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Cooperative Vehicle-Highway Automation (CVHA) Technology: Simulation of Benefits and Operational Issues

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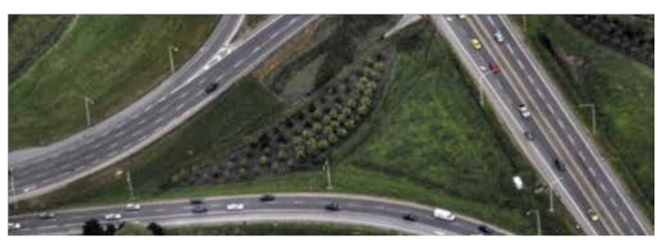

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Final Report

COOPERATIVE VEHICLE–HIGHWAY AUTOMATION (CVHA) TECHNOLOGY: SIMULATION OF BENEFITS AND OPERATIONAL ISSUES

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Executive Summary

The past few years have witnessed a rapidly growing market in assistive driving technologies, designed to improve safety and operations by supporting driver performance. Often referred to as cooperative vehicle–highway automation (CVHA) systems, these assistive technologies commonly utilize radar, light detection and ranging (LiDAR), or other machine-vision technologies, as well as vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) technology, to obtain surrounding roadway and traffic data. Extensive research has been conducted on CVHA technology since the late 1990s. Findings have been generally positive, including potential safety benefits, high potential acceptance rates, and reductions in driver workload, though operations and capacity impacts have been mixed, depending on the technology. Numerous opportunities for further advancement in traffic control strategies that leverage V2V and V2I have been identified and are under development.

However, from the current literature, it is not clear: (1) how some of these systems will operate on the existing infrastructure (e.g., autonomous vehicles), (2) how they will impact traffic congestion and safety, and (3) how state departments of transportation (DOTs) should incorporate this changing vehicle and driver environment in their planning, design, safety, and construction processes. The objective of the current study was to begin to address these concerns to ensure that state DOTs and other practitioners will have the information necessary to make effective policies, procedures, and management decisions regarding CVHA technology.

In seeking to address these concerns, a key finding from this study is related to the underlying modeling approaches utilized to study many of these potential technologies. It is clear that current simulation models are not capable of readily modeling cooperative assist technologies or autonomous vehicles. A critical component in the determination of the impact of many of these technologies is the human interaction with the technology, both those individuals inside the equipped vehicle and those driving other vehicles that interact with the equipped vehicle. Currently, it is not clear how individuals will interact with this technology on a wide scale, particularly when considering autonomous vehicles. To a significant degree, this lack of information is not unexpected. Current in-vehicle technologies are in a state of continual flux, both within and across manufacturers. The "driving" characteristics of an autonomous vehicle are not yet known. Potentially dozens of autonomous vehicles are under development, each with its own logic, algorithms, etc. Critically, how other drivers will interact with autonomous vehicles or other CVHA technology is unknown. Most previous studies have assumed a generally "well-behaved" interaction. However, should drivers choose to "bully" these vehicles, taking advantage of their safety protocols, traffic and safety improvements become much less certain.

Thus, from this study it is clearly necessary to view simulation through a new lens. To date, commercial simulation packages have built-in driver behavior or traffic-flow models. These models contain a limited number of calibration parameters, and a limited range of potential behaviors. For instance, the simulation development in this study shows that while 16 parameters had significant impact on the model performance, only four likely influenced the modeling of autonomous vehicles. However, the researchers present a case study, seeking to model the impact of aggressive manually driven vehicle behavior toward autonomous vehicles. Even with the calibration parameters, significant additional efforts are required to capture driver behavior outside of that reflected by the default modes.

The case study indicates that the introduction of autonomous vehicles resulted in additional instability in the traffic flow. There are several possible reasons for this finding. First, the potential for erroneous modeling must be acknowledged. There is an aspect of the “black box” phenomenon when using any off-the-shelf simulation tool. It is possible that the developed scripts did not correctly interact with the simulation traffic flow logic, resulting in erroneous behavior. A second potential reason for the finding is that for mixed traffic (i.e., manual-driven and autonomous vehicle in the same traffic stream) the resulting behavior may be reasonable. The manually driven vehicles (aggressive and normal), when not in the presence of autonomous vehicles, have similar driving parameters. The demands selected for this experiment were near capacity conditions. When all vehicles have similar characteristics, the flow is homogeneous, likely resulting in optimal flow conditions. By mixing autonomous vehicles into the traffic stream, a heterogeneous flow results (with aggressive behavior by a subset of manually driven vehicles), likely leading to breakdown.

As the definitions of vehicles and drivers enters a constant state of change, the current state of understanding and analysis will no longer be sufficient. The key finding from this effort is that to reflect CVHA it is necessary to design a new simulation and modeling approach, likely from an agent-based simulation point of view, where the vehicle types, behaviors, and abilities may be readily updated. Specific behaviors should not be “hard coded” into a model. Instead, models must provide easily acceptable interfaces, allowing for data exchange with new agents. Modelers must have an ability to create agents (i.e., new drivers, vehicles, etc.) with diverse potential characters and behaviors. From such a modeling tool, analysis into the ever-changing technological environment may then be efficiently conducted.

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1 Introduction

In an attempt to improve safety and reduce driver frustration and congestion, a rapidly growing market in assistive driving technologies is being developed. These technologies are designed to support drivers in performing different driving tasks and help raise the drivers' awareness of potential upcoming hazards. Though referred to by many names (e.g., congestion assistant and adaptive cruise control), these cooperative vehicle–highway automation (CVHA) systems commonly utilize radar, light detection and ranging (LiDAR), and other machine-vision technology, as well as vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) technology, to obtain surrounding roadway and traffic data that can be analyzed and used for assisting driving tasks. For example, an adaptive cruise control (ACC) system automatically maintains the vehicle's speed under a desired maximum while maintaining the following distance from a leading vehicle. Major automobile manufacturers, including Mercedes-Benz, BMW, Audi, and others, are developing higher levels of vehicle driver assistance that control steering and acceleration, with some of these systems already commercially available (Lieberman, 2013; General Motors, 2015).

Extensive research has been conducted on CVHA technology since the late 1990s. In a 2005 study, the coexistence of cooperative autonomous vehicles and non-autonomous vehicles showed promise for the not-too-distant future, with the successful testing of different automated maneuvers in the midst of non-automated vehicles (Baber et al., 2005). Moreover, the interest in automated vehicles also has been increasing worldwide with Europe and Japan leading the way in several key applications of CHVA technologies, including: automated truck platooning, automated buses, personal rapid transit systems, and human factors (Shladover, 2012a; 2012b).

While these systems are being developed and deployed with the intent of reducing driver stress, alleviating congestion, and improving traffic safety, it is not clear: (1) how they will be operated on the existing infrastructure, (2) how they will actually impact traffic congestion and safety, and (3) how state departments of transportation (DOTs) should incorporate this changing vehicle and driver environment in their planning, design, and construction processes. The objective of the current study is to begin to address these concerns to ensure that state DOTs and other practitioners will have the information necessary to make effective policies, procedures, and management decisions regarding CVHA technology.

2 Literature Review

2.1 INTRODUCTION

This section provides a comprehensive review of the literature summarizing the current state of knowledge regarding the impacts of CVHA technology on congestion mitigation, safety, and management of existing transportation infrastructure. It comprises four primary components:

- An overview of the currently available CVHA technology on the market
- A review of existing field/on-road tests of CVHA technology
- A review of existing driver simulator studies evaluating the influence of human factors
- A review of existing microscopic traffic simulation studies evaluating the impacts of CVHA technology on traffic conditions

2.2 OVERVIEW OF CVHA TECHNOLOGY

Before diving into past research, an overview of CVHA technology is essential to provide the necessary foundational knowledge. With the rapid pace of innovation and vast array of CVHA technologies, this overview is not intended to be all-encompassing, but instead provides the context for CVHA studies. Shladover (2008) defines CVHA systems as systems that provide driving control assistance or fully automated driving, and are based on information about the vehicle's driving environment that can be received by communication from other vehicles (V2V) or from the infrastructure (V2I or I2V), as well as from their own on-board sensors. Many assistive driving technologies on the market today are CVHA systems, including those that help the driver perform tasks involving the following:

- Lateral movement
- Forward movement
- Reverse movement
- Crash avoidance/severity reduction
- Parking
- Attention monitoring
- Congestion assistant

Each of these system types is described in the following sections and offered by a cross section of manufactures (Table 1). Note that the names applied in this literature review are used only to describe the systems and should not be taken as their official names.

Table 1. Available Assistive Driving Technologies

Vehicle Manufacturer	Assistive Driving Technologies												
	Lateral Movement			Forward Movement		Reverse Movement		Pre-Crash Systems			Parking Task	Attention Monitor	Congestion Assistant
	Lane Departure Warning	Lane Keeping Assistant	Lane Changing/ Blind Spot Detection	Adaptive Cruise Control	Front Cross-Traffic Monitor	Rear View Camera	Rear Cross-Traffic Monitor	Brake Assistant	Forward Collision Warning	Active Protection			
Audi	Y	Y	Y	Y (radar)		Y		Y	Y	Y	Y (auto)		exp. 2016 (w/o hand)
BMW	Y		Y	Y (radar)		Y		Y	Y	Y	Y (auto)	Y	Y (w/ hand)
Ford/Lincoln	Y	Y	Y	Y (radar)		Y	Y	Y	Y		Y (semi)		exp. 2017
Volvo	Y	Y	Y	Y			Y	Y		Y		Y	exp. 2014
Mercedes-Benz	Y	Y	Y	Y (radar)	Y	Y	Y	Y	Y	Y	Y (semi)	Y	Y (w/ hand)
Cadillac	Y		Y	Y		Y	Y	Y	Y		Y (semi)		
Infiniti/Nissan	Y	Y	Y	Y (laser)		Y	Y	Y					
Acura/Honda	Y	Y		Y		Y			Y				
Lexus/Toyota	Y	Y	Y	Y (radar)			Y	Y		Y	Y	Y	
Kia	Y		Y	Y (radar)		Y	Y	Y		Y	Y		
Hyundai	Y	Y	Y	Y (radar)			Y	Y					

Note: Sources up to 2015, “exp” is expected.

2.2.1 Lateral Movement

There are two CVHA systems that support the vehicle's lateral movement, and a different type of technology is applied to each of those functions. These systems have the potential to impact lane-changing characteristics and, particularly, gap acceptance for lane changing.

2.2.1.1 Lane Keeping

Lane-keeping systems monitor lane markings through built-in cameras located generally above the central rearview mirror, and use this information to determine vehicle position. This technology can provide two types of assistance: (1) a *lane-departure warning* (LDW) system that gives a warning to the driver when the vehicle begins to move out of its lane on freeways and arterial roads (unless a turn signal is on in that direction), and (2) a *lane-keeping assistant* system that includes active intervention to help the driver maintain lane position through automated steering and/or braking. Figure 1 shows how a vehicle equipped with this system will provide automated steering to keep its lane. These systems are currently offered by many vehicle manufacturers (see Table 1) ("2014 Cadenza Features & Specs," 2014; "2014 Lincoln MKS," 2014; "Equipment highlights of the new Audi A8," 2015; "Leading through Innovation," 2014; "2014 LS Features - Safety," 2014; "2014 Q70 Features," 2014; "2014 RLX Features," 2014; "2014 Taurus Features," 2014; "2014 XTS Sedan Trims & Specifications," 2014; "2015 K900 Features & Specs," 2015; "2015 Volvo V60 Features & Options," 2015; "Driver Assistance. Drive smarter, safer and with confidence.," 2014; Ayapana, 2013; Boeriu, 2014; Boeriu, 2013; Lieberman, 2013; Timmins, 2012; Tingwall, 2014; Udy, 2014).

