives. First, this CACC simulation is used to demonstrate the most complex technique for driver modeling (i.e., the use of API). The CACC study is ideal because there are some previous studies that researchers can benchmark the results with, but there are also several aspects that have not been examined. Previous studies have unanimously shown that the capacity and traffic stability improves due to CACC platooning.

However, there are limited studies on the effect of lane restriction policy and the potential emission and consumption benefits from platooning. The second objective is to investigate the impact of lane control in conjunction with CACC operation and to quantify the environmental benefit from CACC operation. Various studies have documented the benefits of two-vehicle platoon with respect to emissions, so it would be interesting to see the impact of a varying length CACC-equipped vehicle platoon on emissions.

4.3.1. Platooning for CACC-Equipped Vehicles

Platooning occurs when one vehicle or more vehicles follow their lead vehicle at a close spacing. CACC-equipped vehicle platooning offers great benefits in terms of increasing the roadway capacity and the traffic stability. This is because CACC-equipped vehicles can follow each other at very close spacing. Also, in CACC-equipped vehicle platoon, the members of the platoons get control information not just about their immediate leader but also from the vehicles that are ahead of their leader. In this study, a variable size platoon is considered, that is platoon size is not predetermined. However, platoons do have a maximum size of 10 vehicles. The platoon formation method that is considered here is also known as ad-hoc clustering. In this platoon formation method, the CACC-equipped vehicles form platoons with nearby equipped vehicles. To obtain maximum benefit from platooning, a platoon should stay intact for as long as possible. To ensure this, lane change logics have been created to preserve a platoon. Moreover, increase in roadway capacity mainly occurs due to close following. To simulate this, the researchers incorporated a desired gap distribution for close following. Different platoon members are assigned different following gaps based on a driver's preference. All the factors for platooning are discussed in detail in the next chapter.

4.3.2. Effect of CACC-Equipped Vehicles on Emissions

The second proof of concept is to demonstrate the impact of CACC system on emissions. Researchers evaluated the impact of platooning on emissions with respect to CACC-equipped vehicles. CACC-equipped vehicles can form tightly spaced platoons, which in turns reduces the wind drag experienced by a vehicle. This reduces the power demand for a vehicle to maintain a particular speed, so there is a reduction in fuel consumption and emissions. Reduction in emissions is directly related to amount of spacing between two vehicles in car length. Since heavy vehicles have longer lengths as compared to light vehicles, the change in emissions would be more noticeable in heavy vehicles as compared to light vehicles. For this study, researchers only considered heavy vehicles equipped with CACC for platooning purposes.

5. SIMULATION EXPERIMENT – A CASE STUDY OF PLATOONING

To evaluate CACC operation, researchers modified the car-following and lane-changing models in the simulation to reflect the changes in driver behavior. Also, vehicle information was required at each time step to implement the vehicle clustering strategy. After going over the requirements, researchers found that altering the calibration parameters would not be enough and using VISSIM COM would be impractical. Driver model API was found to be the best solution for the task. Researchers evaluated several factors that influence CACC characteristics and freeway performance, which include:

- Impacts of dedicated lane strategy on a multilane freeway facility.
- Impacts of wireless communication quality on platooning.
- Impacts of wind drag reduction on emissions and fuel consumptions.

These issues have not been studied in depth before. Researchers evaluated these issues on a realistic multilane freeway facility where multivehicle platoons will be simulated with realistic lane change behavior and realistic wireless reception. Researchers captured emissions and fuel consumption impacts using detailed vehicle trajectory data.

5.1. SIMULATION TEST BED

The simulation test bed is a 26-mile freeway section in Texas, which was built after an eastbound direction of the Dallas I-30 freeway section as shown in Figure 14. The site was located between E. Center St. and North Hampton Rd. in Arlington, TX. The study site was approximately 26 miles. This freeway segment mostly has three lanes. It also has 5-mile, 2-lane high occupancy vehicle (HOV) lanes in parallel with the main lane. All the on and off ramps along the eastbound freeway were not used to simplify the simulation process in this study and to obtain accurate throughput values. The selection of this site with the HOV lane is for future analysis of its weaving impacts but it is currently outside the scope of this study.

Data collection points were placed at the middle of the study freeway segment on every lane to collect speed and throughput data. Travel time was collected when each vehicle left the network. The speed limit of this freeway is 70 mph (113 km/h). The desired speed distribution of all vehicles was set to range from 63 to 77 mph.

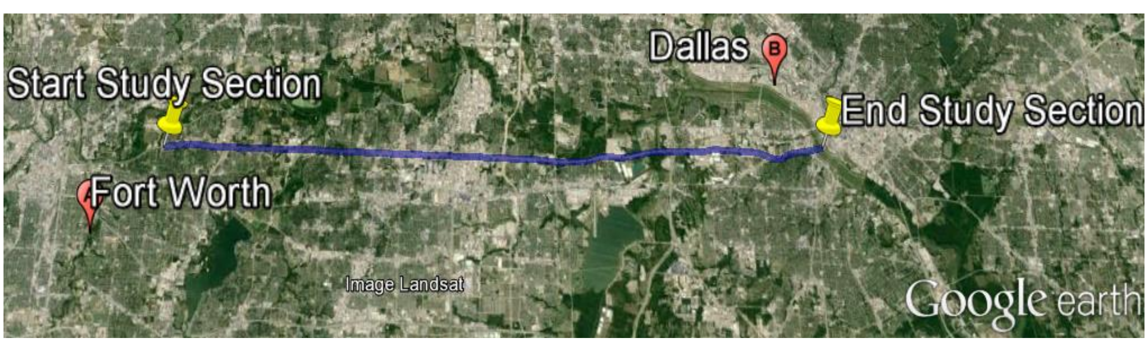


Figure 14: Simulation Study Site.

All the ramp traffic was set to zero for this case study in order to provide a controlled environment for quantifying direct impacts of platooning. The test section can be considered as a basic freeway section. Only CACC-equipped heavy duty vehicles were considered instead of light duty vehicles. This is because heavy vehicles have bigger frontal areas as compared to light vehicles, so the reduction in emission rate is more pronounced for heavy-duty vehicle platoon. The speed limit for heavy-duty vehicles was set at 65 mph and for light duty vehicles was set at 70 mph. The maximum platoon length was fixed at 10 vehicles for stability and safety purposes.

The following sections will cover the specifics of the lane changing and car-following model, vehicle clustering strategy, emission calculation, and the various factors and scenarios that are evaluated.

5.2. CAR-FOLLOWING MODEL

The driver model by Milanes et al. (*34*,*47*) has addressed the short comings of various previous car-following models for CACC-equipped vehicles. Also, unlike other previous models, this model was validated with field data. This model basically has two modes: speed control mode and gap control mode. Speed control mode is activated when the car is in free flow, and there is no leader or the leader is more than 120 m from the ego vehicle. This mode is to address situations when ego vehicles have no immediate leader. In this mode, the objective of the ego vehicle is to reach its desired speed. The second mode is gap control mode. This mode is activated when the distance between the ego vehicle and the leader is less than 100 m. This gap control mode is activated in close following situations, and in this mode, the ego vehicle takes into account the spacing between it and the lead vehicle and their relative speed to take control decisions. To prevent rapid switching between the two modes, a buffer zone (100 to 120 m) is provided. When the spacing between ego and lead vehicle is between 100 and 120 m, the vehicle uses the control mode from the previous time step.

Since different drivers would have different preferred time gaps, researchers assigned the CACC-equipped vehicles a desired time gap based on a random number generated from a normal distribution with a mean of 2 seconds and a standard deviation of 0.4 seconds. The deceleration limit of the original mode (-2 m/s^2) was replaced with a lower limit (-3.4 m/s^2), so the CACC-equipped vehicles were able to handle sudden stop conditions. Below are the equations for the speed and gap control mode.

In speed control mode, the control law is:

$$\begin{aligned}
&v_e = v - v_d \\
&a_{sc} = bound(-0.4v_e, 2, -2) \\
&a = a_{sc} \\
&bound(x, x_{ub}, x_{lb}) = \max(\min(x, x_{ub}), x_{lb})
\end{aligned} \tag{2-27}$$

In gap control the control law is:

$$\begin{aligned}
v_e &= v - v_d \\
a_{sc} &= bound(-0.4v_e, 2, -2) \\
s_d &= T_d.v \\
s_e &= s - s_d \\
a &= bound(\dot{s} + 0.25s_e, a_{sc}, -2)
\end{aligned} \tag{2-28}$$

where:

v = speed of controlled ACC, CACC vehicle (m/s).

v_d = desired speed set by driver or speed limit of road (m/s).

v_e = speed error (m/s).

a_{sc} = acceleration by speed control (m/s^2).

s = spacing between controlled vehicle and its leading vehicle (m).

s_d = desired spacing (m).

T_d = desired time gap (s).

Figure 15 presents the flowchart of the algorithm that was used in the driver model API. This algorithm was invoked at each time step (0.1 seconds) for every CACC-equipped vehicle in the network to calculate the acceleration for that time step.

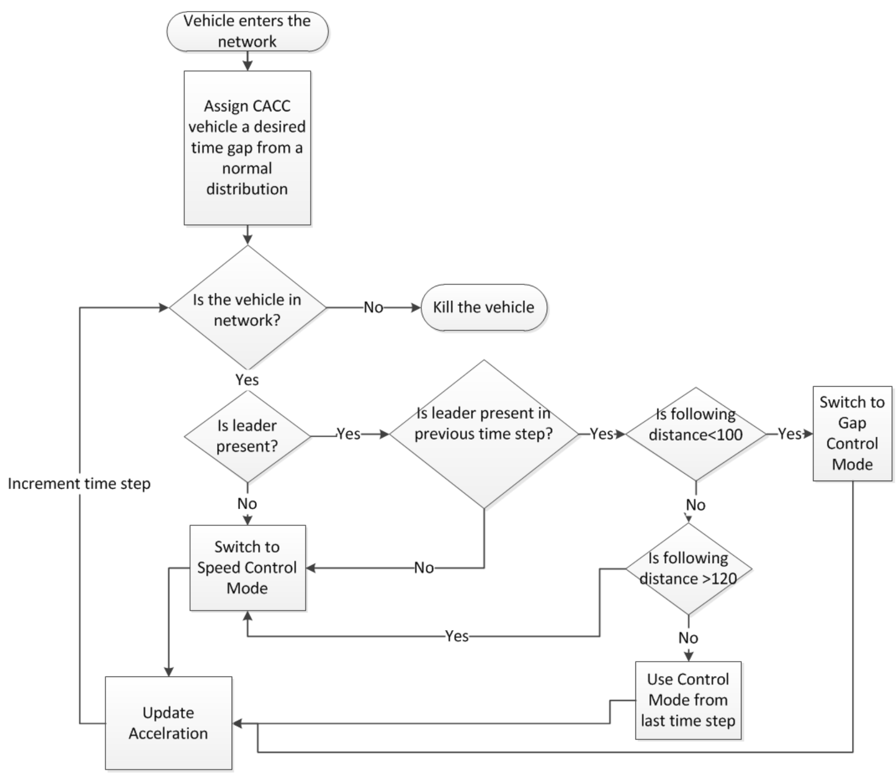


Figure 15: A Car-Following Logic for CACC Simulation.

The CACC-equipped vehicle will use this acceleration instead of its own internal values for longitudinal control. For manually driven vehicles, VISSIM default Wiedemann's model was used.

5.3. LANE CHANGING MODEL

A lane changing model was implemented specifically for the CACC-equipped vehicles. The main objective of this lane change model was to promote platoon formation. Figure 16 shows the algorithm for the lane change model.

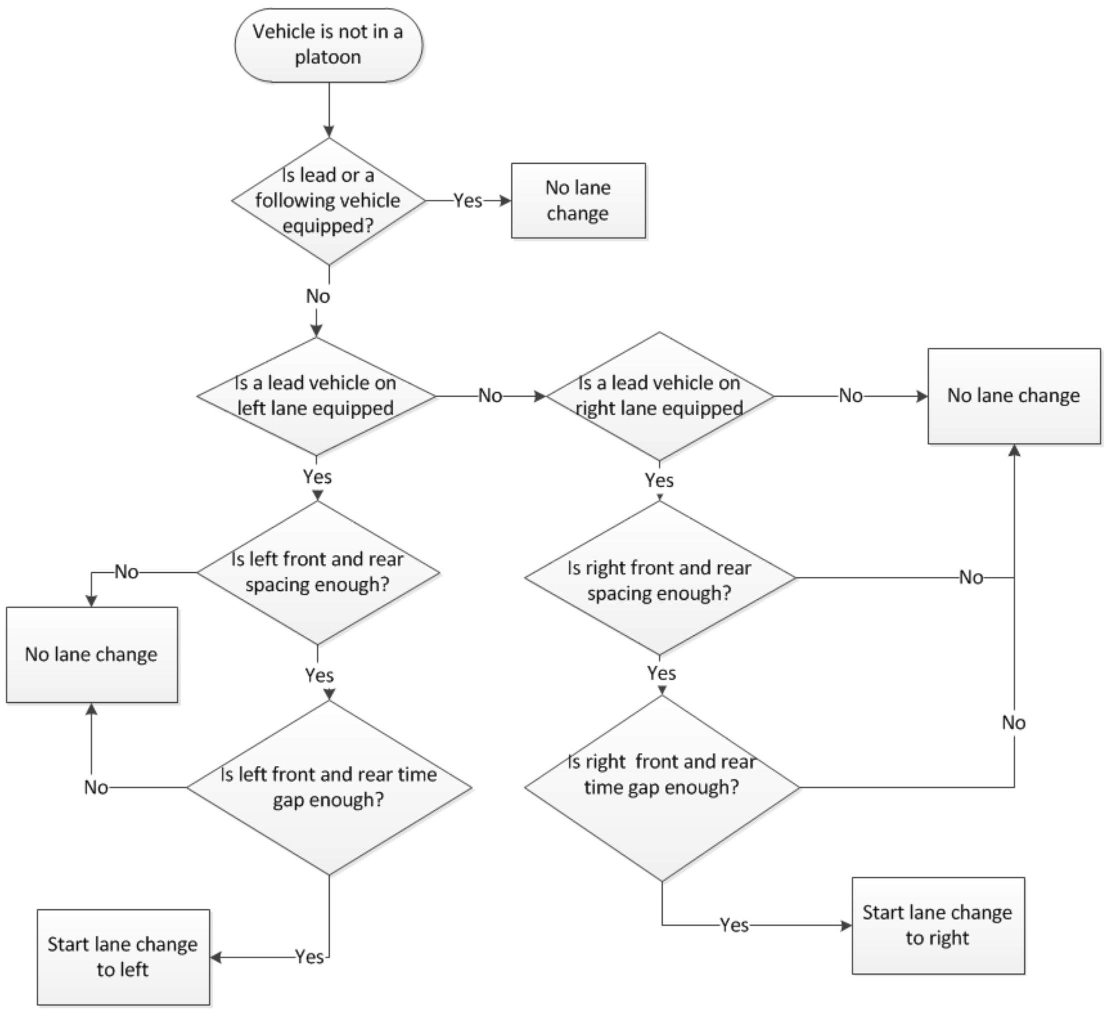


Figure 16: A Lane Changing Logic for CACC Simulation.

A CACC-equipped vehicle looks out for nearby equipped vehicles. If there is an equipped vehicle present and it is the immediate leader, then the ego vehicle will stay in the current lane and form a platoon. On the other hand, if a CACC-equipped vehicle present in one of the adjacent lanes is the immediate leader to the left or the right, then the ego vehicle looks for an opportunity to change lanes. The ego vehicle checks the time gap with respect to the leader and follower on the desired lane. If the gap is sufficient for the ego vehicle to safely change its lane, then it begins a lane change maneuver. Moreover, whenever a CACC-equipped vehicle detects a platoon in the adjacent lanes, it only changes lane if could be last vehicle in the platoon. Thus, the lane change decision is designed only to promote platoon formation and minimize any potential platoon breakups.

The manual driven vehicles follow the default lane change model inside VISSIM. The lane change logics when the vehicles are in a platoon are different and discussed in the next section.

5.4. Platoon Formation and Dissolution

The platoon is formed using ad hoc formation that takes place when the following rules are met:

- Two CACC-equipped vehicles are in the same lane with a spacing of less than 100 m between them.
- To join a platoon, a CACC-equipped vehicle has to follow another CACC-equipped vehicle for at least 10 s (configurable).
- The followers in a platoon are assigned a desired time gap from a multinomial distribution. The distribution has four levels (0.6, 0.7, 0.9, and 1.1 s), and vehicle is assigned a time gap by picking a random level from the distribution.

Once in a platooning state, the vehicles must receive the leader's data wirelessly to continue in a platoon. The wireless reception is using Nakagami probabilistic distribution. The platoon dissolution can take place under the following conditions:

- If a wireless signal drops, the vehicle reverts back to non-platooning mode. In non-platooning status, the driver's desired time gap changes back to the one before platooning.
- The position of a vehicle in the platoon is constantly being checked, and if the vehicle is the eleventh vehicle in a platoon, it leaves the platoon so the platoon size is restricted to 10 vehicles.
- If a regular vehicle is able to cut into the midst of the platoon, the platoon is broken up into two separate platoons if more than two vehicles are present on both sides of the regular vehicle.

Figure 17 summarizes the platooning formation algorithm.

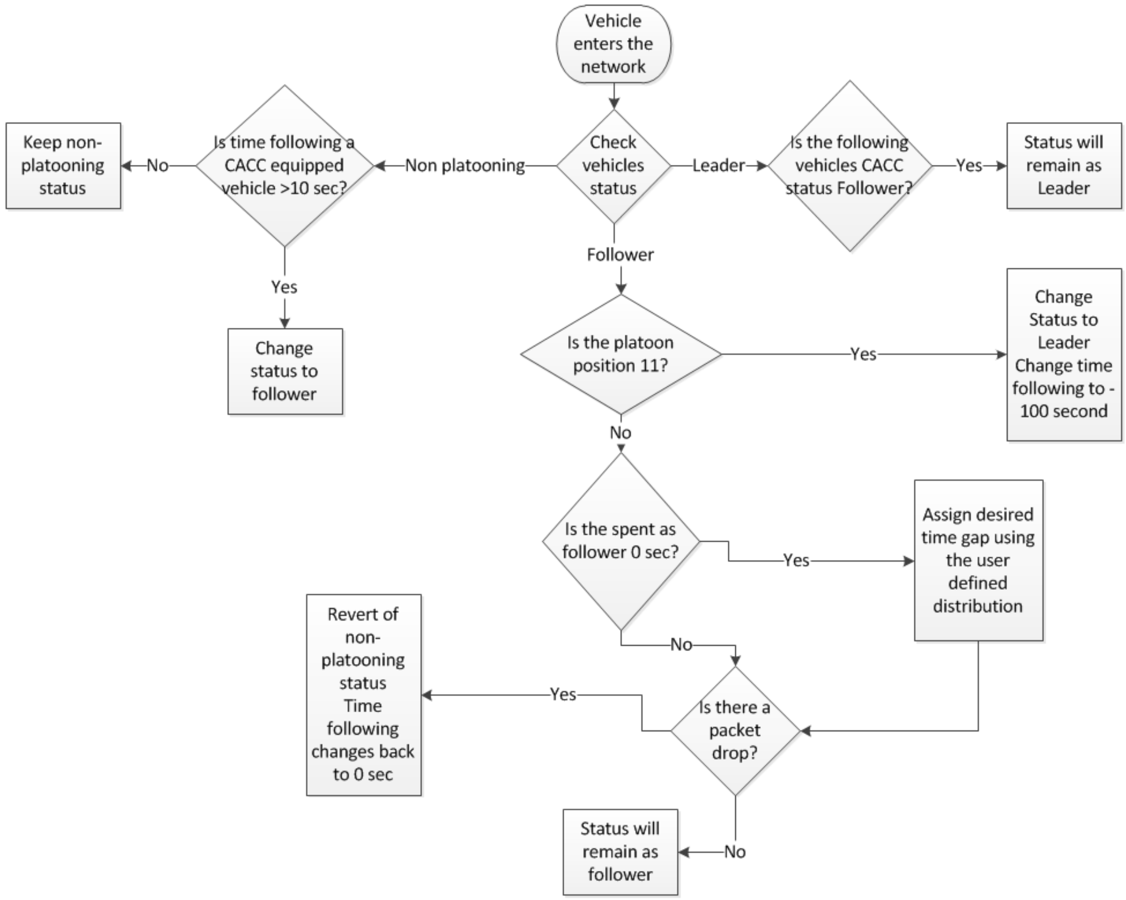


Figure 17: Platooning Algorithm.

5.4.1. Probabilistic Wireless Reception Model

To model wireless data reception, researchers implemented a probabilistic wireless reception model proposed by Killat et al. (*48*) in the API. Killat et al.'s model is based on the Nakagami distribution with m=3. The model for packet drop is based on two key parameters: crossover distance (*CR*) and distance between sender and receiver (*d*). Crossover distance is the communication range of the transmitter. Two crossover distances of 100 m and 250 m were selected in this study to represent poor and good wireless communication quality, respectively.

In our modeling scenarios, the vehicles join a platoon only when the distance between the ego vehicles and the potential leader is less than 100 m, using the packet drop equation for cases when *d* is less than *CR* can be used. Equation (2-29) expresses the probability of receiving a packet:

$$\Pr(d, CR) = e^{-3\left(\frac{d}{CR}\right)^2}\left(1 + 3\left(\frac{d}{CR}\right)^2 + \frac{g}{2}\left(\frac{d}{CR}\right)^4\right) \qquad (2\text{-}29)$$

where:

CR (Crossover distance) = Maximum achievable communication distance.

D = Distance between the sender and the receiver.

g = Gravitational coefficient.

5.5. EMISSION CALCULATION

To estimate the emissions, researchers used second-by-second vehicle trajectory data and following distances from the simulation. Commonly used tools such as MOVES, CMEM, and VT-Micro can all be used to estimate various vehicular pollutants. Researchers used the emission rates of Heavy Duty Vehicle (HDV) from MOVES2014 (*49*) in this study since it is the most up-to-date database publicly available. In order to estimate the emission rates for different vehicles in a timely manner, the core model from MOVES was coded into R, and the trajectory files from VISSIM were post processed using the R software package. Moreover, by using the emission model instead of the software, researchers can adjust the wind drag coefficient based on the second-by-second following distance when the vehicles are in a platooning state and then estimate the emissions accordingly. The following sections discuss the emission calculation process in detail.

5.5.1. Emission Rates

To calculate the emission rate, MOVES uses the concept of operating bins. Speed, acceleration, and scaled tractive power (STP) are used to categorize different operating bins. Different operating bins have different emission rates. The total emissions or emission rate for different vehicle types can be calculated using an operating mode distribution for a vehicle type.

Researchers analyzed a project level scenario. Default values were used for parameters such as fuel composition. A diesel fuel-combination long haul truck was chosen as the target vehicle type. To obtain the emission rate for different operating bins, an operating bin distribution was entered. This distribution specified the percentage of time a vehicle traveled in a particular operating bin. To get the different emission rates for different operating bins, the operating bin distribution was coded such that different links represented different operating modes so the emission rate for any link can be taken as the emission rate for the corresponding operating bin. Table 9 presents the emission rates obtained from the MOVES.

Table 9: Emission Rates for Different Operating Bins.

Operating Bin	Emission Rates (grams/mile)			
	Hydrocarbons	CO	NOx	CO_2
0	0.06	0.09	0.74	340.99
1	0.05	0.15	0.56	168.77
11	0.12	0.26	0.67	223.98
12	0.12	0.31	1.87	643.10
13	0.14	0.44	3.02	1160.50
14	0.15	0.53	4.26	1685.30
15	0.13	0.58	5.34	2125.49
16	0.14	0.69	6.70	2906.19
21	0.11	0.24	0.58	179.85
22	0.14	0.56	2.11	820.95
23	0.13	0.67	3.08	1350.41
24	0.13	0.73	4.43	1945.74
25	0.12	0.78	5.72	2496.49
27	0.12	0.68	7.17	3424.29
28	0.12	0.65	7.79	4794.01
29	0.15	0.83	10.01	6163.72
30	0.18	1.02	12.24	7533.43
33	0.14	0.59	2.04	727.30
35	0.12	0.71	4.50	2199.44
37	0.12	0.67	6.97	3428.05
38	0.12	0.54	8.28	4799.27
39	0.16	0.69	10.65	6170.46
40	0.19	0.85	13.02	7541.68

5.5.2. Scaled Tractive Power

The fraction of time each vehicle spends in different operating modes is used to determine the total emissions or average emission rate. A program logs vehicle trajectories from the simulation into a text file. This file contains second-by-second details such as simulation time, vehicle speed, vehicle acceleration, and spacing. Speed, acceleration, and vehicle mass were used to calculate STP. The vehicle mass was fixed at 33,000 lb. Equation (2-30) shows the STP calculation. STP, speed, and acceleration were then used to allocate the fraction of time a vehicle spends in different operating modes. This was then used with emission rates table to compute the average emission rate for a vehicle.

$$STP_t = \frac{Av_t + Bv_t^2 + Cv_t^3 + Mv_t\left(a_t + g.sin\theta\right)}{f_{scale}} \tag{2-30}$$

where

$STP_t =$ the scaled tractive power at time t [scaled kW or skW].

A = the rolling resistance coefficient [kW-sec/m].

B = the rotational resistance coefficient [kW-sec^2/m^2].

C = the aerodynamic drag coefficient [kW-sec^3/m^3].

M = mass of individual vehicle.

f_{scale} = fixed scale factor (17.1).

v_t = instantaneous vehicle velocity at time t [m/s].

a_t = instantaneous vehicle acceleration at time t [m/s^2].

g = acceleration due to gravity [9.8 m/s^2].

$sin\theta$ = fractional road grade.

The A value corresponds to rolling resistance offered to the vehicle by the roadway surface. Its value is calculated according to (5-5). B is zero for heavy vehicles. The C value is calculated using Equation (5-7).

$$A = 0.0661 \times M \left(M \text{ is in metric ton} \right) \tag{2-31}$$

$$B = 0 \tag{2-32}$$

$$C = 0.5 C_D \times \rho \times A \tag{2-33}$$

where

A = Frontal area of truck (12.5 m^2).

ρ = Air density (1.225 kg/m^3).

C_D= aerodynamic drag coefficient (0.65).