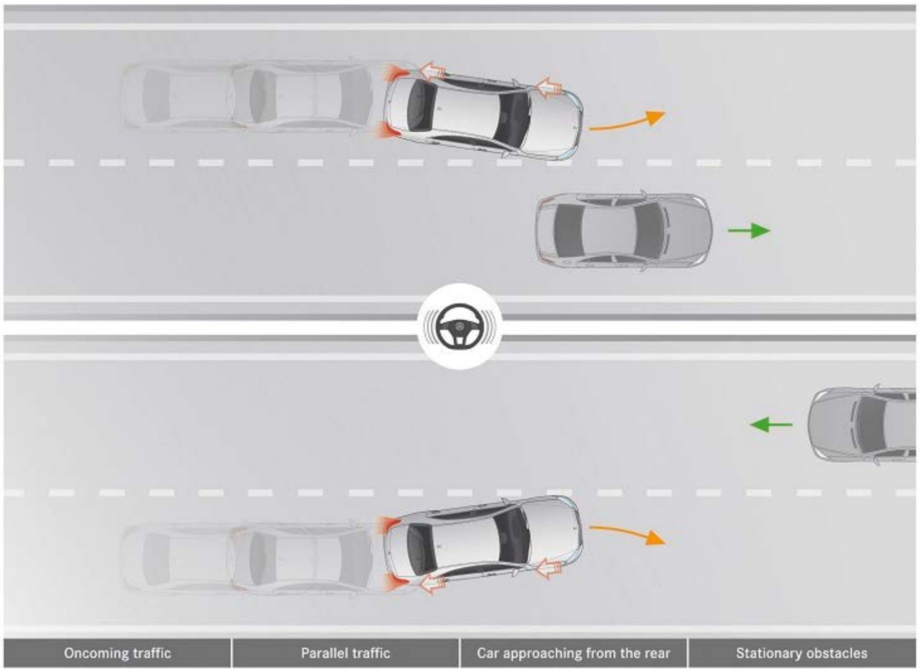


Figure 1. Lane-Keeping Assistant System Maintaining Vehicle Position in Lane (“Lane Keeping Assist: Always on the Right Track,” 2014)

2.2.1.2 Lane Changing

Lane-changing systems warn drivers of the presence of traffic in the target lane, where the target lane is indicated through turn signals or the driver actively changing lanes. This feature uses short-range radar sensors commonly located in the front and rear bumpers that monitor the zones to the sides and rear of the car. If the system detects a vehicle alongside the car in the blind spot area, it will display a warning symbol in or near the associated side mirror. If the driver ignores the warning and signals a lane change, further alerts and warnings are given inside the car. This system operates in high speeds and typically is not used in heavy inner-city traffic since the system would provide too frequent a warning. These systems are also known as *blind spot detection* systems (“2014 Cadenza Features &

Specs," 2014; "2014 Lincoln MKS," 2014; "Equipment highlights of the new Audi A8," 2015; "Leading through Innovation," 2014; "2014 LS Features - Safety," 2014; "2014 Q70 Features," 2014; "2014 Taurus Features," 2014; "2014 XTS Sedan Trims & Specifications," 2014; "2015 K900 Features & Specs," 2015; "2015 Volvo V60 Features & Options," 2015; "Driver Assistance. Drive smarter, safer and with confidence.," 2014; Ayapana, 2013; Boeriu, 2014; Boeriu, 2013; Lieberman, 2013; Timmins, 2012; Tingwall, 2014; Udy, 2014).

2.2.2 Forward Movement

Several CVHA systems also support the vehicle's forward motion. These systems have the potential to significantly impact car-following and lane-changing characteristics, as they provide distance headway-control and brake-assist functions.

2.2.2.1 Adaptive Cruise Control

Adaptive cruise control monitors traffic ahead of the vehicle through radar or laser sensors and cameras, detects any vehicles in the same lane, and calculates and maintains the distance and speed of the vehicle relative to the leading vehicle. The driver can set the desired following distances and maximum speeds of the vehicle, as shown in Figure 2. When the vehicle approaches a slower vehicle ahead or when another vehicle pulls in front, the system automatically slows down the vehicle and maintains the desired distance. If the required rate of deceleration exceeds 30 percent of the vehicle's maximum stopping power, visual and audible warning signals will prompt the driver to apply the brakes manually. ACC systems with laser sensors are typically lower in cost but have difficulty with adverse weather and non-reflective vehicles. ACC systems with radar sensors are typically higher in cost but overcome the laser sensors' drawbacks and can be hidden behind plastic. Most vehicle manufacturers offer ACC in their higher end vehicles (see Table 1) ("2014 Cadenza Features & Specs," 2014; "2014 Lincoln MKS," 2014; "Equipment highlights of the new Audi A8," 2015; "Leading through Innovation," 2014; "2014 LS Features - Safety," 2014; "2014 Q70 Features," 2014; "2014 RLX Features," 2014; "2014 Taurus Features," 2014; "2014 XTS Sedan Trims & Specifications," 2014; "2015 K900 Features & Specs," 2015; "2015 Volvo V60 Features & Options," 2015; "Driver Assistance. Drive smarter, safer and with confidence.," 2014; Ayapana, 2013; Boeriu, 2014; Boeriu, 2013; Lieberman, 2013; Timmins, 2012; Tingwall, 2014; Udy, 2014).

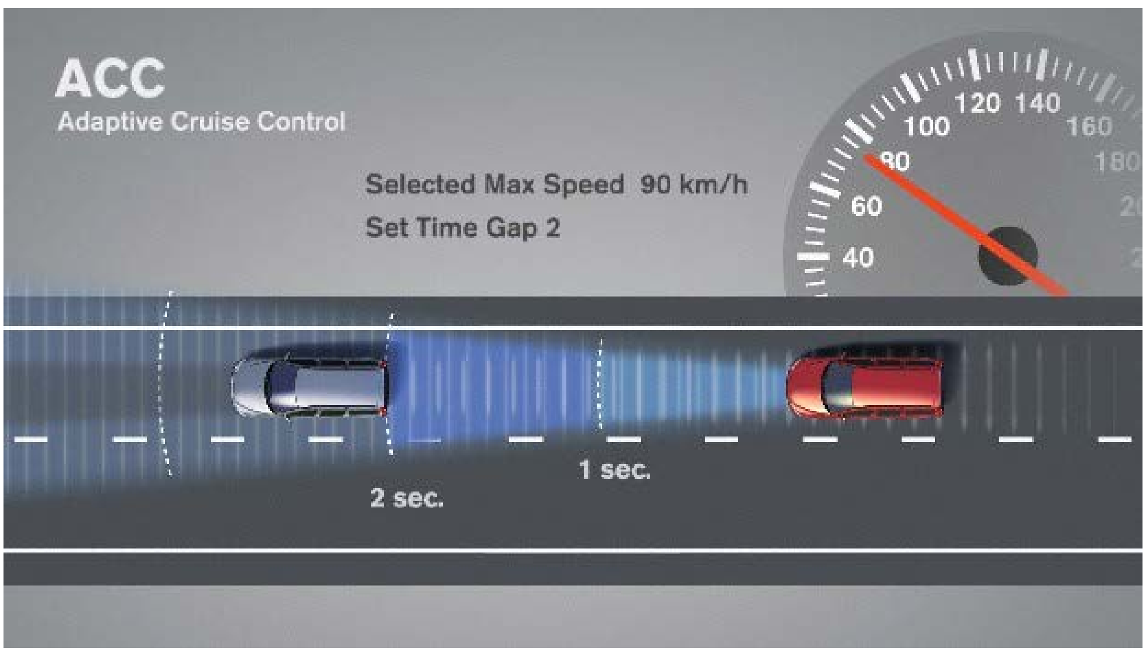


Figure 2. Adaptive Cruise Control Showing Selected Maximum Speed and Time Gap Setting (Johnson, 2012)

2.2.2.2 Front Cross-Traffic Monitoring

Front cross-traffic monitoring systems use cameras and a color display screen to minimize danger of collisions when approaching crossings or T-intersections. If the system detects a risk of collision, it boosts the braking power applied by the driver until it is sufficient to prevent a crash or reduce the amount of damage (i.e., see Section 2.2.4 Crash Avoidance/Severity Reduction). This feature is currently offered only by Mercedes-Benz (Ayapana, 2013; "Leading through Innovation," 2014; Lieberman, 2013).

2.2.3 Reverse Movement

There are two types of CVHA systems that aid the vehicle's reverse movement: (1*) rear view camera* and (2) *rear cross-traffic monitoring.*

Available in most vehicle makes ("2014 Cadenza Features & Specs," 2014; "2014 Lincoln MKS," 2014; "Equipment highlights of the new Audi A8," 2015; "Leading through Innovation," 2014; "2014 Q70 Features," 2014; "2014 RLX Features," 2014; "2014 Taurus Features," 2014; "2014 XTS Sedan Trims & Specifications," 2014; "2015 K900 Features & Specs," 2015), the *rear view camera* provides the driver with a camera view of the area behind the vehicle, which is activated as soon as the driver engages the reverse gear. This technology alone does not provide any automated braking or steering. The *rear cross-traffic monitoring* system uses cameras and a color display screen to minimize danger of collisions when performing a reverse movement, much like the *front cross-traffic monitoring* system ("2014 Cadenza Features & Specs," 2014; "2014 Lincoln MKS," 2014; "Leading through Innovation," 2014; "2014 LS Features - Safety," 2014; "2014 Q70 Features," 2014; "2014 Taurus Features," 2014; "2014 XTS Sedan Trims & Specifications," 2014; "2015 K900 Features & Specs," 2015; "2015 Volvo V60 Features & Options," 2015; Udy, 2014). The two functions may exist separately or work together to provide a more comprehensive system.

2.2.4 Crash Avoidance/Severity Reduction

These systems recognize imminent incidents through the use of cameras and on-board sensors, and alert the driver and/or control the vehicle to allow for crash avoidance or reduction in crash severity. There are three types of such crash avoidance/severity reduction systems: (1) *forward collision warning* (FCW), (2) *brake assistant*, and (3) *active protection* system.

The *forward collision warning* system detects potential crashes and warns the driver without active intervention. The *brake assistant* takes the same information obtained for the FCW system and applies the appropriate braking force to lessen impact severity or potentially enable the driver to avoid the collision. This system can also work in conjunction with a *cross-traffic monitoring* system. The *active protection* system works together with the FCW and *brake assistant* systems. When an emergency stop is performed or if a crash is imminent, the system prepares the vehicle by closing its windows and sunroof, tightening seatbelts, and placing seats upright. At least one of these three crash avoidance systems is available in most vehicle makes (see Table 1) ("2014 Cadenza Features & Specs," 2014; "2014 Lincoln MKS," 2014; "Equipment highlights of the new Audi A8," 2015; "Leading through Innovation," 2014; "2014 LS Features - Safety," 2014; "2014 Q70 Features," 2014; "2014 RLX Features," 2014; "2014 Taurus Features," 2014; "2014 XTS Sedan Trims & Specifications," 2014; "2015 K900 Features & Specs," 2015; "2015 Volvo V60 Features & Options," 2015; "Driver Assistance. Drive smarter, safer and with confidence.," 2014; Ayapana, 2013; Boeriu, 2014; Boeriu, 2013; Lieberman, 2013; Timmins, 2012; Tingwall, 2014; Udy, 2014).