5.5.3. Wind Drag Reduction

To model the benefits of platooning on emissions, researchers accounted for the wind drag reduction that a vehicle will experience when it is closely following another vehicle. Researchers used wind drag reduction tables by Hong et al. (*50*) for modeling. These tables (Table 10 and Table 11) consist of wind drag reduction at different car spacing for the leader and follower. This table is for spacing up to one car length; however, in the study by Hong et al., there is some reduction for follower and for leader up to around four and two car lengths spacing, respectively. This can be observed in Figure 18 The values from the table were extrapolated to get the wind drag reduction at car lengths more than one. Also wind drag reduction for missing car spacing values were estimated by interpolation.

Table 10: Wind Drag Reduction for Leader.

Car Spacing (Car Length)	CD/CNeutral
0.2344	0.6380
0.2865	0.5910
0.3802	0.6111
0.5521	0.7848
0.7448	0.8808
1	0.9541

Table 11: Wind Drag Reduction for Follower.

Car Spacing (Car Length)	$C_D/C_{Neutral}$
0.2344	0.7278
0.2865	0.6657
0.3802	0.6978
0.5521	0.6259
0.7448	0.6724
1	0.7379

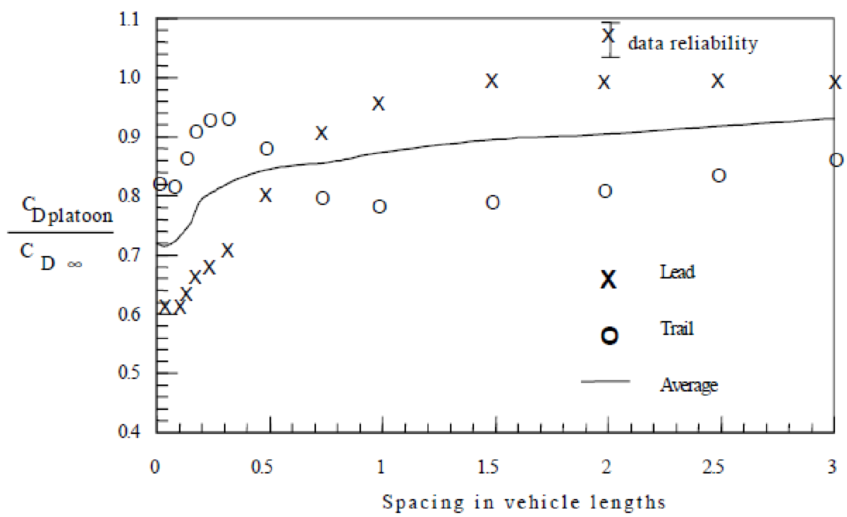


Figure 18: Reduction in Wind Drag Coefficient (*51*).

5.6. EVALUATION SCENARIOS

Various operational and technological factors can affect freeway performance measures. Researchers evaluated some of the important factors pertaining to CV environment to find out how each factor or combination of factors effect different freeway performance measures. Table 12 summarizes the factors that are evaluated in this study.

Table 12: Variables and Levels Evaluated in the Simulation Study.

Factors	Levels	Comments
Volume (Vehicle/Hour)	2500 and 4000	This represents low and high volumes.
Market Penetration Rate CACC (%)	10, 30, 50, and 70	All the CVs are assumed to be HDV.
Transmission Power (meter)	100 and 250	Transmission power is the range of DSRC.
Gap Distribution	• Aggressive (70% with 0.6, 20% with 0.7, 7% with 0.9 and 3% with 1.1 second desired gap) • Conservative (3% with 0.6, 7% with 0.7, 20% with 0.9 and 70% with 1.1 second desired gap)	Desired gap is the time gap which a vehicle wants to maintain with its lead vehicle.
Lane Control Setting	• CACC Left Lane • Free Lane Selection	All CACC-equipped vehicles are in left lane in CACC left lane setting.

The consideration of the levels used in each factor was:

- Traffic Volume – Traffic volume levels represent the opportunity for CACC-equipped vehicles to form platoons.
- Market Penetration Rate of CACC – The 10 percent level represents the near future scenarios and higher values represent future scenarios when more and CVs are on the roadways. A maximum market penetration rate of 70 percent was used because it is very time consuming to run VISSIM at higher market penetration rate.
- Transmission Power – The high and low transmission power represent the good and poor wireless communication quality. The probability of wireless reception depends on the distance between a pair of CVs. The increase in the distance will reduce the reception probability.
- Gap Distribution – Different drivers in a platoon would have different desired time gap. In order capture this, some drivers are assigned smaller time gaps and some are assigned larger time gaps based on a multinomial distribution. Two distributions were considered. One in which the majority of the drivers preferred smaller time gaps and the other one in which the majority of the drivers preferred bigger time gaps.
- Lane Control Setting – Lane selection setting restricts a platoon to change lanes once it is formed. This is done to preserve a platoon for as long as possible. The second setting restricted all the CACC-equipped vehicles in the left lane. Manual driven vehicles were free in any lane. This lane setting promotes platoon formation. Longer and more stable platoons are expected from this setting.

5.7. BASE CASE SCENARIOS

Base case scenarios are when the CVs are in the network but their CACC features are not activated so these vehicles become regular vehicles. Their operating and emission characteristics can then be individually compared to the scenarios where CACC are activated. There are a total of eight base cases from a factorial combination of two volume levels and four levels of market penetration. Without CACC activation, the vehicles are operating as human driving using

VISSIM's default driver models. Emission rates for different vehicles were obtained using the procedure mentioned in section 5.5. These emission rates also serve as base cases for these CVs to determine the impact when the CACC feature is activated.

5.8. Simulation Runs

The simulation period was 1 hour 15 minutes. The first 5 minutes were the warm-up period. Also, the first one-kilometer section was excluded from the analysis as it was influenced by the new vehicle input. Researchers combined different factors mentioned in section 5.6 to form 64 scenarios. Four of the combinations with CACC vehicles in the left lane, 4000 vehicle/hour volume, and 70 percent market penetration rate were removed from the evaluation. This was done because the flow rate in the left lane for these four scenarios exceeded 1800 vehicles/hour. A higher flow rate would have reduced the speed and caused oversaturated flow. This led to a total of 60 scenarios for evaluation. In addition to these 60 scenarios, eight more scenarios for base case were evaluated. The details of these scenarios are present in Appendix 2.

A data collection point was placed in the middle of the section to get data on headway, speed, and acceleration. Table 13 shows a sample output from the data collection point.

In addition, two different files were generated from the external driver model DLL. One file was used to record vehicle trajectory data and packet drop data. Table 14 shows a sample data from this file. This file contained data for all the vehicles in the network at one second time interval. In order to increase the simulation speed, the data were logged at every 300 seconds. This file contained control data such as vehicle speed, acceleration, and distance from the leader and follower. These data also had a reception column that contained information regarding signal drop. A value of one for reception means that the ego vehicle successfully received the packets from the leader is a particular time step, and zero means that there was a signal drop in that time step. A value of −99 means that the vehicle is not in platooning mode, so this column is not relevant. This file was used calculate the emissions for CACC-equipped vehicles.

Table 13: Selected Data from Data Collection Point.

LaneNo.	Entry Time	Exit Time	VehNo	Vehicle type	v[mph]	acc[ft/s2]	VehLength[ft]
1	695.08	-1	1	100	73.4	0	12.3
1	-1	695.19	1	100	73.4	0	12.3
2	726.16	-1	2	100	70.3	0	12.3
2	-1	726.28	2	100	70.3	0	12.3
1	730.28	-1	16	100	72.3	0	15.24
1	-1	730.43	16	100	72.3	0	15.24
1	733.33	-1	14	100	71.8	0	13.16
1	-1	733.46	14	100	71.8	0	13.16
3	733.48	-1	8	100	70.7	0	12.3
3	-1	733.6	8	100	70.7	0	12.3
1	734.44	-1	6	100	72.6	0	15.12
1	-1	734.58	6	100	72.6	0	15.12
3	734.66	-1	15	100	71.2	0.82	15.12
3	-1	734.8	15	100	71.3	0.82	15.12
3	735.87	-1	26	100	70.4	2.11	15.62
2	736.08	-1	5	100	69.7	0	15.62

Table 14: Sample Output from External Driver Model DLL for Vehicle Trajectory.

vehID	simtime_sec	speed_mph	acc_fps2	status	front_gap_ft	rear_gap_ft	Reception
351	342	63.489	-0.45	201	222.59	323.56	-99
351	343	63.232	-0.32	201	219.37	325.54	-99
351	344	63.053	-0.22	201	216.79	327.03	-99
351	345	62.938	-0.13	201	214.76	327.45	-99
351	346	62.878	-0.057	201	213.18	326.89	-99
351	347	62.862	0.0025	201	211.97	325.43	-99
355	347	63.256	0.00056	201	150.41	282.59	-99
351	348	62.882	0.05	201	211.08	323.12	-99
355	348	63.256	0.00037	201	152.15	282.65	-99
351	349	62.931	0.087	201	210.45	320.89	-99
355	349	63.256	0	201	153.87	282.71	-99
358	349	63.222	0.009	201	215.7	232.97	-99
351	350	63.257	1	203	209.95	319.67	1
355	350	63.256	0	201	154.73	282.76	-99
358	350	63.228	0.0075	201	215.75	228.73	-99
351	351	63.287	-0.63	201	209.13	319.91	-99

The second file that was generated from the external driver model DLL contained information on platoon length. This file contained data regarding all the platoons in a network. Platoon size of all the platoons at a time step was extracted. The frequency of measurement was once every minute. This file logged data at one-minute time interval. Table 15 shows a sample of the data that was logged in this file.

Table 15: Sample Output of Platoon Length Data.

sim_time	Platoon_length
300	2
360	2
420	3
420	2
420	2
420	2
480	2
480	2
480	2
480	2
540	2
540	3
540	2
540	2
540	2
540	2
600	2

The next chapter describes the analysis and results from the simulation study, specifically, the effect of CACC on traffic flow, platooning characteristics, safety, and the environment from the simulation results.

6. ANALYSIS AND RESULTS

Researchers collected the simulation data using both VISSIM data collection features and customized individual vehicle data logging implemented in the API. Table 16 summarizes the analysis and issues examined in this case study.

Table 16: Analysis of Simulation Results.

Categories	Issues	Descriptions
Traffic Flow Performance	How does platooning impact the mobility of the freeway corridor? How does the CACC-only lane impact the operation?	CACC platoons can potentially improve the throughput with tighter headways. The CACC-only lane will restrict the platoon only in the left lane, which may also reduce difficult lane changing situations for regular cars.
Platooning Characteristics	How does the wireless communication quality impact the platooning performance? How does the CACC-only lane impact the platooning characteristics?	Previous CACC studies often assume perfect wireless communications. This study allows for imperfect wireless communications using Nakagami probabilistic reception model. It assumes that the platoon will break up upon the loss of communications.
Safety	How does the CACC impact the stability of the traffic flow?	The stability of the traffic flow is commonly used as surrogate safety measures for freeway operation.
Environment	How does the CACC impact the fuel consumption and emissions?	A close following vehicle will experience reduced wind drag so it requires less engine power in a platooning situation. This study will evaluate the platooning benefits in terms of fuel consumption and emissions.

6.1. EFFECT OF CACC ON TRAFFIC FLOW PERFORMANCE

CACC platooning directly affects the flow rate. The flow rates were collected at 5-minute intervals in the middle of the test bed. The effect of CACC-equipped vehicles on flow rate is measured using the 85th percentile flow rate, which represents the upper limit of the freeway throughput for the evaluated scenario.

Table 17 shows the 85th percentile flow rate for different volume and market penetration rate combination. Results are also divided according to the lanes for the cases in which all the CACC-equipped vehicles were on left lane. Middle lane and right lane results are combined and displayed together. For high volume, market penetration rate, and when CACC vehicles are in the left lane, the flow rate in the left lane is relatively higher as compared to the other two lanes. This is because in these scenarios a large number of CACC-equipped vehicles are in platoon.

Table 17: Flow Rate Summary.

Volume	% CV	Lane Setting	Lane Group	85th Percentile Flow Rate (Vehicles/Hour)
2500	10	CACC Left Lane	Non-Left Lanes	1843.97
2500	10	CACC Left Lane	Left Lane	901.32
2500	10	CACC Left Lane	All Lanes	2665.47
2500	10	Free Lane Selection	All Lanes	2682.90
2500	30	CACC Left Lane	Non-Left Lanes	1673.50
2500	30	CACC Left Lane	Left Lane	1132.15
2500	30	CACC Left Lane	All Lanes	2845.98
2500	30	Free Lane Selection	All Lanes	2825.34
2500	50	CACC Left Lane	Non-Left Lanes	1271.34
2500	50	CACC Left Lane	Left Lane	1543.41
2500	50	CACC Left Lane	All Lanes	2781.17
2500	50	Free Lane Selection	All Lanes	2878.32
2500	70	CACC Left Lane	Non-Left Lanes	779.15
2500	70	CACC Left Lane	Left Lane	1968.64
2500	70	CACC Left Lane	All Lanes	2700.62
2500	70	Free Lane Selection	All Lanes	2814.82
4000	10	CACC Left Lane	Non-Left Lanes	2975.08
4000	10	CACC Left Lane	Left Lane	1399.51
4000	10	CACC Left Lane	All Lanes	4312.39
4000	10	Free Lane Selection	All Lanes	4280.90
4000	30	CACC Left Lane	Non-Left Lanes	2720.58
4000	30	CACC Left Lane	Left Lane	1601.43
4000	30	CACC Left Lane	All Lanes	4206.11
4000	30	Free Lane Selection	All Lanes	4317.93
4000	50	CACC Left Lane	Non-Left Lanes	2107.62
4000	50	CACC Left Lane	Left Lane	2085.70
4000	50	CACC Left Lane	All Lanes	4068.88
4000	50	Free Lane Selection	All Lanes	4409.95
4000	70	Free Lane Selection	All Lanes	4369.13

6.2. PLATOONING CHARACTERISTICS

Longer platoons result in higher flow rates. As the number of platoons increases in the network, the emission benefits will also increase. Thus platoon length statistics act as a barometer for driver’s convenience and freeway performance. Following performance measures were calculated:

- Median Platoon Length –explains how different factors affect the platoon length.
- Mean Platoon Length –explains how different factors affect the platoon length.
- Standard Deviation Platoon Length –signifies the stability of platoon.

- Mean Number of Platoon –gives an idea about how many platoons are in the network at each time step.
- Standard Deviation Number of Platoon –can help gauge the platoon formation and dissolution.

Table 18 and Table 19 show the platoon-related statistics.

Table 18: Platoon Length Statistics.

% CV	Volume (Vehicle/Hour)	Lane Setting	Transmission Power (meters)	Median Platoon Length	Mean Platoon Length	St.Dev Platoon Length
10	2500	CACC Left Lane	100	2	2.24	0.55
10	2500	CACC Left Lane	250	3	3.38	1.85
10	2500	Free Lane Selection	100	2	2.22	0.51
10	2500	Free Lane Selection	250	2	2.86	1.35
30	2500	CACC Left Lane	100	2	2.46	0.83
30	2500	CACC Left Lane	250	4	5.16	2.83
30	2500	Free Lane Selection	100	2	2.35	0.72
30	2500	Free Lane Selection	250	3	3.71	2.15
50	2500	CACC Left Lane	100	2	2.68	1.06
50	2500	CACC Left Lane	250	7	6.52	2.94
50	2500	Free Lane Selection	100	2	2.39	0.75
50	2500	Free Lane Selection	250	3	4.25	2.51
70	2500	CACC Left Lane	100	3	3.26	1.67
70	2500	CACC Left Lane	250	8	7.05	2.92
70	2500	Free Lane Selection	100	2	2.45	0.83
70	2500	Free Lane Selection	250	4	4.73	2.70
10	4000	CACC Left Lane	100	2	2.39	0.80
10	4000	CACC Left Lane	250	3	3.82	2.26
10	4000	Free Lane Selection	100	2	2.27	0.60
10	4000	Free Lane Selection	250	2.5	3.07	1.55
30	4000	CACC Left Lane	100	2	2.66	1.03
30	4000	CACC Left Lane	250	6	6.13	3.04
30	4000	Free Lane Selection	100	2	2.42	0.78
30	4000	Free Lane Selection	250	3	4.14	2.44
50	4000	CACC Left Lane	100	3	3.90	2.29
50	4000	CACC Left Lane	250	8.5	7.15	2.96
50	4000	Free Lane Selection	100	2	2.54	0.96
50	4000	Free Lane Selection	250	4	4.84	2.79
70	4000	Free Lane Selection	100	2	2.59	1.01
70	4000	Free Lane Selection	250	5	5.35	2.90

The key findings are:

- The wireless communication quality has direct impact on platoon length. It can be seen that the mean and median platoon length is higher for 250 m transmission power as compared to 100 m transmission power when all other factors are the same.
- Good wireless communication leads to more stable platoons. The variation in platoon length is more for 100 m transmission, thus the 250 m setting. This is because with 100 m transmission power, there are more occurrences of wireless reception loss resulting in platoons breaking up more frequently.

- Dedicated CACC lanes promote longer platoon formation. When all the CACC-equipped vehicles are required to stay in the left lane, the platoon size is longer because of the increase in opportunity to locate another equipped vehicle.
- A higher market penetration rate of CACC results in longer platoons.

Table 19: Number of Platoon Statistics.

% CV	Volume (Vehicle/Hour)	Lane Setting	Transmission Power (meters)	Mean No of Platoon	St.Dev No of Platoon
10	2500	CACC Left Lane	100	16.02	5.69
10	2500	CACC Left Lane	250	22.12	4.99
10	2500	Free Lane Selection	100	12.61	4.44
10	2500	Free Lane Selection	250	21.00	5.11
30	2500	CACC Left Lane	100	64.04	13.61
30	2500	CACC Left Lane	250	54.69	9.88
30	2500	Free Lane Selection	100	52.58	12.72
30	2500	Free Lane Selection	250	69.19	12.94
50	2500	CACC Left Lane	100	119.10	24.94
50	2500	CACC Left Lane	250	73.33	12.16
50	2500	Free Lane Selection	100	98.72	22.31
50	2500	Free Lane Selection	250	105.42	17.13
70	2500	CACC Left Lane	100	183.80	34.61
70	2500	CACC Left Lane	250	96.89	16.20
70	2500	Free Lane Selection	100	144.43	28.13
70	2500	Free Lane Selection	250	136.64	21.61
10	4000	CACC Left Lane	100	26.96	6.36
10	4000	CACC Left Lane	250	33.66	6.48
10	4000	Free Lane Selection	100	22.46	5.55
10	4000	Free Lane Selection	250	34.21	6.75
30	4000	CACC Left Lane	100	113.89	19.75
30	4000	CACC Left Lane	250	74.75	12.61
30	4000	Free Lane Selection	100	93.52	16.61
30	4000	Free Lane Selection	250	101.63	17.31
50	4000	CACC Left Lane	100	188.97	36.16
50	4000	CACC Left Lane	250	109.04	19.05
50	4000	Free Lane Selection	100	176.53	31.21
50	4000	Free Lane Selection	250	150.31	22.70
70	4000	Free Lane Selection	100	257.83	45.54
70	4000	Free Lane Selection	250	197.85	30.79

Figure 19 shows the platoon length distribution for different transmission powers. As noted, the platoon lengths are longer for higher transmission power. The mean platoon length for 100 m transmission power is concentrated around two vehicle platoons because of more frequent platoon breakups.

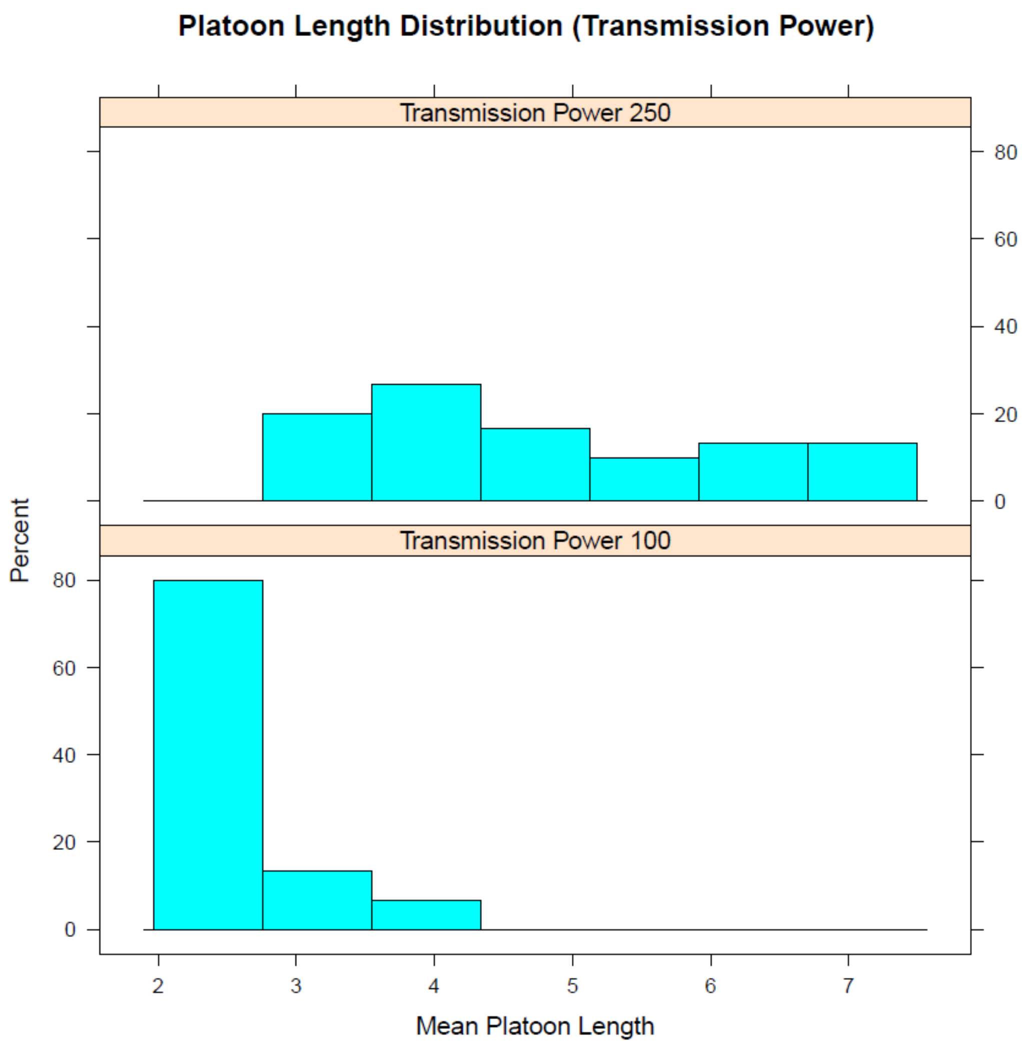


Figure 19: Platoon Length Distribution for Different Transmission Powers.

From Figure 20, the platoon length and the number of platoons are both affected by lane control policy and wireless communication quality:

- With a good wireless communication (250 m transmission power), the platoon lengths are longer because of less wireless reception loss.
- When the platoons are only allowed in the leftmost lane, the platoon lengths become longer on average while the total number of platoons in the network also reduces because they are concentrated in one lane.

In summary, a combination of good wireless communication quality and a lane restriction policy will lead to a condition where there will be fewer but longer platoons in the corridor.

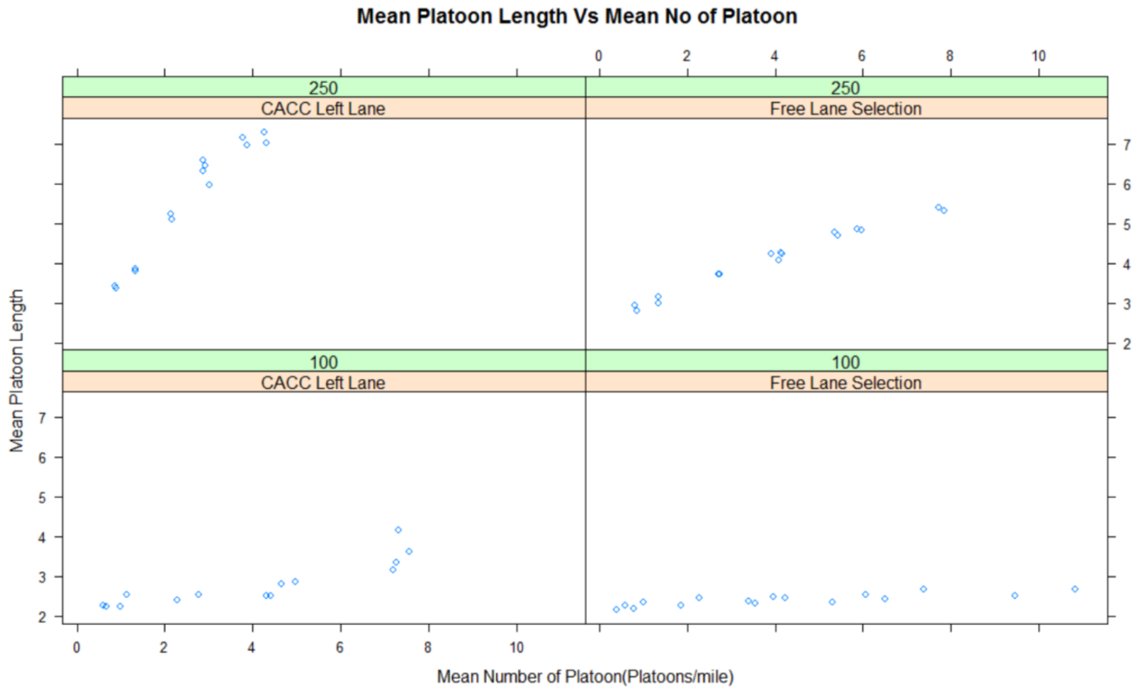


Figure 20: Mean Platoon Length versus Mean Number of Platoons.

6.3. Safety

Safety cannot be directly quantified using crashes from the simulation but the stability of the traffic flow is commonly accepted as a surrogate safety indicator in a simulation environment. Higher perturbation in traffic flow generally means an increase in crash risk. Traffic flow stability can be measured by the speed variations and acceleration variations. Less variation in speed and acceleration indicates a relatively stable flow and vice versa. The measures calculated from the results by lane types and vehicle types are:

- Average speed and 85th percentile of speed –generally describe freeway performance. Ideally, proper platooning operation should not have any negative impacts on traffic speeds.
- Standard deviation of speed –can be used to evaluate the traffic stability. Lower values indicate a more stable flow.
- Root mean square of acceleration –is also a measure of stability. It can be used to gauge how comfortable a journey was. Lower values mean that a vehicle did not have any steep acceleration on deceleration.
- Standard deviation of acceleration –can also be used to gauge the traffic stability.