2.2.5 Parking

These systems assist the driver in performing the parking task and are generally activated when the driver engages the reverse gear and when the vehicle speed is below 10 miles per hour. There are generally two system types: (1) a *parking space finder* that uses radar sensors and cameras to aid in searching adjacent areas for adequate parking spaces ("2014 Cadenza Features & Specs," 2014; "2014 LS Features - Safety," 2014; "2015 K900 Features & Specs," 2015); and (2) the *active parking assistant* that aids in the search for a parking space, as well as automatically parking the vehicle (Figure 3). The *active parking assistant* system also differs slightly between vehicle manufacturers; some systems are equipped to fully park the vehicle without any driver input while other systems automate only the steering wheel but require the driver to control gear-shifting, accelerating, and braking ("2014 Cadenza Features & Specs," 2014; "2014 Lincoln MKS," 2014; "Equipment highlights of the new Audi A8," 2015; "Leading through Innovation," 2014; "2014 LS Features - Safety," 2014; "2014 Q70 Features," 2014; "2014 RLX Features," 2014; "2014 Taurus Features," 2014; "2014 XTS Sedan Trims & Specifications," 2014; "2015 K900 Features & Specs," 2015; "Driver Assistance. Drive smarter, safer and with confidence.," 2014).

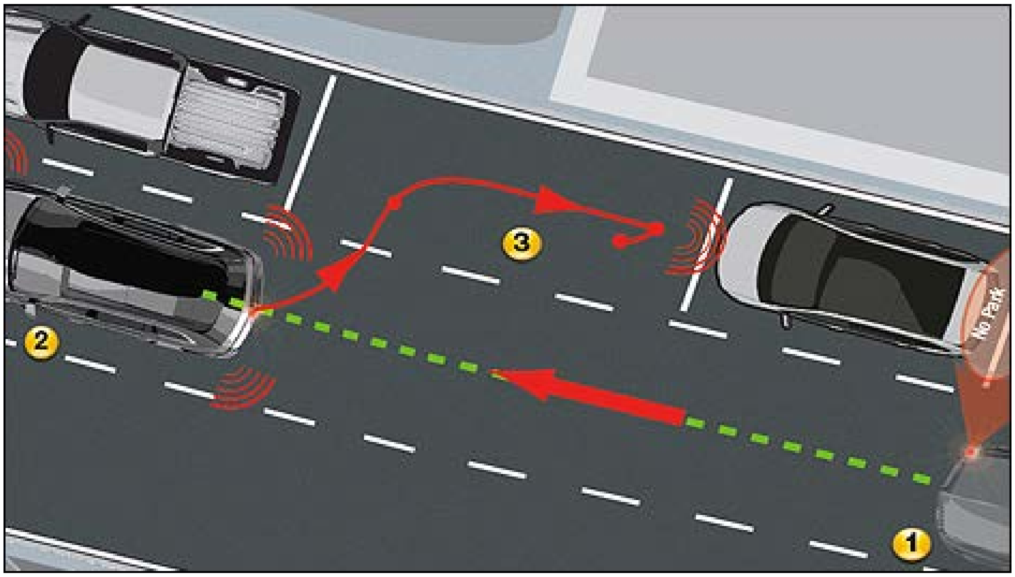


Figure 3. Ford's Active Park Assist ("Ford's New Active Park Assist Aims to Curb Stress," 2009)

2.2.6 Attention Monitoring

These systems monitor driver attention through facial analysis. They detect specific prolonged facial features that may suggest driver fatigue (such as closed eyes or not looking forward), as well as certain steering behaviors that suggest the onset of drowsiness. These systems are designed to consider several of these factors and conclude whether the potential for driver fatigue exists. If the system determines that the driver is fatigued, an alert is displayed that encourages the driver to stop for a rest. Currently BMW, Volvo, Mercedes-Benz, and Lexus offer this driving feature ("Leading through Innovation," 2014; "Driver Assistance. Drive smarter, safer and with confidence.," 2014; "2014 LS Features - Safety," 2014; "2015 Volvo V60 Features & Options," 2015).

2.2.7 Congestion Assistant

These systems are very similar to the ACC system but are designed to operate during congested conditions. Like the ACC system, *congestion assistant* systems monitor traffic ahead and calculate the distance and speed relative to the leading vehicle. These systems relieve drivers from the task of congestion driving and take control of the vehicle's braking, acceleration, and lane-keeping tasks. Several manufacturers require the driver to have a hand on the steering wheel, while others require no touch at all from the driver. These systems are beginning to enter the market with BMW and Mercedes-Benz as forerunners, and they are expected to reduce congestion, increase throughput, and improve safety (Ayapana, 2013; Boeriu, 2013, 2014; "Ford Develops 'Traffic Jam Assist' and New Parking Technology to Help Address Future Mobility Challenges," 2012; Hammerschmidt, 2012; Lieberman, 2013; Max, 2012; Miersma, 2014; Stertz, 2012; Timmins, 2012). Figure 4 shows an Audi dashboard interface when congestion assistant is active.

Figure 4. Audi's Traffic Jam Assistant Interface
("Audi Traffic Jam Assistant Photos," 2014)

2.2.8 Summary of CVHA Technology

Table 1 summarizes the available CVHA technologies that currently exist. While this table is not exhaustive, and new systems are constantly entering the market, it does provide conceptually many of the existing systems. It is also clear that driving characteristics are rapidly changing and there exists a need to evaluate the impacts on the aggregate performance of the transportation system.

2.2.9 Full Automation

Researchers have studied the topic of autonomous vehicles extensively all over the world. Shladover (2012a) summarized the European CVHA research in two different approaches: one emphasizes partial automation systems in mixed traffic, and the other emphasizes driverless settings in dedicated roadway infrastructure. LIVIC, a research laboratory in France, has been exploring vehicle automation and interactions with human drivers for more than 10 years. Germany's research on vehicle automation is driven primarily by the automotive original equipment manufacturers (OEMs). The OEMS have taken the leadership role in vehicle innovation with the initial aim to promote their competitiveness in the high-end automotive market. As a result, Germany's research on CVHA is more inclined to developing vehicle systems rather than infrastructure systems.

The SARTRE project (Bergenhem, C.; Hedin, E.; Skarin, 2012), led by the United Kingdom and sponsored by the European Commission, was highly ambitious in the level of automation at the time. The project implemented an experiment with close-formation automated vehicle platoons under mixed-traffic environments, with the objective of enhancing lane capacity and reducing energy consumption. The platoon forms on a manually driven leading truck, followed closely by a fleet of automated vehicles. A safety concern in this approach is the platoon being highly dependent on the behavior of the leading truck. For each individual vehicle in the platoon, the lateral movement of entering or leaving the platoon is steered manually by the human driver, while the longitudinal movement of following the lead truck is automated with the help of a comprehensive suite of sensor systems.

Another project (Hoeger, R.; Amditis, A.; Kunert, M.; Hoess, A.; Flemish, F.; Krueger, H., Bartels, A.; Beutner, 2008) sponsored by the European Commission is HAVEit. This project developed an experiment scenario for four levels of automation and driver–vehicle interaction, ranging from full manual control to highly automated systems with longitudinal and lateral automated control. This project incorporated test vehicles with the existing commercial sensors and driving assistance systems in 2008 to collect test-drive data. A driving simulator study also tested human drivers' interactions with the four levels of automation. SMART 64, which aims to investigate the strategies and challenges of vehicle automation systems, has described such automation concepts under three kinds of road environments.

The KONVOI project (Wille, M.; Röwenstrunk, M.; Debus, 2008) conducted in Germany examined the impacts of a truck-platooning system on traffic flow and energy consumption under a public, mixed-traffic environment. The platoon formation of this project was somewhat similar to the SARTRE project, in which the leading truck was manually driven with a driver-assistance system. An automated system controlled the following trucks, although control could be taken over by a human driver in case of failure or emergency. As a measure of safety, the following trucks would perform hard braking if other vehicles attempted to pull in front of the truck. The results in this project showed some energy savings when the experiment was conducted on the test track. However, due to the disturbances from other vehicles to the traffic dynamics of the platoon, the study showed no energy savings when tested on the public highway. According to the summary of Shladover's report (2012a), "The minimum allowable gap between trucks was set at 10 m (33 ft) based on analyses of the effects of cut-ins at highway entrance ramps, where hard braking of the following truck could be required." When testing against emergency braking maneuvers with the first truck decelerating at 0.7 g (22.5 ft/s^2), the second truck would close the gap from 33 ft to 16 ft but avoid the crash. Through that study, it is realized that successfully mixing the truck platoon with manual traffic will be imperative for efficient and stable traffic. As stated in the report, "The traffic dynamics generated by all the other vehicles imposed disturbances on the truck platoon that prevented it from smoothing out its driving profile enough to actually save significant fuel. The cut-ins required expanding and contracting the gaps within the platoon, by decelerating and then accelerating, subsequently interrupting constant-speed cruising."

2.3 CVHA FIELD TESTS & EXPERIMENTS

Several field tests and experiments have been performed in the past to evaluate the use of CVHA technology on vehicles and drivers. The results of these studies have shown promise, and a few examples are discussed in further detail.

2.3.1 Adaptive Cruise Control

In 1998, Fancher et al. performed a field operational test on ACC technology. A fleet of 10 passenger cars was equipped with ACC and given to 108 volunteer drivers to use as their personal cars for two or five weeks. The central finding was that ACC was remarkably attractive to most drivers. Participants frequently utilized the system over a broad range of conditions and adopted tactics that prolonged the time span of each continuous engagement. Moreover, participants were completely successful at operating the ACC over some 35,000 miles of system engagement. However, Fancher et al. also observed that there were subtle issues relating to the shared-control nature of ACC driving (i.e., where drivers still need to have steering control while the ACC controls speed and headway) whose long-term safety and traffic implications were not yet known (Fancher et al., 1998).

2.3.2 Forward Collision Warning

In 2011, Forkenbrock et al. examined how distracted drivers respond to forward collision warning alerts in a crash-imminent scenario. A diverse sample of 64 drivers was recruited to participate. The researchers asked each participant to follow a moving leading vehicle within the confines of a controlled test course and, while attempting to maintain a constant headway, to perform a series of four tasks intended to divert his or her attention briefly away from a forward-viewing position. With the participant fully distracted during the final task, the leading vehicle was abruptly steered out of the travel lane, revealing a stationary vehicle in the participant's immediate path (a realistic-looking full-size balloon car). At a time to collision of 2.1 seconds from the stationary vehicle, the participant was presented with one out of eight FCW alerts. The results found that the haptic seat belt alert elicited the most effective crash avoidance performance. Other FCW alerts included a visual-only alert; an auditory-only alert; combinations of visual, auditory, and/or haptic seat belt alerts; as well as a no-alert reference scenario (Forkenbrock et al., 2011).

2.3.3 Cooperative Adaptive Cruise Control

In 2010, a study was performed by the University of California at Berkeley to evaluate drivers' choices of following distances while operating a vehicle with cooperative ACC (CACC). The CACC system, an enhancement to the already existing ACC system, further enabled by wireless V2V communication, was installed on two test vehicles. The results show that drivers of the CACC selected vehicle-following gaps that were approximately half of the length of the gaps they selected when driving the ACC system; the latter gaps were comparable to vehicle-following gaps in congested highway driving. The study also found that male drivers were more likely to choose shorter gaps in both ACC and CACC driving. In both cases, the likelihood of drivers choosing shorter gaps will contribute to highway lane-capacity increases (Nowakowski, Shladover, & Cody, 2010). A similar study in 2014 also found that the use of CACC resulted in reduced gap variability, indicating the potential for CACC to attenuate disturbances, improve highway capacity, and improve traffic flow stability (Milanés et al., 2014).