Table 20 and Table 21 show the speed and acceleration statistics. Manually driven vehicles have higher speeds compared to CACC-equipped vehicles for a similar combination of factors. This is because CACC-equipped vehicles are heavy vehicles and are assigned a lesser speed limit of 65 mph as compared to manually driven vehicles that are assigned a speed limit of 70 mph.

For the same levels of flow rate and percent CV, the average speed when all CACC-equipped vehicles are in left lane is less than the free lane selection mode. This is because when all CACC-equipped vehicles are in left lane, longer platoons are formed and the speed of platoon leader governs members.

Table 20: Speed Statistics.

% CV	Volume	Lane Setting	Lane Group	Vehicle Type	Mean Speed (mph)	85th Percentile Speed (mph)	St.Dev Speed (mph)
10	2500	CACC Left Lane	Left	CACC	61.43	63.68	2.45
		CACC Left Lane	Left	Manual	69.17	72.44	3.50
		CACC Left Lane	Non-Left Lanes	Manual	68.56	71.73	2.92
		Free Lane Selection	All Lanes	CACC	62.69	65.71	2.66
		Free Lane Selection	All Lanes	Manual	68.84	72.02	2.99
30	2500	CACC Left Lane	Left	CACC	60.09	61.92	1.85
		CACC Left Lane	Left	Manual	70.04	73.17	3.65
		CACC Left Lane	Non-Left Lanes	Manual	68.81	72.00	2.88
		Free Lane Selection	All Lanes	CACC	61.06	63.38	2.34
		Free Lane Selection	All Lanes	Manual	68.51	71.95	3.32
50	2500	CACC Left Lane	Left	CACC	59.33	61.05	1.64
		CACC Left Lane	Left	Manual	70.33	73.59	3.75
		CACC Left Lane	Non-Left Lanes	Manual	69.00	72.08	2.89
		Free Lane Selection	All Lanes	CACC	60.36	62.48	2.30
		Free Lane Selection	All Lanes	Manual	67.60	71.46	3.87
70	2500	CACC Left Lane	Left	CACC	57.52	60.10	2.61
		CACC Left Lane	Left	Manual	72.17	73.34	2.17
		CACC Left Lane	Non-Left Lanes	Manual	69.42	72.45	2.91
		Free Lane Selection	All Lanes	CACC	60.25	62.18	2.09
		Free Lane Selection	All Lanes	Manual	66.14	71.15	4.65
10	4000	CACC Left Lane	Left	CACC	60.62	63.03	2.32
		CACC Left Lane	Left	Manual	67.78	71.77	4.33
		CACC Left Lane	Non-Left Lanes	Manual	67.67	70.75	2.89
		Free Lane Selection	All Lanes	CACC	61.48	64.44	3.01
		Free Lane Selection	All Lanes	Manual	67.70	71.15	3.35
30	4000	CACC Left Lane	Left	CACC	59.05	61.13	2.03
		CACC Left Lane	Left	Manual	67.52	72.20	5.13
		CACC Left Lane	Non-Left Lanes	Manual	67.77	70.88	2.91
		Free Lane Selection	All Lanes	CACC	61.19	63.47	2.72
		Free Lane Selection	All Lanes	Manual	67.66	70.91	3.93
50	4000	CACC Left Lane	Left	CACC	56.35	60.00	3.51
		CACC Left Lane	Left	Manual	68.95	73.97	5.46
		CACC Left Lane	Non-Left Lanes	Manual	68.11	71.20	2.95
		Free Lane Selection	All Lanes	CACC	59.55	61.92	2.66
		Free Lane Selection	All Lanes	Manual	65.19	69.79	4.50
70	4000	Free Lane Selection	All Lanes	CACC	59.22	61.45	2.43
		Free Lane Selection	All Lanes	Manual	63.40	68.77	4.70

Table 21: Acceleration Statistics.

% CV	Volume	Lane Setting	Lane Group	Vehicle Type	85th Percentile Acceleration (m/s2)	St.Dev Acceleration (m/s2)
10	2500	CACC Left Lane	Left	CACC	0.05	0.20
		CACC Left Lane	Left	Manual	0.22	0.23
		CACC Left Lane	Non-Left Lanes	Manual	0.20	0.21
		Free Lane Selection	All Lanes	CACC	0.02	0.11
		Free Lane Selection	All Lanes	Manual	0.18	0.22
30	2500	CACC Left Lane	Left	CACC	0.05	0.11
		CACC Left Lane	Left	Manual	0.11	0.21
		CACC Left Lane	Non-Left Lanes	Manual	0.05	0.18
		Free Lane Selection	All Lanes	CACC	0.04	0.14
		Free Lane Selection	All Lanes	Manual	0.19	0.21
50	2500	CACC Left Lane	Left	CACC	0.05	0.18
		CACC Left Lane	Left	Manual	0.08	0.24
		CACC Left Lane	Non-Left Lanes	Manual	0.01	0.17
		Free Lane Selection	All Lanes	CACC	0.06	0.18
		Free Lane Selection	All Lanes	Manual	0.21	0.24
70	2500	CACC Left Lane	Left	CACC	0.08	0.19
		CACC Left Lane	Left	Manual	0.00	0.09
		CACC Left Lane	Non-Left Lanes	Manual	0.00	0.13
		Free Lane Selection	All Lanes	CACC	0.05	0.16
		Free Lane Selection	All Lanes	Manual	0.25	0.27
10	4000	CACC Left Lane	Left	CACC	0.05	0.20
		CACC Left Lane	Left	Manual	0.25	0.31
		CACC Left Lane	Non-Left Lanes	Manual	0.25	0.28
		Free Lane Selection	All Lanes	CACC	0.10	0.27
		Free Lane Selection	All Lanes	Manual	0.25	0.28
30	4000	CACC Left Lane	Left	CACC	0.07	0.19
		CACC Left Lane	Left	Manual	0.25	0.31
		CACC Left Lane	Non-Left Lanes	Manual	0.25	0.27
		Free Lane Selection	All Lanes	CACC	0.09	0.25
		Free Lane Selection	All Lanes	Manual	0.19	0.30
50	4000	CACC Left Lane	Left	CACC	0.11	0.22
		CACC Left Lane	Left	Manual	0.19	0.25
		CACC Left Lane	Non-Left Lanes	Manual	0.25	0.25
		Free Lane Selection	All Lanes	CACC	0.09	0.18
		Free Lane Selection	All Lanes	Manual	0.25	0.33
70	4000	Free Lane Selection	All Lanes	CACC	0.08	0.21
		Free Lane Selection	All Lanes	Manual	0.25	0.35

For the same volume, as market penetration rate of CACC increases, the average speed of the CACC-equipped vehicles decrease.

From standard deviation of speed, for the same market penetration rate of CACC and volume level, the variation in speed is less when all CACC-equipped vehicles are in the left lane as compared to free lane selection setting. The only exception to this case is when the market penetration rate of CACC is 50 percent and volume is 4000 vehicles/hour. This can be because at that high market penetration rate and volume, all the lanes have longer platoons, which are more stable.

Root mean square acceleration shows the fluctuation in acceleration irrespective of sign. The average RMS acceleration and standard deviation of acceleration for 70 percent market penetration rate of CACC is the lowest. This indicates that the magnitude of acceleration was small in this scenario. Traffic flow at higher market penetration rate is more stable as compared to lower market penetration rates of CVs.

Figure 21 shows the box plot for speed. Base cases with the VISSIM default driver model have the highest speed. When CACC platoons are allowed to stay only in the left lane, reseachers observed lower median speed as compared to free lane selection. This is also because CACC platoons only consist of HDVs, which have lower desired speeds.

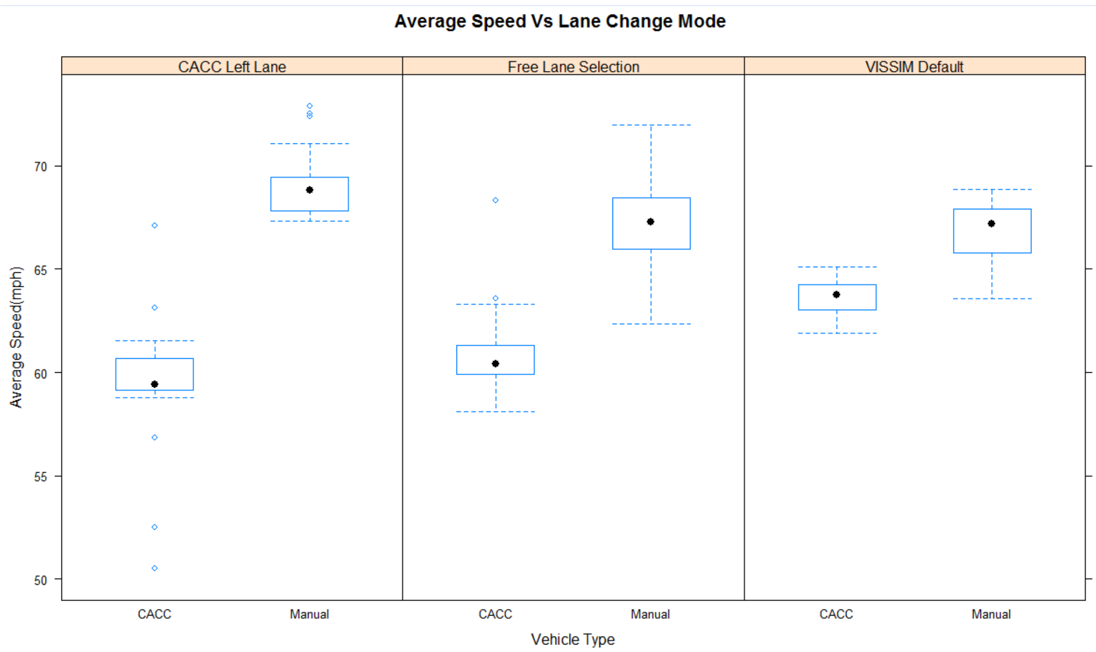


Figure 21: The Effect of Lane Restriction Policy on Speeds.

6.4. Effect of CACC on Environment

CACC platooning has immense potential to reduce the emission rates for heavy vehicles. In this section, the emission rates for different vehicles for different factors are compared with the base cases, which have the same volume and percentage of heavy vehicles.

Figure 22 shows the percentage change in CO_2 for different factors. Aggressive gap distribution demonstrates significant reduction in CO_2 in a few of the cases. However, when comparing the interquartile range, the change in CO_2 is similar to conservative cases. At a higher market penetration rate, a conservative gap distribution resulted in more reduction in CO_2 as compared to aggressive gap distribution when only the interquartile range is compared. A similar trend was observed for CO and NO_x.

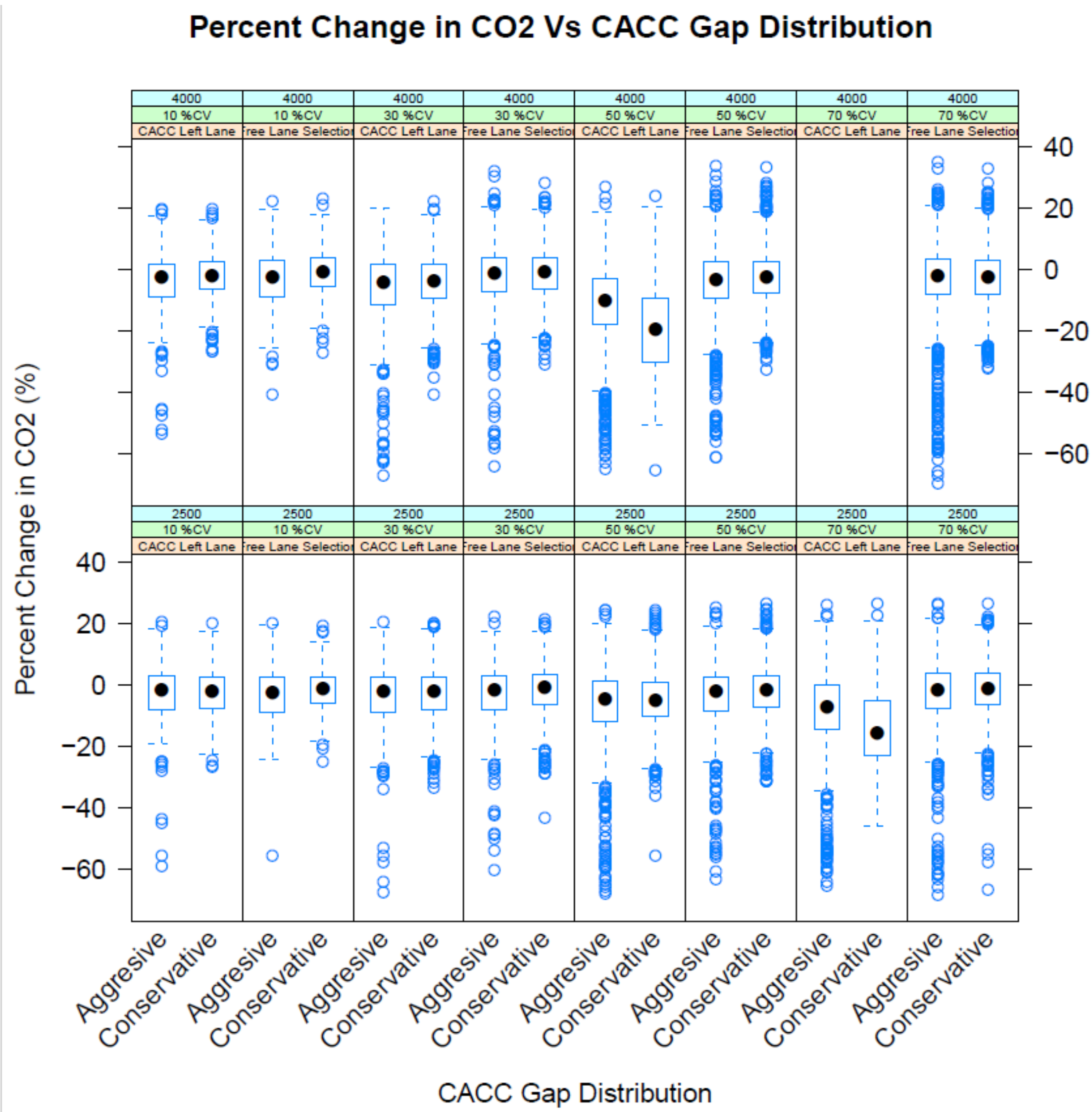


Figure 22: Percent Change in CO_2 versus CACC Gap Distribution.