From these studies, different vehicle-following gaps are seen between CACC and ACC. Drivers' willingness to travel shorter time gaps with CACC is expected to increase throughput. However, a potential negative implication is that shorter time gaps may reduce time for corrective actions due to poor judgment (Jones, 2013). In the Atlanta context, existing vehicle-following gaps are already short and it would be interesting to see whether these gaps can be made uniform across all vehicles (thereby improving traffic throughput), and/or if drivers would choose even shorter gaps.

2.3.4 Parking Assist Technologies

In 2010, Reimer et al. evaluated driver reactions to new vehicle parking assist technologies developed to reduce driver stress. Their study used heart rate as an objective physiological arousal measure, along with more traditional self-reported ratings to evaluate the extent to which two particular technologies (i.e., active park assist [APA] and cross traffic alert [CTA]) impact driver stress levels. After becoming familiar with the technology, participants rated their stress levels significantly lower when using APA, and recordings of heart rates provided confirmation of a lower state of stress. Mean self-report and heart-rate data suggested some reduction in stress levels with CTA, as well, though these differences were not statistically significant. Overall, the general rating of APA and CTA were positive with 76.1 percent of participants stating that the system makes it easier to park (Reimer, Mehler, & Coughlin, 2010).

2.4 DRIVER SIMULATOR STUDIES

As technology continues to push toward more complex assistance and automation, there is a challenge, a risk, and a chance for human factors to either contribute to, or help to handle, the complexity of tomorrow (Flemisch, Kelsch, Löper, Schieben, & Schindler, 2008). Consequently, extensive research has been done using driver simulators to understand the interaction between humans and machines in the area of vehicle automation. A number of studies have used driver simulators simply as a tool to find the most effective combination of driver alerts. Other studies have used driver simulators to gauge the impacts that vehicle automation will have on driver acceptance and performance.

2.4.1 Driver Acceptance

As stated in a 2005 study by Biester and Bosch (Biester & Bosch, 2005), the interaction between human and machine will change fundamentally within the next decades. The technological sophistication and complexity of systems in the intelligent transportation sector is increasing, propelling the need for further understanding of driver acceptance of such technologies. An understanding of driver acceptance will inform the collective knowledge regarding driver and machine interactions, as well as the assumptions about the market penetration rates of future CVHA technology.

Flemisch et al. (2008a) were among the first to point out that while assistance and automation can have benefits, such as improved safety or lower driver workload, they may also come with challenges regarding the interplay between the driver and the technology. In their evaluation of different human–vehicle interfaces for assistance and automation, Flemisch et al. found that the haptic design of the interface was well accepted as useful, easy to understand, safe, and pleasant compared to manual driving. Forkenbrock et al. (2011) found the same result in their field experiment of forward collision warning, and Flemisch et al. (2008a) also found a high acceptance of the fully automated condition.

Similar positive findings about driver acceptance were found by Biester and Bosch (Biester & Bosch, 2005). They conducted a driving simulator experiment in which the driver had to perform several standardized overtaking maneuvers on a two-lane German highway, either manually, cooperatively, semi-automatic, or fully automatic in a between-subjects design. In terms of cooperative automation in vehicles, the participants indicated that they accepted the general concept, though no extremely positive feedback was received. Compared to manual, semi-automatic, and fully automatic driving, participants indicated that they were most aware of the situation and most trusting of cooperative driving—a finding similar to that of Flemisch et al. (2008a).

Encouragingly, positive results can be found with not only ACC systems but with other CVHA systems, as well. Brookhuis et al. (2009) and Van Driel et al. (2007) found in their driver simulator experiments of a congestion assistant prototype that participant acceptance levels were generally positive of the system. Reimer et al. (Reimer et al., 2010) likewise found that participants had positive outlooks on parking-assist technologies.

While most studies have found clear positive results on driver acceptance of CVHA technology, Eriksson et al. (2013) did not have such straightforward findings. They investigated, using a driver simulator experiment, whether drivers more readily accepted either rumble strips or a lane-departure warning system in unintentional lane departures. The results indicated that while participants showed more satisfaction from using the LDW, they also showed more trust in the rumble strips. An interesting finding in this study was that about 25 percent of participants thought it would be good to present both types of warning in parallel, suggesting that they prefer a combination of visual, auditory, and haptic alerts—a finding that was also observed in other studies (Flemisch, Kelsch, Loper, et al., 2008b; Forkenbrock et al., 2011).

2.4.2 Mental Workload

An understanding of the impacts of CVHA technology on the mental workload of drivers is also critical to ultimately successful implementation. The majority of studies done in this area using driving simulators has consistently shown decreases in the mental workload of participants when using some type of CVHA technology. In a study that evaluated participant stress levels when utilizing an active park assistant, Reimer et al. (2010) found that heart rate readings decreased significantly when using the CVHA, confirming a lower state of stress. In another study that evaluated driver mental workload and acceptance when driving with a congestion assistant prototype, Brookhuis et al. (2009) found that participants' mental workload with the CVHA system was lower when driving in congestion but higher in the approach phase toward the congestion. This suggests that increasing familiarity and trust of the technology could reduce the latter finding as well, through a higher level of automation that also takes control of driving in the approach to congestion. This is suggested by Flemisch et al. (2008b) where they found that the effort that participants reported (i.e., workload) decreases with higher automation levels. In conditions of manual and assisted driving, the mental demand of the driving task in combination with secondary tasks is relatively high in comparison to fully automated driving.

2.4.3 Driver Performance

One Swedish study attempted to evaluate driver performance using a driver simulator. In their study involving lane-departure warning systems and rumble strips, Eriksson et al. (2013) collected four measures to evaluate driver performance: (1*) response completion time*—the time from when warning was given to the completion of a response maneuver; (2) *time to back in lane*—the time from when warning was given to when all wheels are back in the lane; (3) *lane exceedance area*—the amount of road surface exceeded from the driving lane; and (4) *standard deviation of lateral lane position*. The study yielded some mixed results: the mean response completion time was longer for participants driving with

LDW than for participants driving with only roadway rumble strips, while the remaining three measures were not significantly different between driver groups. Ultimately, the authors found no major overall differences in driving performance between the uses of LDW and rumble strips, and that more research is needed in this area for an improved understanding.

2.5 MICROSCOPIC SIMULATION STUDIES

The most current tool in modeling and evaluating traffic flow and operations is the microscopic traffic simulation model. However, current traffic simulation software is based on algorithms that were not designed to address most CVHA technologies. To properly analyze the traffic impacts of these systems, changes and additions to existing simulation models have to be implemented to incorporate the elements of driver behavior and CVHA systems design that could affect traffic flow dynamics (Elefteriadou et al., 2011).

This section discusses work that has been conducted previously to evaluate the impacts of CVHA systems on traffic flow and safety using traffic simulation models. Most of the research undertaken using microscopic simulation models has been on ACC and has focused on analyzing its impact on traffic flow. However, as advancements in the automated vehicle technology occur, research has begun to explore other technologies and applications.

2.5.1 Adaptive Cruise Control

In 1999, Minderhoud & Bovy conducted a simulation study to assess the impacts of intelligent cruise control (ICC), an early ACC prototype, on roadway capacity. They investigated 10 different ICC designs and compared those to a base without-ICC reference, and studied several penetration rates. Capacity gains of 4 percent were found to be possible at a headway setting of 1.0 second, while no significant changes were observed for any of the ICC designs at a headway setting of 1.2 seconds. In that study, headway setting had a large impact on roadway capacity, especially at penetration rates above 20 percent.

Continuing on the work performed in that study, Hoogendoorn & Minderhoud (2001; 2002) conducted further studies in the early 2000s. One of the CVHA systems studied was autonomous intelligent cruise control (AICC), another early ACC prototype. They found similar results in that AICC had positive effects on bottleneck capacity at all penetration rates and bottleneck layouts. However, the extent of the improvements and the optimal penetration level were dependent on the considered bottleneck layout. This study likewise found that headway setting was an important factor in evaluating impacts on roadway capacity.

Wang and Rajamani (2004) specifically evaluated the importance of headway settings with respect to capacity impacts of ACC vehicles. They focused on a common ACC systems design characteristic where a constant time-gap is maintained between vehicles. However, they developed in their study a new inter-vehicle spacing policy in which the inter-vehicle spacing is a nonlinear function of vehicle speed. This new *variable time-gap policy* was shown through traffic simulations to lead to improved traffic flow and an increased highway capacity.

In 2007, Kesting et al. (Kesting, Treiber, Schönhof, & Helbing, 2007; Kesting, Treiber, Schonhof, Kranke, & Helbing, 2007) found additional positive results with the use of ACC. At penetration rates as low as 10 percent, the maximum travel-time delay of individual drivers can be reduced by about 30 percent and the cumulated time delay by 50 percent. The ACC vehicles also significantly reduced the maximum queue length. Ultimately, their study showed that even at small penetration rates, there was a marginal increase in free and dynamic capacity leading to a drastic reduction of traffic congestion, a finding that supports those of Minderhoud & Bovy (1999), and Hoogendoorn & Minderhoud (2001; 2002).

However, not all evaluations of ACC have yielded positive results. Shladover et al. (2012) used AIMSUN as a simulation tool to model ACC and estimate its effect on highway capacity with varying market penetration rates. Their results show that conventional ACC is unlikely to produce any significant change in highway capacity because drivers are only comfortable with the ACC system at gap settings similar to the gaps they choose when driving manually. Similarly, Davis (2004) found that at high speeds, congestion occurs for penetration rates of 10 percent or less. Positive impacts are only found starting at a 20 percent penetration rate, while a 50 percent rate only yields modestly reduced travel times and larger flow rates. Finally, Elefteriadou et al. (2011) also concluded that ACC could significantly increase speeds for congested conditions even at a market penetration rate of 20 percent, but that bottlenecks can be created at locations where a significant number of drivers are likely to turn their ACC off.

While more studies are needed to determine the optimal headway/gap settings, based on the available studies the potential benefits of ACC appear to be more definite at higher market penetration rates.

2.5.2 Congestion Assistant

A few researchers have looked also at evaluating a technology similar to ACC for use during congested conditions: the *congestion assistant* or *traffic jam assistant*. As early as 1999, Minderhoud & Bovy included a special stop-and-go design in their study of the impact of intelligent cruise control. However, they found this design not to improve the traffic-flow quality. Extensive work on a congestion assistant prototype has been done by Van Driel and Van Arem (Van Driel & Van Arem, 2008; Van Driel, 2007). In those studies, they adopted the ITS Modeler as a traffic simulation tool and modeled a congestion assistant system consisting of a stop-and-go feature and an active pedal system that supports the braking process during the approach to congestion. Several different combinations of the congestion assistant were implemented, differing in headway settings and distance-to-congestion settings. These were assessed in a four-lane roadway segment with a left lane drop scenario. Results showed that the average delay time could be reduced by 30 percent with a 10 percent penetration rate and up to 60 percent with a 50 percent penetration rate. The stop-and-go function was found to increase hard braking due to its shorter time gaps, but the active pedal function reduced the amount of hard braking in the approach of congestion, thereby making a safer transition to congested driving.

2.5.3 Vehicle-to-Vehicle and Vehicle-to-Infrastructure Communications

CVHA technologies are not only sensor-based technologies; they can also be supported by V2V and V2I technology (Shladover, 2008). To optimize and achieve full vehicle automation, connectivity needs to be achieved between vehicles as well as with infrastructure. The convergence of communication- and sensor-based technologies has the potential to obtain better safety, mobility, and self-driving capabilities than either technology could achieve on its own (Silberg et al., 2012). The following subsections review some of the simulation research undertaken to evaluate V2V- and V2I-supported CVHA systems.

2.5.3.1 V2V-supported CVHA

While many CVHA systems can be enhanced with use of V2V communication, most studies that have been performed on V2V-supported CVHA have been undertaken on cooperative adaptive cruise control—an enhancement of the ACC system by which vehicles are enabled to wirelessly communicate with other vehicles.

2.5.3.1.1 Cooperative Adaptive Cruise Control

Researchers have found mixed results regarding CACC. Using MIXIC as their simulation software, Alkim et al. (2000) found that after the introduction of CACC, the speed variance of vehicles in one lane and the speed difference between lanes were decreased—a finding that is also supported by Wang et al. (2014). However, Alkim et al. also found that roadway capacity decreased as CACC penetration rates were decreased, which contradicts the expectation that roadway capacity would be improved when vehicles use shorter, more uniform headways. However, it was unclear whether this finding was a result of CACC or a limitation of the mandatory lane-change model of MIXIC. Similar findings were found by Van Arem et al. (2006) in their MIXIC evaluation of CACC. Although their results also indicated that CACC has the ability to improve traffic flow, the extent of improvement depends heavily on the specific traffic flow conditions and the CACC penetration rate.

They concluded that the introduction of CACC is unlikely to produce enhancements to highway capacity.

In contrast, Shladover et al. (2012) found that CACC could substantially increase highway capacity when it reaches a moderate to high market penetration rate. Their effort assumed that the higher dynamic response capabilities would give drivers confidence that they could follow safely at shorter gap settings. They found that the maximum lane capacity at full penetration of CACC could be increased to 4000 vehicles per hour. In addition, the capacity benefits of CACC can be accelerated, or obtained at somewhat lower market penetrations, if the rest of the non-CACC vehicle population are equipped with vehicle awareness devices (VADs), allowing them to serve as lead vehicles for CACC following vehicles. A VAD is a device that provides basic GPS coordinates, vehicle speeds, and heading information.

Other studies have shown that capacity benefits from CACC can be obtained when the system is applied during specific situations. For example, a specific application of CACC used in merging situations (i.e., 'cooperative merging') has been found to improve throughput and increase distance traveled in a fixed time (Davis, 2007). Davis found that if an on-ramp demand is moderate, cooperative merging produces significant improvement in throughput (e.g., 20 percent) and increases up to 3.6 km in distance traveled per 600 seconds for a 50 percent penetration rate. Similarly, when CACC vehicles were given priority access to HOV lanes, Arnaout and Bowling (2014) found that highway capacity could be significantly improved with a penetration rate of as low as 20 percent.

To obtain the desired benefits from such a system, Calvert et al. (2012) investigated what the theoretical optimum headway setting would be for a CACC system. They found that 0.9 second is the optimum number, although the default setting of the CACC system they modeled was 1.2 seconds. Comparison of the network performance between the two time headways shows a large improvement for intermediate CACC penetration rates of 50 and 75 percent. At 100 percent penetration, the default setting seemed to have resolved all congestion and, hence, further improvement was not possible.

2.5.3.1.2 Other V2V Applications

With recent advancements in vehicle positioning and wireless communication technologies, such as the increasing availability of real-time traffic information, many opportunities to develop more sophisticated traffic control and information strategies are present. For instance, when an upstream incident occurs, drivers could have the potential to obtain travel-time information that uses the distance from their current location to the incident location and, thus, recognize that their future travel plans are controllable. To this goal, Yeo et al. (2010) proposed a V2V hazard alert system and showed that the deployment of such a system has the potential to mitigate traffic congestion with higher penetration rates if it can provide lane-specific information. The feasibility of this concept was further explored by Rim et al. (2011) wherein they proposed a methodology for estimating lane-level travel times. Their analysis showed that a 6 to 8 percent error rate is achievable with at least a 20 percent market penetration rate for a representative section's travel time, showing great potential for this particular application of V2V communications.

All these potential enhancements to the transportation system do come with limitations, however. Proposed systems rely on either onboard range sensors or V2V communications to obtain pertinent information about surrounding vehicles and to decide on appropriate acceleration or deceleration commands, and a critical element that has been ignored in the study of these innovations is delay in data acquisition. Liu et al. (2006) attempted to quantify the safety effects created by this delay through the use of traffic simulation. Their results indicated that this delay can affect the operation of these CVHA systems, particularly when delays result in the use of information older than a certain threshold, found in this case to be 0.5 second.

2.5.3.2 V2I-supported CVHA

Research also has shown the great potential of V2I systems in not only improving traffic conditions and safety, but also positively influencing emissions and other environmental concerns.

In 1999, Hogema evaluated an early model of ACC combined with roadside-vehicle communication in MIXIC. The roadside system was designed to perform a homogenizing function; that is, when traffic volume increases and speed decreases, the beacon starts to influence traffic upstream to try to create a homogeneous, steady traffic stream. This system should prevent a breakdown in traffic for as long as possible. The study found that as the penetration level of V2I-equipped vehicles and roadside systems increases, traffic could become safer and smoother through decreases of the mean speed, speed standard deviation, and percentage of critical time to collisions.

Another investigation of V2I systems with positive results was conducted by Lee et al. (2011). They defined V2I systems as cooperative vehicle infrastructure systems (CVIS), and their goal was to investigate the safety aspects of a CVIS-based urban traffic control system. They performed a simulation-based case study on a hypothetical arterial consisting of four intersections with four traffic congestion cases covering high- to low-volume conditions. When compared to coordinated actuated control, the CVIS control dramatically improved the urban corridor, where between 92 and 100 percent of delay time reductions were estimated for the volume of cases tested. However, taking into consideration that these improvements were obtained by ensuring high-speed crossing at intersections, the CVIS control would likely result in more dangerous situations as indicated by the reduction of the average time to collision (TTC) and post-encroachment time (PET) by 0.69 and 1.94 seconds, respectively. Nonetheless, the CVIS control reduced the frequency of such dangerous situations where the number of rear-end conflict events was decreased by 58 percent under the CVIS-based control, indicating safer driving conditions.

Finally, Wu et al. (2010) discovered through modeling in PARAMICS that V2I systems could also reduce vehicle fuel consumption and CO_2 emissions by up to 40 percent. They tested two types of V2I systems: (1) a stationary system based on roadside infrastructure, such as changeable message signs (CMSs), and (2) an in-vehicle system much like a V2I-supported CVHA system. Simulation results showed that the in-vehicle system offered greater benefits in terms of fuel consumption and emissions in most of their tested cases.

Although there is great potential in V2I systems as shown through these studies, these proposed systems would be affected by the quality of wireless communications (Lee et al., 2011; Y. Liu et al., 2006). Thus, the aspect of communication must be incorporated in future research for a more realistic assessment of benefits.

2.5.4 Speed Limiters

Speed limiters have also received some attention in the academic world with their potential to control maximum speeds of vehicles so equipped, and the results have been positive. Simulation-based evaluations of speed limiters have shown their potential at reducing average traffic speeds, suppressing momentary high speeds in traffic, and reducing speed variation, which in turn is likely to have a beneficial impact on safety (Liu & Tate, 2004; Toledo et al., 2007). Additionally, while speed limiters reduced excessive traffic speeds, the researchers found that they did not affect average journey times. In particular, Liu and Tate (2004) found that the total vehicle-hours travelling at speeds below 10 km (6.2 mph) per hour were not changed, indicating that the speed control did not induce more slow-moving queues to the network. A statistically significant reduction in fuel consumption also was found with 100 percent speed limiter market penetration (Liu & Tate, 2004).

2.6 CONCLUSIONS

There are several CVHA systems already available, particularly in high-end vehicles, by several manufacturers. While these systems have significant potential to reduce driver stress, alleviate congestion, and improve traffic safety, it is not clear how they will be operated on the existing infrastructure, how they will impact traffic congestion and safety, and how state DOTS and other transportation agencies should incorporate this changing vehicle and driver environment in its planning, design, and construction process.

Research has been conducted from as early as the late 1990s to gain better understanding of the public's acceptance and the potential benefits and limitations of these systems. Findings include the following:

- A number of driver simulator studies have found that participants/drivers have highly accepted these systems.
- Driver simulator studies also have found that participants' mental workloads are reduced when using these systems, especially during congestion, and they are further reduced as automation levels are increased. During approaches to congestion, however, participants' mental workload was observed to be higher when driving with a CVHA system.
- Traffic simulation studies have found mixed results with respect to the operational impacts of adaptive cruise control. However, when benefits have been observed, they are generally in both low and high market-penetration levels of ACC. More importantly, these studies have found that the potential capacity benefits are driven by the headway/gap times that the ACC-equipped vehicles are using during following conditions.
- Since cooperative adaptive cruise control enables vehicles to communicate with one another, this system has the potential to smooth traffic and lower headway/gap settings over that of ACC (although research has shown mixed results as well).
- Capacity benefits from CACC can be obtained from applying specific strategies instead of waiting for a general market penetration threshold, such as requiring CACC during merging situations (i.e., cooperative merging) and dedicating lanes for equipped vehicles (e.g., similar to HOV).

- Optimal headway/gap settings need to be determined and could be a potential area where DOTs and other transportation agencies can provide guidance and regulation.
- With the advancement of vehicle positioning and wireless communication technologies, V2V and V2I applications also show great potential in further improving traffic conditions with many opportunities to develop more sophisticated traffic control and information strategies. However, a limitation to this would be delay in data acquisition since all these proposed systems rely heavily on dependable data.

Additional study is necessary to further researchers' understanding of the impacts of CVHA technology: for instance, research to replicate and confirm previous findings that headway/gap setting is an important factor that could influence potential capacity benefits. More importantly, however, since CVHA systems are already available, studies should be conducted to determine and evaluate strategies to be implemented to optimize the benefits of these systems as they arrive. Strategies that should be evaluated include: (1) using a dedicated lane similar to an HOV lane, (2) providing regulations as to allowable headway/gap settings, and (3) providing regulations as to when and where CHVA systems should be active. Critical to all of these studies will be modeling assumptions and calibrations. The next chapters will explore these issues.