Figure 23 shows the box plot for reduction in CO_2 at different levels of transmission power conditioned on volume, market penetration rate of CVs, and lane change settings. At higher transmission powers, there is a huge reduction in CO_2 in a few of the vehicles compared to manual driving. This is because platoons are more stable at higher transmission power. However, when comparing the interquartile range, the lower transmission power performs better. Lower transmission power is also a surrogate for smaller platoon size. Smaller platoons might lead to more reduction in CO_2 emissions. Similar trends were observed for CO and NO_x.

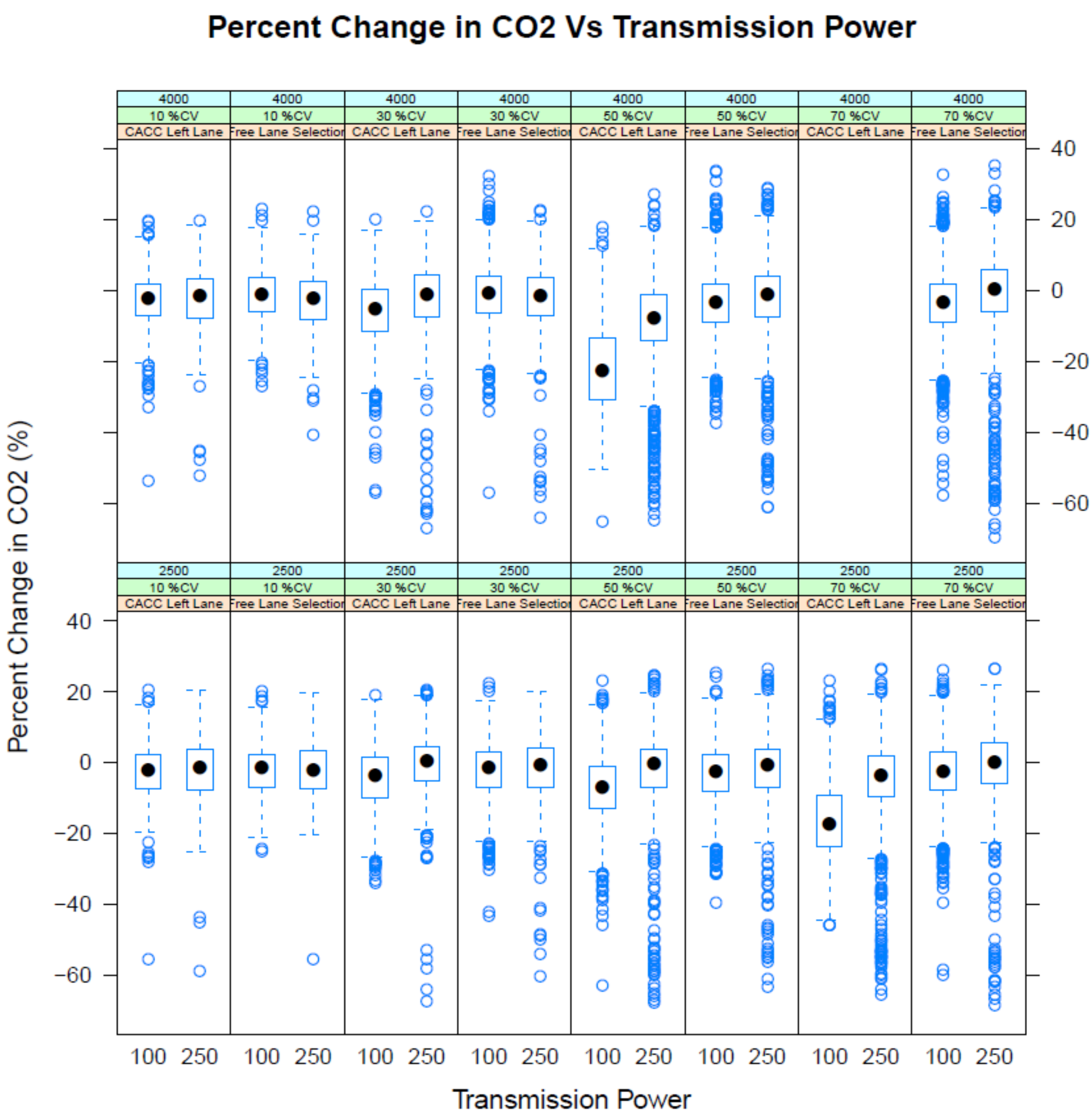


Figure 23: Percent Change in CO_2 versus CACC Transmission Power.

Figure 24 presents the box plot for percent change in CO_2 for different lane change setting. When platooning is allowed only in the leftmost lane, it results in more reduction in CO_2 for all combinations of different factors. This is because when all the equipped vehicles are in one lane, the chances of forming a platoon increase.

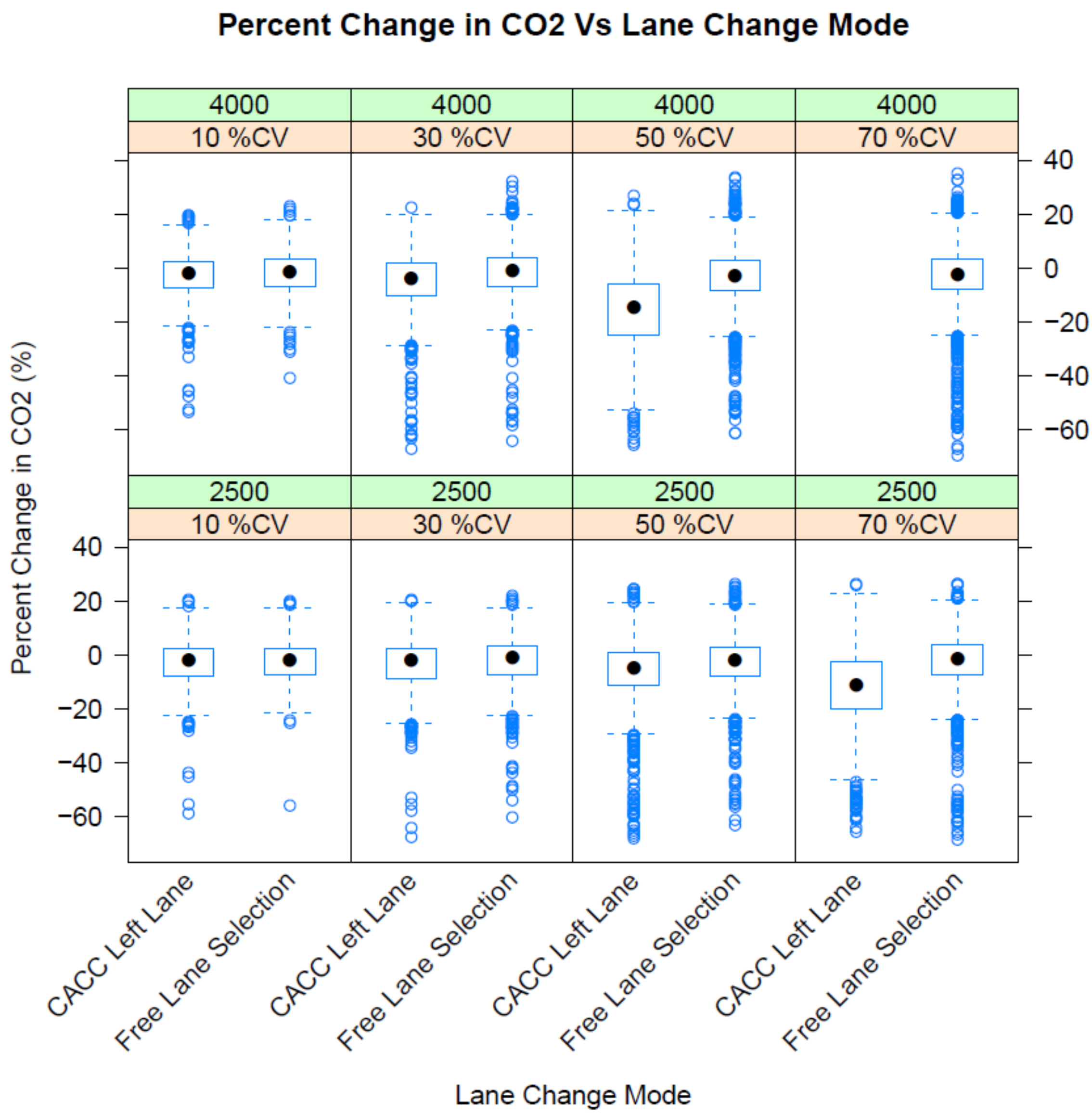


Figure 24: Percent Change in CO_2 versus Lane Change Mode.

Figure 25 presents the scatter plot of average front gap and percentage reduction in CO_2 for different factors. The average front gap here corresponds only to situation in which the vehicle is in platooning mode. Smaller clearance results in less emissions. Smaller clearance means that there would be greater reduction in wind drag, so platooning helped in reducing CO_2 emissions. Similar results were seen for CO and NO_x.

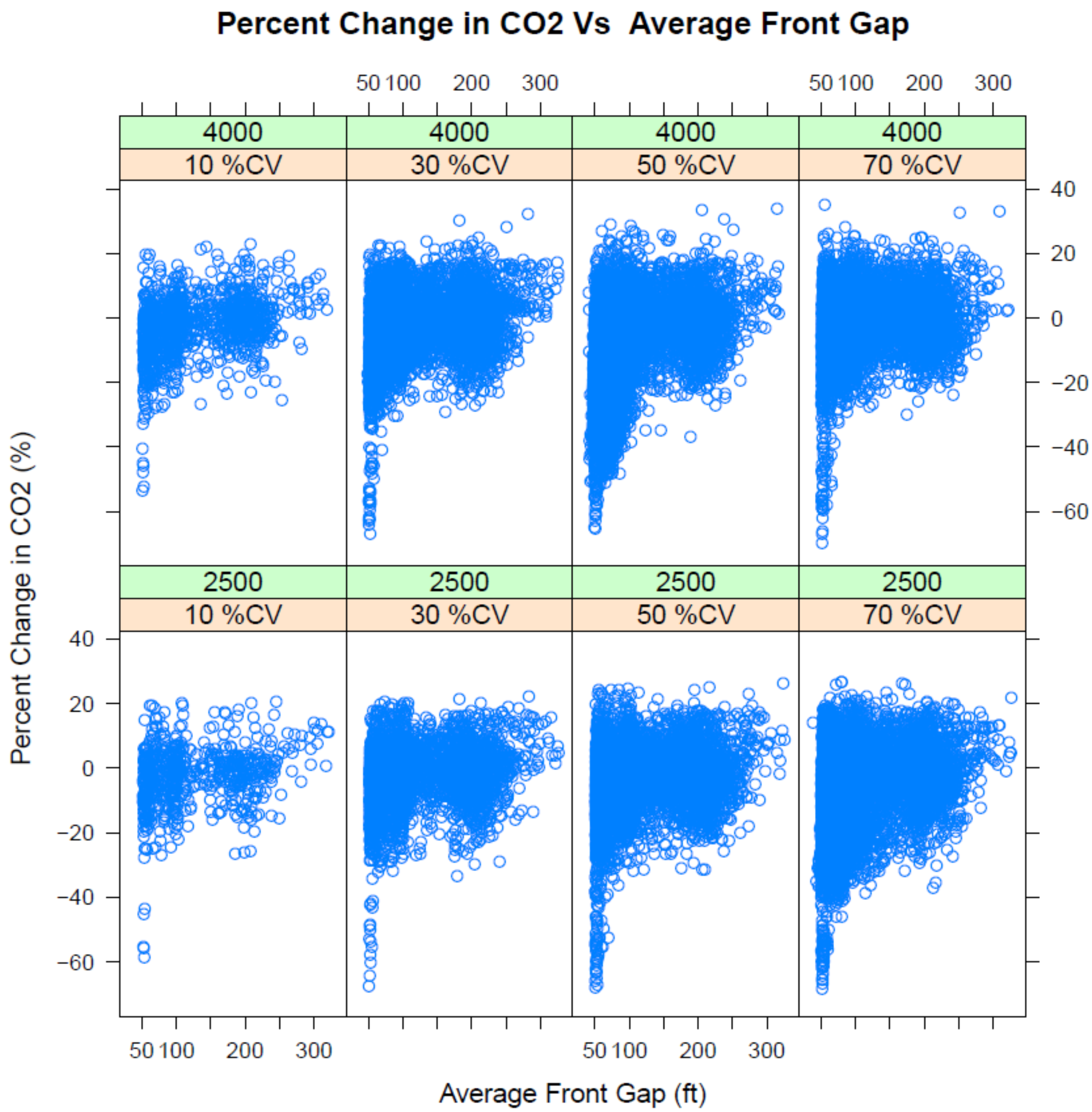


Figure 25: Percent Change CO_2 versus Average Front Gap.