3 Simulation Development

3.1 DIFFERENCES BETWEEN CVHA AND MANUALLY DRIVEN VEHICLES

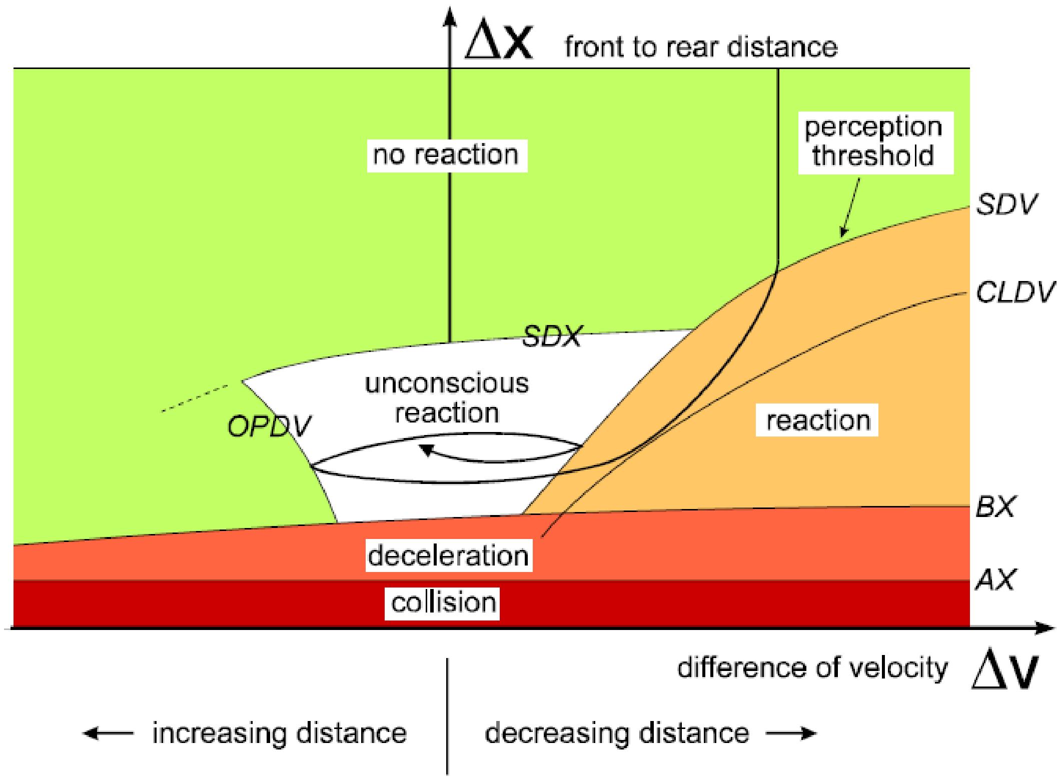
For this effort, the research focuses on how CVHA technologies may affect traffic operations, efficiency, and safety. This report also specifically highlights automated or autonomous vehicles, as this technology represents the ultimate CVHA application; the human driver is removed entirely from the CVHA vehicle while interaction is maintained with other manually driven vehicles on the roadway. Chapter 4 presents a simulation-based case study for the autonomous vehicle in such a mixed environment, built on the efforts presented in this chapter.

To prepare for the case study in Chapter 4, this chapter first considers the capabilities of commercially available models to simulate CVHA and autonomous vehicles. Commercially available microscopic traffic simulation packages employ models developed and calibrated to represent the behavior of human drivers. While many of the variables and behaviors in those models may be used without adjustment when modeling CVHA and autonomous vehicle applications, others need to be adjusted to account for the difference between these technologies and human-driver behavior. This research utilizes the VISSIM microscopic simulation model. Consequently, the traffic-flow model and parameters discussed are specific to VISSIM. However, an approach similar to that presented within this chapter could be taken with other commercially available models. This chapter begins with a description of observations and assumptions regarding the differences in driving behavior between human-driven vehicles and automated vehicles.

The chapter then presents the results of a study that determines the parameters that should be considered for calibration, to configure a VISSIM model to reflect both human-driven and automated vehicles.

3.1.1 Observations and Assumptions

The most significant aspect of a simulation influencing results is the underlying traffic-flow or car-following model. VISSIM uses the Wiedemann car-following model to simulate traffic. The basic concept of the Wiedemann car-following model, according to the VISSIM 5.20 User Manual (*PTV Vision, VISSIM 5.20 User Manual.*, 2009), is that there are four driving states: free driving, approaching, following, and braking. The driver switches from one mode to another when parameters such as driver-desired speed and safety distance reach given thresholds. These thresholds vary from one driver to another, one of the means by which VISSIM introduces stochasticity into its modeling framework. As a human driver cannot perceive the exact speed and acceleration of the lead vehicle, an oscillation between thresholds will simulate a human driver's behavior. Figure 5 shows how the current driving state of a following vehicle is determined by the relative difference in speed and distance with the lead vehicle. In this figure, the zones labeled "no reaction," "reaction," "unconscious reaction," and "deceleration" correspond to the driving states of free driving, approaching, following, and braking, respectively.



Car following logic (Wiedemann 1974)

Figure 5. Psychophysical Car-Following Model by Wiedemann (1974) (Source: VISSIM 5.20 User Manual, 2009)

3.1.1.1 Safety Distance

Two different Wiedemann car-following models, based on the concept in Figure 5, are available in VISSIM. The Wiedemann 74 model is generally suitable for urban traffic, while the Wiedemann 99 model is generally suitable for freeway traffic. As the case study in Chapter 4 concentrates on freeway operations and capacity, the Wiedemann 99 model is discussed here. Both models compute the safety distance using the following equation:

$$dx_{safe} = CC0 + CC1 * v$$

where, CC0 (standstill distance) represents the desired distance between stopped vehicles and CC1 (headway time) represents the driver-desired time gap when the vehicle is moving. The safety distance (dx_{safe}) is defined as the minimum distance a driver will keep while following another car (VISSIM 5.20 User Manual, 2009). A vehicle maintaining this safety distance is in the car-following driving state. When the distance between the leading and following vehicles drops below this value, the following vehicle will go into the "braking" driving state. The higher the value of CC0 and CC1, the more conservatively a driver reacts to the lead vehicle. The safety distance (and thus CC0 and CC1) tend to be critical parameters when considering the influence of driver (or autonomous/CVHA vehicle) behavior on the capacity of a roadway. These two parameters belong to the set of 10 car-following parameters of the Wiedemann 99 model. Other parameters in this set influence the acceleration and deceleration characteristics, how much oscillation is allowed in maintaining the safety distance, etc. A full list of parameters may be found in Section 3.2, later in this chapter.

3.1.1.2 Lane Changes

Lane-changing behavior logic can also significantly influence results in a simulation, and is often one of the most difficult aspects of a model to calibrate. The lane-changing logic in VISSIM (Willmann, 1978; Sparmann, 1979) comprises two kinds of lane changes: necessary lane changes and free lane changes (VISSIM 5.20 User Manual, 2009). Lane selection is the first step of a lane-changing maneuver. In a necessary lane change, the desired lane is identified as the one that allows the driver to follow the intended route with the least number of necessary lane changes. In a free lane change, the desired lane is identified as the lane that provides either a higher speed or a better interaction situation (Fellendorf & Vortisch, 2010). In a vehicle's lane-changing maneuver, decisions on gap acceptance as well as cooperative merging are involved in seeking the best chance for a successful lane change.

Both of these criteria can be calibrated. The Wiedemann model has been well calibrated for human driver lane changing and is generally accepted for most traffic simulation applications. However, the method by which a CVHA vehicle, in particular an autonomous vehicle, selects lane-change opportunities may not be well represented by current calibrations. For instance, autonomous vehicles' reaction to traffic relies on more precise sensors and the capability of instantaneous reaction to maintain a following distance—a capability that is nearly impossible to achieve in a human-driven vehicle. However, the autonomous vehicle, when compared to human drivers, may not have the same anticipatory abilities and its aggressiveness (or required safety) in merging may differ. While some level of following distance variability is necessary for passenger comfort (otherwise the trip would be a constant oscillation between acceleration and braking), the driving behavior differences between autonomous/CVHA vehicles and human drivers will require new calibrations that could significantly influence model results.

3.1.2 Adapting Existing Microscopic Simulation Models

With increased adoption of CVHA technologies, simulations capable of modeling mixed fleets of manually driven, CVHA-assisted, and automated vehicles are becoming increasing necessary. To reflect these new driving characteristics, it is desirable to develop a methodology for calibrating existing microscopic simulations. The first step in such a calibration is to determine the model parameter set that affects traffic flow. It is then necessary to determine which of these parameters may need calibration to reflect CVHA and autonomous vehicles' operation. It is critical to realize that, at the current time, it may not be possible to definitively calibrate these parameters, as new CVHA technologies are continually being introduced and updated, and the behavior of autonomous vehicles remains for the most part unknown. Until these technologies are adequately standardized, future studies will be limited to sensitivity analysis on these parameters, to determine the range of potential facility operations as these vehicles are introduced into the fleet.

3.2 VARIABLES IMPACTING MODEL PERFORMANCE

3.2.1 Method

To test which parameters impact model performance, the researchers developed a test scenario for a Monte Carlo simulation by varying parameter values, consistent with previous research (Miller et al., 2012). In these tests, travel time and capacity were utilized as critical measures of effectiveness (MOEs) to determine influence of a parameter on the model.

The modeled test site consisted of a 12.5-mile, three-lane freeway segment with an on-ramp at a point 9.5 miles downstream of the beginning of the section (Figure 6). A 650-ft acceleration lane connected the on-ramp with the mainline, after which the acceleration lane dropped. In Figure 6, “EB-Long,” “EB-Short,” “Ramp-Long,” and “Ramp-Short” refer to sections over which performance measures were collected (Table 2).

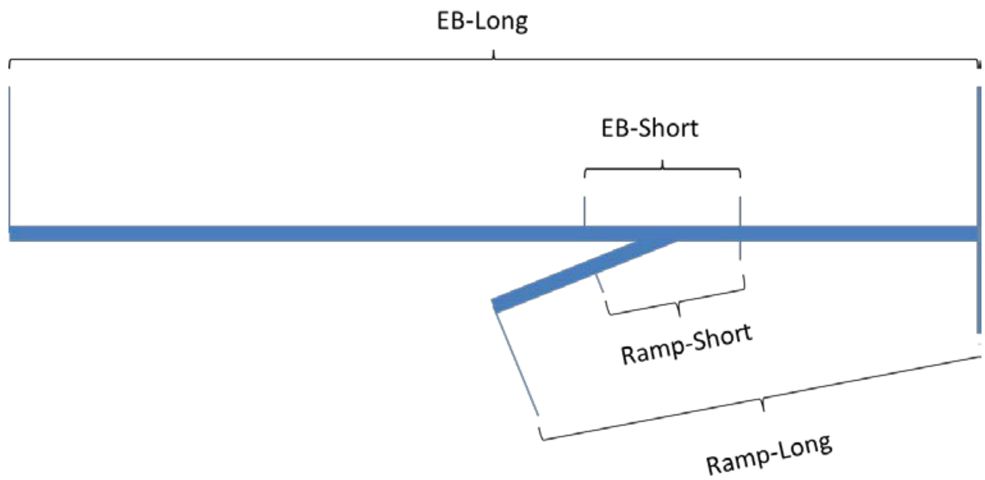


Figure 6. Study Site Configuration

Table 2. Study Section Definitions

MOE Section Name	Starting Point	Ending Point
EB-Long	Mainline entrance	Mainline exit
EB-Short	1000 ft upstream of merge point on mainline	1000 ft downstream of merge point on mainline
Ramp-Long	On-ramp entrance	Mainline exit
Ramp-Short	1000 ft upstream of merge point on on-ramp	1000 ft downstream of merge point on mainline

A list of 29 parameters in VISSIM's car-following and lane-changing model were selected as the initial input set (Table 3) (Miller et al., 2012).

Table 3. List of Parameters Studied

#	Parameter	Initial Range
1	Desired speed distribution range	(avg. 65 mph) 0.0–15.0 mph
2	Look ahead distance min. (ft)	0–900 ft
3	Look ahead distance max. (ft)	500–1000 ft
4	Number of observed vehicles	2–8 veh
5	Look back distance min. (ft)	0–1000 ft
6	Look back distance max. (ft)	0–1000 ft
7	CC0 standstill distance (ft)	0–15 ft
8	CC1 headway time (s)	0–5 s
9	CC2 following variation (ft)	5–50 ft
10	CC3 threshold for entering ‘following’	−25–0
11	CC4 negative following threshold	−5–0
12	CC5 positive following threshold	0–5
13	CC6 speed dependency of oscillation	0–15
14	CC7 oscillation acceleration (ft/s^2)	0–5 ft/s^2
15	CC8 standstill acceleration (ft/s^2)	0–15 ft/s^2
16	CC9 acceleration at 80 km/hr (ft/s^2)	0–15 ft/s^2
17	Maximum deceleration (own)	−20–0 ft/s^2
18	Maximum deceleration (trailing)	−20–0 ft/s^2
19	Accepted deceleration (own)	−6–0 ft/s^2
20	Accepted deceleration (trailing)	−6–0 ft/s^2
21	Reduction rate (as ft per 1 ft/s^2) (own)	20–300
22	Reduction rate (as ft per 1 ft/s^2) (trailing)	20–300
23	Waiting time before diffusion	0–80 s
24	Minimum headway (front/rear)	1–30 ft
25	Safety distance reduction factor	0–1
26	Maximum deceleration for cooperative braking	−40–0 ft/s^2
27	Emergency stop distance	0–35 ft
28	Lane change distance	0–1500 ft
29	Random seed value	1–999

For capacity MOEs, two methods were adopted: 95th percentile of overall flows, and 95th percentile of flows with speed ≥60 mph. There were three throughput data collection points in the network: start of mainline, merge point, and end of mainline.

The Monte Carlo method is an iterative process. In each iteration, parameter ranges are further refined or parameters are eliminated that do not significantly influence the MOEs. The iterations continue until no further parameter range refinements or eliminations can be justified. The parameters remaining after the last iteration in this study are those that should be calibrated in a CVHA modeling effort. The Monte Carlo process was implemented as follows:

1. For each iteration, generate 1000 sets of combinations of parameter values for the parameters under study. For the initial iteration set, each parameter is randomly set to a value within the ranges in Table 3. The initial iteration set contains all 29 variables in Table 3. New random seeds are used for each parameter set, in each iteration.
2. Generate a VISSIM input file for each parameter set. All input files have a simulation length of 8 hours, with the same network and volume input configuration. During the simulation, mainline volume is increased from a value well under-capacity, to over-capacity, allowing for identification of the demand at capacity. Volume levels utilized throughout each simulation run are listed in Table 4.
3. Execute each input file for 1000 total VISSIM runs and generate MOEs for each model run. These data are used in the sensitivity analysis and parameter elimination.

4. Determine parameters to eliminate as non-significant (i.e., parameter has minimal influence on MOEs) or refine the range given in Table 3 as follows:
   a. For each MOE, create a scatter plot relative to each parameter. Perform a linear regression for the sample mean, 5^{th} percentile, and 95^{th} percentile of the given parameter. Figure 7 provides example scatter plots of travel time over two different segments versus the CC1 parameter value.
   b. Compute the effect on the mean (EOM) as the slope of the linear regression on the mean multiplied by the parameter range.
   c. (For odd iterations steps only) Adjust parameter ranges from Table 3 manually, based on the scatter plots. The objective of this iteration is to refine the parameter ranges to eliminate the generation of VISSIM parameter sets resulting in non-reasonable MOEs.
   d. (For even iteration steps only) Eliminate those parameters with three or more EOMs less than 5 percent, while examining their variability change manually (by reviewing scatter plots for significant changes in variability; i.e., the width changes between the 5 percent and 95 percent regression lines).
5. Iterate through steps 1 through 4, until no parameter eliminations or refinements occur.

Table 4. Input Volume Variation over Simulation Time

Simulation Time (hour)	Input at Mainline Entrance (veh/hr)	Input at On-ramp Entrance (veh/hr)
0–1	500	500
1–2	1000	500
2–3	1500	500
3–4	1700	500
4–5	1900	500
5–6	2100	500
6–7	2300	500
7–8	2500	500

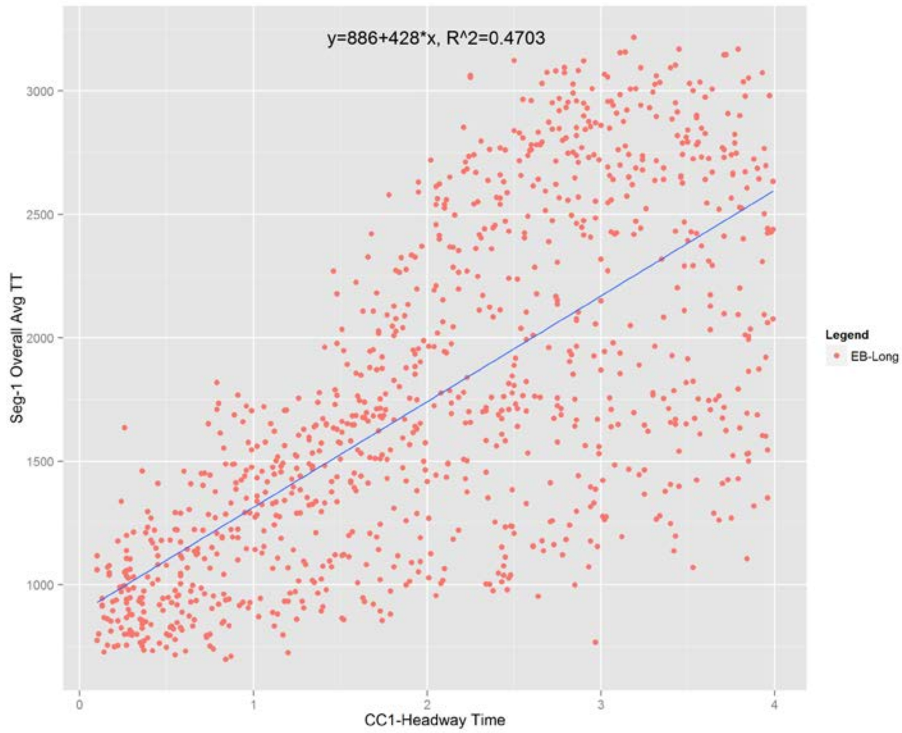
3.2.2 Results

The list of parameters (16 parameters) remaining at the end of 25 iterations, and their new ranges are shown in Table 5. The number of parameters identified that could potentially influence the travel time and capacity MOEs is large, possibly resulting in an untenable calibration or analysis process. In conducting any calibration for autonomous-vehicle or CVHA technology, it is not necessary that all parameters be calibrated, but only those that may be influenced by the given technology. An example would be standstill acceleration, which is associated with passenger comfort rather than vehicle technology. Other parameters, such as standstill distance and threshold for following, may not require direct calibration utilizing field data; instead, they can be set to known values associated with the new technology. Finally, other variables, such as headway times, will need to be tested under a range of values, allowing for a sensitivity analysis across potential technology assumptions. Examples of the findings for several individual parameters are provided in Table 5.

Table 5. Significant Parameters

#	Parameter	Range
4	Number of observed vehicles	2–8 veh
7	CC0 standstill distance (ft)	0–15 ft (0–4.6 m)
8	CC1 headway time (s)	0.4–2.0 s
9	CC2 following variation (ft)	5–39.4 ft (1.6–12 m)
10	CC3 threshold for entering 'following'	−25–(−4)
11	CC4 negative following threshold	−3–0
12	CC5 positive following threshold	0–3
14	CC7 oscillation acceleration (ft/s^2)	0–3 ft/s^2 (0–0.9 m/s^2)
15	CC8 standstill acceleration (ft/s^2)	5–15 ft/s^2 (1.5–4.6 m/s^2)
18	Maximum deceleration (trailing)	−20–(−8) ft/s^2 (−6.1–[−2.4] m/s^2)
24	Minimum headway (front/rear)	1–16.4 ft (0.3–5 m)
25	Safety distance reduction factor	0.1–0.9
26	Maximum deceleration for cooperative braking	−40–(−14.8) ft/s^2 (−12.2–[−4.5] m/s^2)
27	Emergency stop distance	5–35 ft (1.5–10.7 m)
28	Lane change distance	80–1500 ft (24.4–457.2 m)

Figure 7 shows the average travel-time plots with respect to CC1 (headway time) for the EB-long overall segment. The range is reduced from 0–5 s to 0.4–2.0 s. (When considering the shorter headway values, recall that in VISSIM the safe following distance also includes the standstill distance.) The variability stabilizes when the range is adjusted to the appropriate scale by excluding headways that contain extreme values of average travel time. Only where a given technology would imply longer headways should values outside this range be considered.



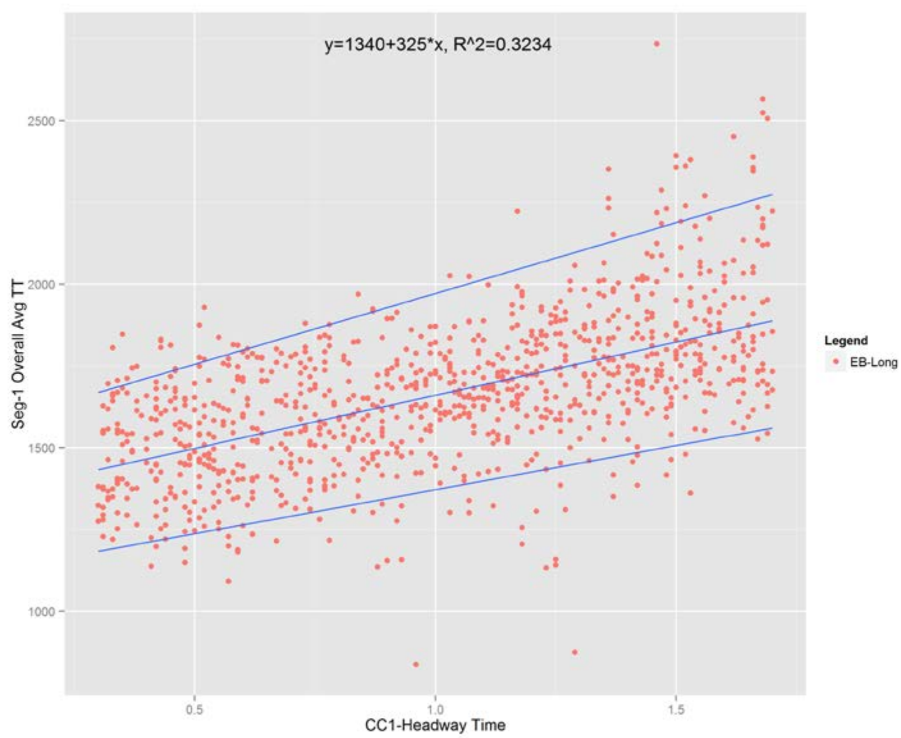


Figure 7. Travel-time vs Headway (CC1), Original Range (top) and Reduced Range (bottom)

Figure 8 shows the average travel-time plots for the EB-long overall segment, with respect to the safety distance reduction factor, a parameter that measures the safety distance reduction when a vehicle performs a lane change. In the first plot, the range is 0–1 while in the second plot the extreme values of 0 and 1 are removed as a vehicle may not disregard the safety distance when lane changing (value of 0), and it is unlikely that the vehicle will maintain the same safety distance as it maintains at free-flow speed (value of 1). The trend in the data can be observed more clearly in the second plot after eliminating the responses to the extreme values.

Figure 9 shows the average travel-time plots with respect to minimum look-ahead and minimum look-back distance, respectively, for the EB-long overall segment. The slope of the regression on the mean is not significant, and the variability change is not obvious; therefore, these two parameters are eliminated.