Figure 26 shows the effect of variation of front gap on percent change in emissions. The graphs are conditioned by volume and market penetration rate of connected vehicles. Less variation in front gap is related to more reduction in CO_2. Less variation implies that the vehicle did not accelerate or decelerate much during the platooning. Acceleration requires a lot of power, so moving at a steady speed would reduce emissions. Similar results were seen for CO and NO_x.

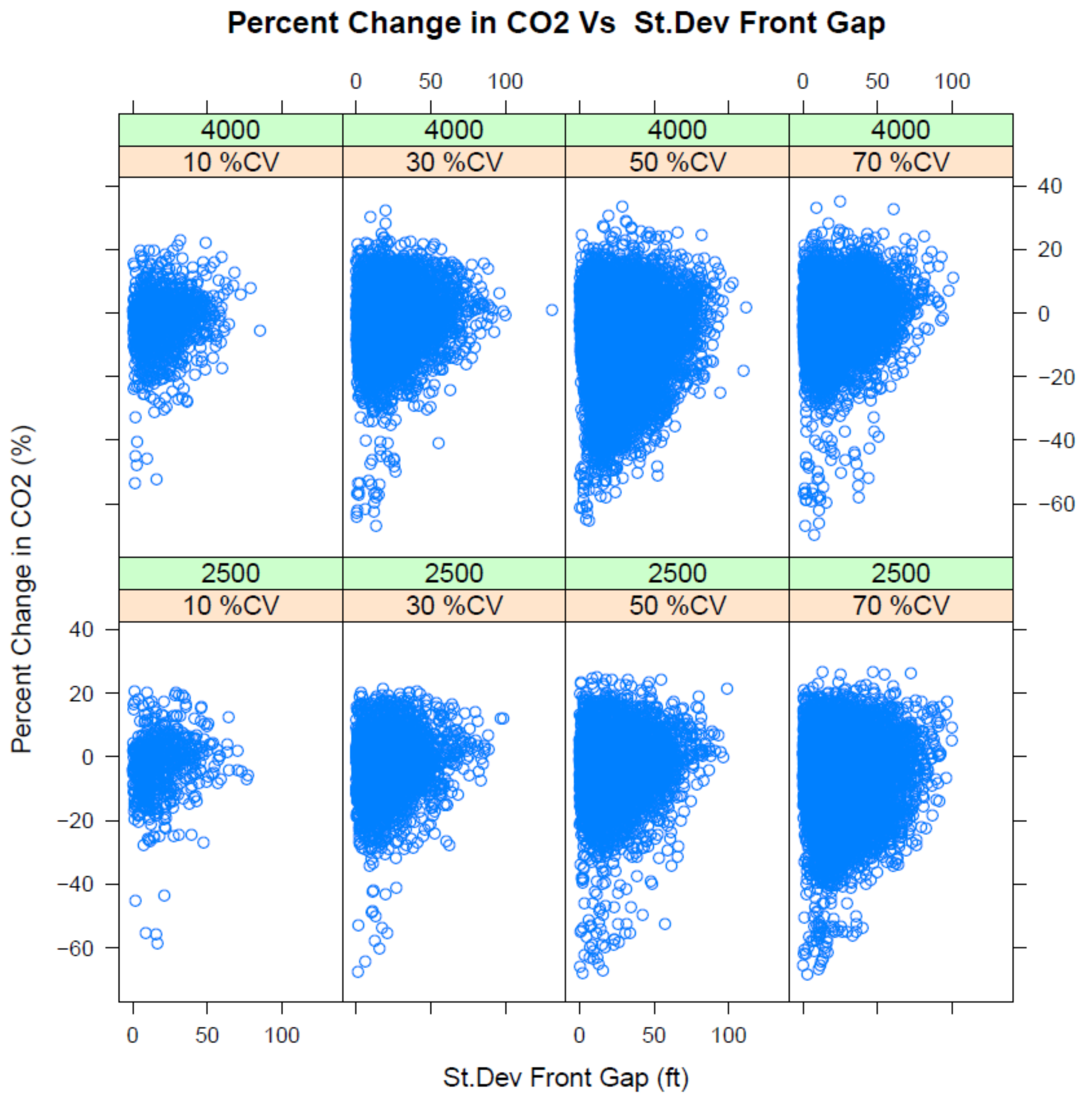


Figure 26: Percent Change CO_2 versus Variation in Front Gap.

The percentage of time a vehicle spends as a follower in the platoon is related to the reduction in emissions experienced by it. When the vehicle is in a platoon, it has small spacing as compared to when it is not in a platoon, so the reduction in CO_2 and other pollutants is more when the vehicles is in a platoon. Figure 27 shows the relationship of emission reduction with the amount of time spent as a follower. As the percentage of time spent as follower increases, the reduction in CO_2 also increases.

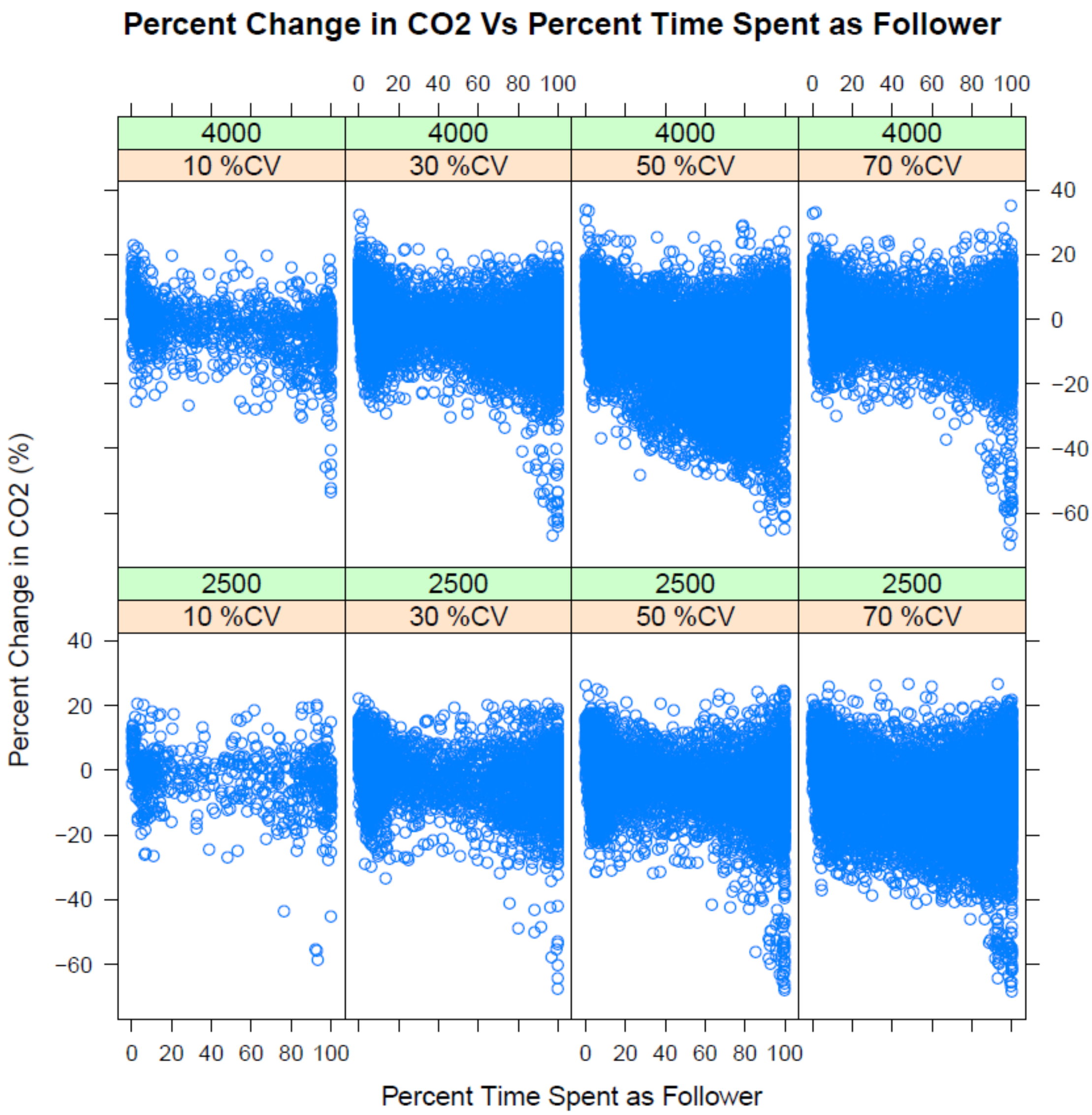


Figure 27: Percent Change is CO_2 versus Percent of Time Spent as a Follower.

Researchers calibrated a linear regression model to explain a relationship between the percentage change in CO_2 and other variables. Table 22 presents the results of the regression model. The R^2 value for model is 0.31. The t-statistics values for different parameters are shown in the table. From the modeling results, researchers found the following:

- Except for the 30 percent CV factor, all other factors are significant at 95 percent confidence level.
- The coefficient of average front gap and standard deviation of front gap are positive so as they increase, the reduction in emission decreases.
- The coefficient of percent of time spent as a follower is negative, so the more time a vehicle spends as a follower, the more reduction in CO_2 will occur.

- There is a reduction of 1.6 times in CO_2 when the volume level is 4000. This is because at a higher volume, the number of CACC-equipped vehicles increases, and there are more opportunities to form a platoon.
- When all CACC-equipped vehicles are in the left lane, more reduction in CO_2 is observed as compared to the free lane selection mode.
- When the transmission power is 250 m, the reduction in CO_2 increases by 9.76 percent. This can be because at a higher transmission power, the platoon size is longer so there is more acceleration and deceleration to maintain the desired spacing between the vehicles.
- From t-statistics, there is not much of a difference in percentage change is CO_2 when the market penetration rate of CACC-equipped vehicles increases from 10 percent to 30 percent. However, there is a reduction in CO_2 as the market penetration rate increases to 50 percent and 70 percent.

Table 22: Regression Model for Percentage Reduction in CO_2.

Coefficients	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-11.769	0.449	-26.173	<2e-16
Average Front Gap	0.042	0.001	23.211	<2e-16
St.Dev Front Gap	0.087	0.003	26.153	<2e-16
Percentage of Time Spent as a Follower	-0.073	0.003	-22.885	<2e-16
Volume (4000 Vehicles/Hour)	-1.597	0.098	-16.183	<2e-16
Lane Change Setting (Free Lane Selection)	6.452	0.101	64.063	<2e-16
Transmission Power (250 meters)	9.756	0.125	78.191	<2e-16
1 if Market Penetration Rate = 30%, 0 if Otherwise	-0.151	0.246	-0.611	0.541
1 if Market Penetration Rate = 50%, 0 if Otherwise	-4.272	0.238	-17.984	<2e-16
1 if Market Penetration Rate = 70%, 0 if Otherwise	-3.471	0.242	-14.369	<2e-16

In summary, the key findings from the emissions analysis are:

- For high volume, market penetration rate, and when CACC vehicles are in the left lane, the flow rate in the left lane is relatively higher as compared to the other two lanes.
- The wireless communication quality has direct impact on platoon length. Platoon length is higher for 250 m transmission power (good quality) as compared to 100 m transmission power (poor quality) when all other factors are the same.
- Good wireless communication leads to more stable platoons. The variation in platoon length is higher when the wireless communication quality is poor.
- Dedicated CACC lanes can promote longer platoon formation.
- CACC results in longer platoons for market penetration rates of 50 and 70 percent.

- For same levels of flow rate and market penetration rate of CACC, the average speed when all CACC-equipped vehicles are required to stay in the left lane is less than the free lane selection mode.
- For the same market penetration rate of CACC and volume level, the variation in speed is less when all CACC-equipped vehicles are in the left lane as compared to free lane selection setting.
- As the average front gap and variation in front gap increase during platooning, the emissions increase.
- The emission rate is less when all CACC-equipped vehicles are in the left lane. This is because when all the CACC-equipped vehicles are in left lane, the chance for these vehicles to become a part of a platoon increases. Once a vehicle joins a close spaced platoon, it experiences wind drag reduction, which in turn reduces emissions.
- As the market penetration rate increases, the emission rate of pollutants (CO_2, CO, and NO_x) decreases. This can be seen from the regression model and the graphs. For 50 percent market penetration rate, the reduction in CO_2 is 4.27 percent more compared with the scenarios when the market penetration rate is 10 percent.

7. CONCLUSIONS AND FUTURE WORK

7.1. Proposed Driver Modeling Framework

This study describes the framework to incorporate realistic driver behavior for CVs in microscopic traffic simulation. The framework consists of three levels of driver behavior adjustment—event based, continuous, and semi-automated. The framework provides several examples and details on how various applications can be properly modeled in a traffic simulation environment.

To illustrate the use of proposed framework, researchers conducted a simulation using CACC as a case study. The CACC (also known as platooning) application enables the vehicles to follow each other in a very tight formation using wireless connectivity and automated longitudinal control. In this manner, the CACC application ideally evaluates CV/AV functionality in a simulation.

To model CACC in a microsimulation platform, researchers replaced the car-following model and lane-change model of the CACC-equipped vehicles using the driver model API. Platooning for semi-automated driving was also analyzed. A platooning model was created and added for the CACC-equipped vehicles. This model controlled the platoon formation and maintenance logic. Researchers also incorporated a wireless reception model to evaluate the impacts of wireless communication quality of platooning operation. In the case of good communication, there will be less reception loss. Evaluated factors in the simulation were: volume, market penetration rate of CV, transmission power, gap distribution of platoons, and special lane control policies for CV. The performance measures examined from the simulation include platooning characteristics, environment, and safety performance.

7.2. Summary of Findings

The following are the important findings from this study:

- Traffic Flow – Researchers observed that platooning can increase freeway throughput, which is consistent with the findings from several previous studies. In our study, researchers observed the 85th percentile flow rate of about 2,100 vphpl, but this lane consists of mainly CACC-enabled trucks, which means further increase in flow when converted to passenger car units.
- Platooning Characteristics – Researchers observed that the platoon formation frequency and length strongly correlates with the wireless communication quality. A higher transmission power provides continuous transmission throughout the platooning period, so CACC-equipped vehicles get the opportunity to form long and stable platoons. Also, having a dedicated lane for CVs would help improve the platoon formation. The highest mean platoon length is about 7 vehicles for the case when the market penetration rate is 50 percent, and all the CACC-equipped vehicles are directed to the leftmost lane.

- Safety – Higher market penetration rate of CVs helps to improve the traffic stability and flow rate. This is because CACC-equipped vehicles are assigned smaller desired gaps when they are in platooning mode.
- Environment – Researchers observed that the emission reduction strongly correlates the length and time spent in platooning. Aggressive gap distribution for platoon is favorable for reduction in the emissions. Emission benefits are also more pronounced when there is a dedicated lane for CVs.

7.3. FUTURE WORK

Following are the recommendations for future work:

- Only a basic freeway section was considered in this study, so merging and diverging traffic was not modeled. It would be interesting to examine the impact of merging and weaving section on freeway performance under CV environment.
- The lane change model considered for CVs is still passive and does not allow the vehicle to actively plan and form platoons. More advanced models can be developed to enable equipped vehicles to proactively search for other CVs in their range and can perform necessary maneuvers to join other CACC-equipped vehicles and form a platoon.
- This study demonstrates the platoon formation and propagation dynamics; however researchers did not model intentional platoon dissolution logics such as the situation when the drivers need to leave the platoon to take an exit ramp. Future work should incorporate a planned platoon dissolution algorithm.
- The effects of other potential applications such as SPDHARM can be implemented and evaluated in the future to examine potential synergy between several CV applications.

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APPENDIX 1. VISSIM DRIVER MODEL API

At minimum, the following source code files must be implemented to compile a DLL for Driver Model Interface:

- DriverModel.h: This file should not be changed. It contains the definitions of all types and number constants used by VISSIM when calling the DLL functions.
- DriverModel.cpp: This is where calculations and driver behavior algorithms should be added. Contents of this source code will be introduced in detail later in this section.

An External Driver Model DLL contains three functions in the DriverModel.cpp source code: DriverModelSetValue (**Set**), DriverModelGetValue (**Get**), and DriverModelExecuteCommand (**Execute**).

DriverModelSetValue function passes data on driver behaviors from VISSIM to the DLL algorithm. But the value will be updated every time the Set function is called, so it is necessary to record the useful data values in a variable outside the Set function. The Set function can be called several times in each time step.

The **Set** function has six major parameters. The first and the most important one is the Type parameter. The Type parameter specifies what data are currently passed by this function from VISSIM. The possible data that can be passed via this function include:

- Data about the target vehicle.
- Data of the nearby vehicles.
- Data of the current link and lanes.
- Data of the current and upcoming environment.
- Data of the next signal head, reduced speed area, or previous desired speed decision.
- Behavior data suggested by VISSIM's internal model.

In the Set and Get functions, each possible type of data has its own case and code block. Users can write codes in the corresponding code block of the data they want to modify and leave other data types unchanged. Once a code block of one type of data is changed, it should return 1 to tell the caller if this call is successful. Figure 28 shows the structure of **Set** function.

```
DRIVERMODEL_API  int  DriverModelSetValue (long   type,
                                           long   index1,
                                           long   index2,
                                           long   long_value,
                                           double double_value,
                                           char   *string_value)
```

Figure 28: Set Function Structure.

Set function will pass the current data item indicated by **type** and indexed by **index1** and sometimes **index2.** The value is passed in **long_value**, **double_value,** or ***string_value** depending on type.

DriverModelGetValue function has a similar structure as **Set** function. But **Get** function is used to retrieve value of data item indicated by **type** and indexed by **index1** and sometimes **index2** and feed it back to VISSIM. Before returning the function, values must be written to one of the three pointers ***long_value**, ***double_value,** or ***string_value**. The function must return 1 for all types that are not marked as optional in the VISSIM DriverModel DLL Interface documentation. For optional types, it can return 0 to VISSIM indicating that it does not handle this type. Unlike the **Set** function, **Get** function can only modify certain types of data items (see Table 23).

The **Set** and **Get** functions are like the bricks of DriverModel DLL. The **DriverModelExecuteCommand** function uses them to build the castle. The **Execute** function only has one parameter indicating what kind of command is to be implemented. There are four types of command:

- Init: This command is called at the start of a VISSIM simulation run to initialize the driver model DLL.
- CreateDriver: This command is called whenever a new vehicle is put into the network.
- MoveDriver: This command is called each time step for each vehicle of the type using external driver model DLL.
- KillDriver: This command is called when a vehicle reaches its destination and leaves the network.

Each command calls a sequence of **Set** and **Get** functions. The detailed sequence of **Set** and **Get** functions called in each command is listed in the VISSIM DriverModel DLL Interface. The **Execute** function is not meant to be modified by users. Users can only control the driving behavior through **Set** and **Get** functions.

In DLL, lane changing can either handled by VISSIM itself or by user defined algorithms. When the DRIVER_DATA_SIMPLE_LANECHANGE and DRIVER_DATA_WANTS_SUGGESTION are all set to 1 by Get function, lane changing will be handled by VISSIM. If users want to define his own lane changing model, there are some data items related to lane changing in Table 23 and the VISSIM DriverModel DLL Interface documentation.

Table 23: Get Function Data Items.

Data Item	Description	Notes
DRIVER_DATA_STATUS	Used in **Execute** (Init) function	optional; *long_value
DRIVER_DATA_VEH_TURNING_INDICATOR	left=1, right=-1, none=0,both =2	*long_value
DRIVER_DATA_VEH_DESIRED_VELOCITY	desired speed in m/s	*double_value
DRIVER_DATA_VEH_COLOR	vehicle color (24 bit RGB value)	*long_value
DRIVER_DATA_WANTS_SUGGESTION	When set to 1, VISSIM will send a suggestion whenever it detects a lane changing is necessary	*long_value
DRIVER_DATA_DESIRED_ACCELERATION	New acceleration in m/s^2	*long_value; limited by VISSIM max. and min acceleration (deceleration) parameters
DRIVER_DATA_DESIRED_LANE_ANGLE	Desired angle relative to the middle of the lane in rad. Positive=turning left	*double_value, optional
DRIVER_DATA_ACTIVE_LANE_CHANGE	Direction of active lane change movement, +1 = to the left, 0 = none, -1 = to the right	*long_value
DRIVER_DATA_TARGET_LANE	Target lane, +1 = next one left, 0=current lane, -1 = next one right	*long_value
DRIVER_DATA_SIMPLE_LANECHANGE	When set to 1, VISSIM will handle the lane change.	*long_value

APPENDIX 2. LIST OF SCENARIOS

Table 24 presents the different high volume scenarios that were evaluated. Each column contains different levels of the variables that are analyzed in this study. Table 25 presents the different low volume scenarios that were evaluated. Each column contains different levels of the variables that are analyzed in this study. Table 26 shows the eight base cases that were created to form a benchmark for different scenarios of connected vehicles.

Table 24: High Volume Scenarios.

Scenario	Volume	Lane Setting	Gap Distribution	% CV	Trans Power
Scenario_1	4000	CACC Left Lane	Aggressive	10	100
Scenario_2	4000	CACC Left Lane	Aggressive	10	250
Scenario_3	4000	CACC Left Lane	Aggressive	30	100
Scenario_4	4000	CACC Left Lane	Aggressive	30	250
Scenario_5	4000	CACC Left Lane	Aggressive	50	100
Scenario_6	4000	CACC Left Lane	Aggressive	50	250
Scenario_8	4000	CACC Left Lane	Aggressive	70	250
Scenario_9	4000	CACC Left Lane	Conservative	10	100
Scenario_10	4000	CACC Left Lane	Conservative	10	250
Scenario_11	4000	CACC Left Lane	Conservative	30	100
Scenario_12	4000	CACC Left Lane	Conservative	30	250
Scenario_13	4000	CACC Left Lane	Conservative	50	100
Scenario_14	4000	CACC Left Lane	Conservative	50	250
Scenario_17	4000	Free Lane Selection	Aggressive	10	100
Scenario_18	4000	Free Lane Selection	Aggressive	10	250
Scenario_19	4000	Free Lane Selection	Aggressive	30	100
Scenario_20	4000	Free Lane Selection	Aggressive	30	250
Scenario_21	4000	Free Lane Selection	Aggressive	50	100
Scenario_22	4000	Free Lane Selection	Aggressive	50	250
Scenario_23	4000	Free Lane Selection	Aggressive	70	100
Scenario_24	4000	Free Lane Selection	Aggressive	70	250
Scenario_25	4000	Free Lane Selection	Conservative	10	100
Scenario_26	4000	Free Lane Selection	Conservative	10	250
Scenario_27	4000	Free Lane Selection	Conservative	30	100
Scenario_28	4000	Free Lane Selection	Conservative	30	250
Scenario_29	4000	Free Lane Selection	Conservative	50	100
Scenario_30	4000	Free Lane Selection	Conservative	50	250
Scenario_31	4000	Free Lane Selection	Conservative	70	100
Scenario_32	4000	Free Lane Selection	Conservative	70	250

Table 25: Low Volume Scenarios.

Scenario	Volume	Lane Setting	Gap Distribution	% CV	Trans Power
Scenario_33	2500	CACC Left Lane	Aggressive	10	100
Scenario_34	2500	CACC Left Lane	Aggressive	10	250
Scenario_35	2500	CACC Left Lane	Aggressive	30	100
Scenario_36	2500	CACC Left Lane	Aggressive	30	250
Scenario_37	2500	CACC Left Lane	Aggressive	50	100
Scenario_38	2500	CACC Left Lane	Aggressive	50	250
Scenario_39	2500	CACC Left Lane	Aggressive	70	100
Scenario_40	2500	CACC Left Lane	Aggressive	70	250
Scenario_41	2500	CACC Left Lane	Conservative	10	100
Scenario_42	2500	CACC Left Lane	Conservative	10	250
Scenario_43	2500	CACC Left Lane	Conservative	30	100
Scenario_44	2500	CACC Left Lane	Conservative	30	250
Scenario_45	2500	CACC Left Lane	Conservative	50	100
Scenario_46	2500	CACC Left Lane	Conservative	50	250
Scenario_47	2500	CACC Left Lane	Conservative	70	100
Scenario_48	2500	CACC Left Lane	Conservative	70	250
Scenario_49	2500	Free Lane Selection	Aggressive	10	100
Scenario_50	2500	Free Lane Selection	Aggressive	10	250
Scenario_51	2500	Free Lane Selection	Aggressive	30	100
Scenario_52	2500	Free Lane Selection	Aggressive	30	250
Scenario_53	2500	Free Lane Selection	Aggressive	50	100
Scenario_54	2500	Free Lane Selection	Aggressive	50	250
Scenario_55	2500	Free Lane Selection	Aggressive	70	100
Scenario_56	2500	Free Lane Selection	Aggressive	70	250
Scenario_57	2500	Free Lane Selection	Conservative	10	100
Scenario_58	2500	Free Lane Selection	Conservative	10	250
Scenario_59	2500	Free Lane Selection	Conservative	30	100
Scenario_60	2500	Free Lane Selection	Conservative	30	250
Scenario_61	2500	Free Lane Selection	Conservative	50	100
Scenario_62	2500	Free Lane Selection	Conservative	50	250
Scenario_63	2500	Free Lane Selection	Conservative	70	100
Scenario_64	2500	Free Lane Selection	Conservative	70	250

Table 26: Base Case Scenarios.

Scenario	Volume	% CV
Scenario_400010	4000	10
Scenario_400030	4000	30
Scenario_400050	4000	50
Scenario_400070	4000	70
Scenario_250010	2500	10
Scenario_250030	2500	30
Scenario_250050	2500	50
Scenario_250070	2500	70