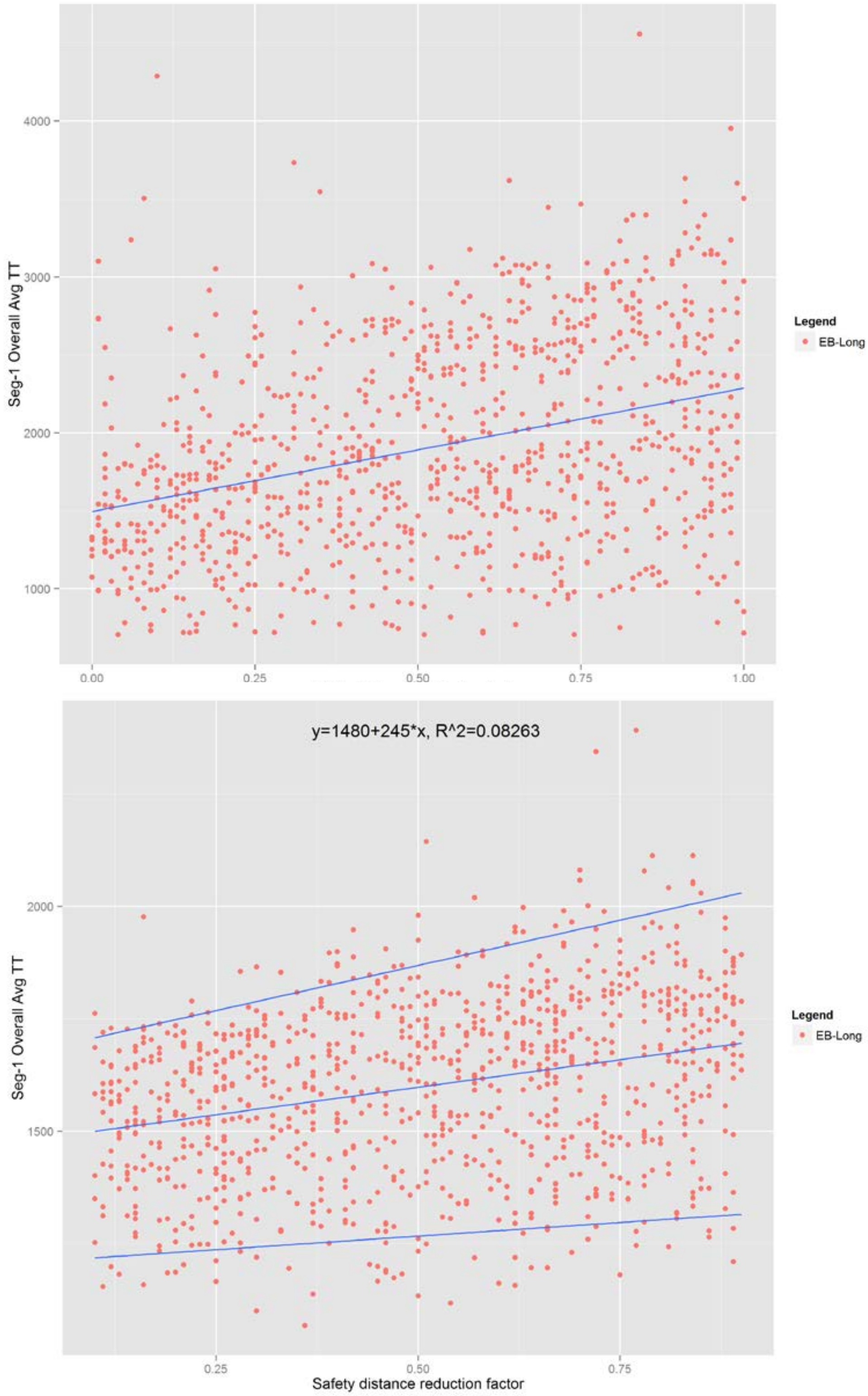


Figure 8. Travel-time vs Safety Distance Reduction Factor, Original Range (top) and Reduced Range (bottom)

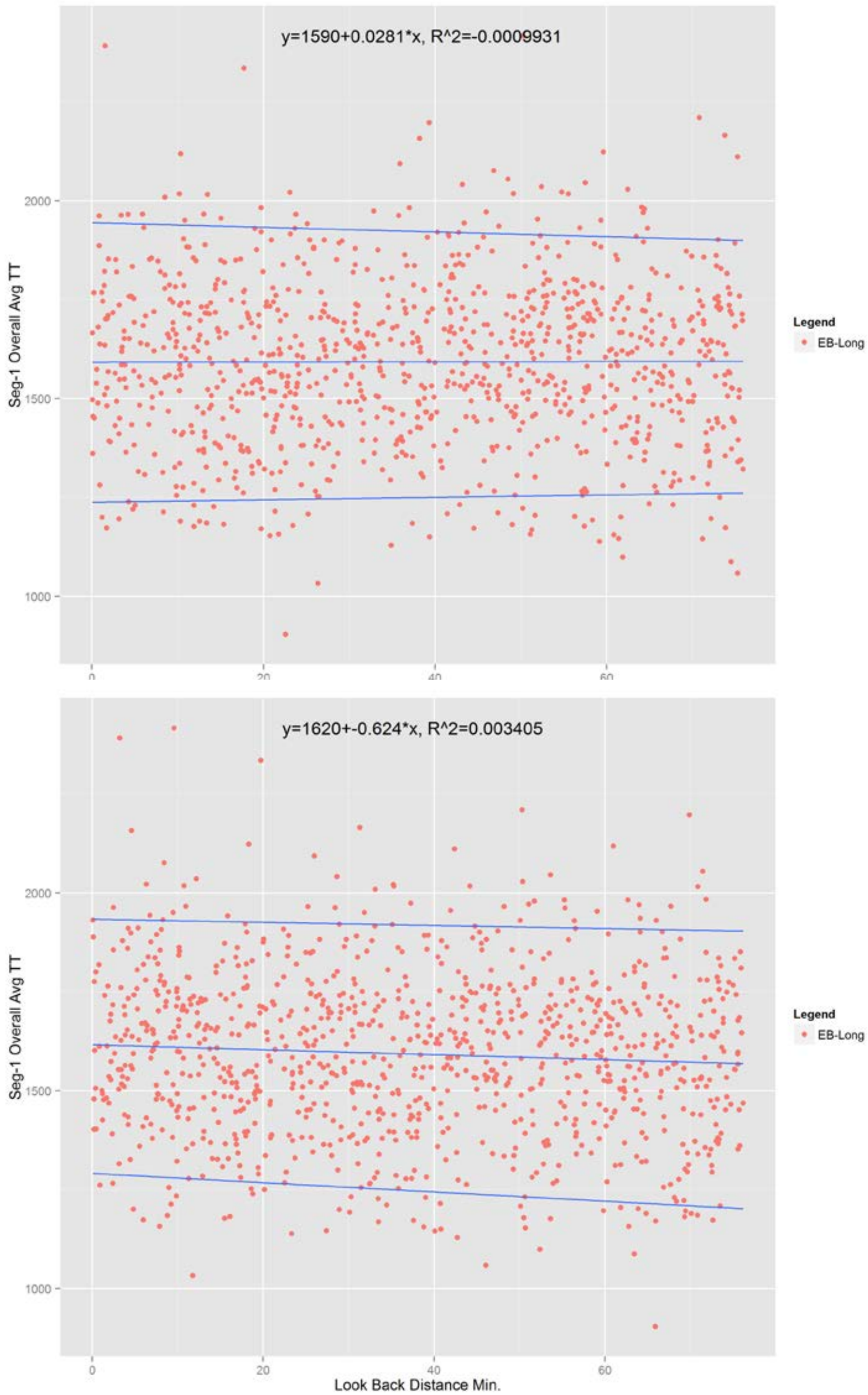


Figure 9. Travel-time vs Look-ahead Distance (top) and Travel Time vs Look-back Distance (bottom)

3.3 RECOMMENDATIONS FOR SIMULATION ANALYSIS

The results showed that 16 parameters had a significant impact on the performance of the model as reflected by the response of the MOE. While changes to these parameters impact model performance, changes to all variables are not necessary to elicit the differences in behavior between automated and non-automated vehicles. For instance, from the list of 17 parameters, the following four are critical to changing the behavior of vehicles in VISSIM to reflect automated and human driving characteristics.

1. *Variable 8—CC1 headway time:* Many of the benefits identified in the literature related to automated vehicles, are a result of reductions in headway time. The assumption is that, particularly in platooning with an essentially 0-second reaction time, autonomous vehicles may maintain significantly shorter headways. However, in a mixed-traffic environment autonomous vehicles may be more cautious than typical freeway drivers and, as a result, headway time could be higher for automated vehicles. Thus, operation alternatives should be studied over a range of headway values.
2. *Variable 9—CC2 following variation:* Automated vehicles are expected to have less variation in their car-following distance when compared to human-driven vehicles. Therefore, following variation distance should be reduced for automated vehicles.
3. *Variable 25—Safety distance reduction factor:* Safety distance reduction factor is used to represent human behavior where humans are willing to accept smaller gaps or following distances than usual when performing a driving maneuver such as a lane change. Automated vehicles are anticipated to follow safety rules uniformly,

so this value will likely be higher than that for human drivers. As with headway, however, this parameter may be scenario-specific and related to the particular vehicle manufacturer. Future studies should consider a range of potential values.

4. *Variable 26: Maximum deceleration for cooperative braking:* Cooperative braking represents how much drivers are willing to brake to widen a gap for a vehicle changing from an adjacent lane. This value should be adjusted according to potential level of automation. If an automated vehicle is assumed to be cooperative, this value should be increased in magnitude to represent greater willingness to brake. If an automated vehicle is assumed to have no situational awareness outside of its lane, this value should be decreased in magnitude to represent a lack of response due to inability to respond to vehicles in adjacent lanes.

4 Use Case: Simulating Freeway Diverges

4.1 INTRODUCTION

Building on the efforts of Chapter 3, this chapter presents an initial attempt to model the potential impact of a CVHA use case, focusing on autonomous vehicles. As discussed in Chapter 3, the rapid advances in technology during the past decade and the availability of increasingly advanced, accurate, and affordable sensors has contributed significantly to the development of automated systems. Numerous autonomous technologies are being pilot tested on public streets. However, the establishment of an understanding of how these systems will influence traffic has lagged the advance of the technology. Thus, the objectives of this case study are three-fold:

1. To demonstrate a methodology for modeling autonomous vehicles in a mixed-fleet (i.e., autonomous and manually driven vehicles) environment, highlighting challenges with the approach.
2. Based on the results of the case study, to contribute to the understanding of how autonomous vehicles may operate on existing infrastructure and how they may affect traffic congestion and safety.
3. To provide a discussion on how state DOTs may need to respond, or be proactive, to the introduction of this technology.

4.2 ASSUMPTIONS

It is all but assured that autonomous vehicles will be widely commercially available in the future, through individual vehicle ownership, fleet mobility services, or some other means. However, even as such technology becomes widely available, this research assumes that manually driven vehicles, without or with limited communication or automation technology, will remain part of the traffic fleet on the roadways for the foreseeable future, likely many decades.

There has been significant focus on the potential operational and safety benefits of the interaction between technology-enabled vehicles on the roadway. However, when considering the interaction of vehicles with mixed levels of technology, the understanding of effects on traffic system operational efficiency and safety is less certain. Further, where research has occurred there is often an underlying assumption of cooperation between autonomous and manually driven vehicles. That is, it is assumed that manually driven vehicles will behave toward autonomous vehicles in a manner similar to their behavior toward other manually driven vehicles. While this may not be an explicit assumption of a study, it often implicitly exists in the underlying model. As seen in Chapter 3, it is necessary to calibrate a model to reflect the driving characteristics related to the introduction of autonomous vehicles. While the necessity to develop driving characteristics for the autonomous vehicle is clear, consideration must be given to the calibration of the human driver characteristics. The calibration of current models represents human drivers interacting with human drivers; however, it is likely that human driver behavior may alter when interacting with autonomous vehicles. Where manual-driver characteristics are not calibrated for this interaction the implied assumption is that their interaction with the autonomous vehicles will be the same as with other manually driven vehicles. This study demonstrates that such an implicit assumption can significantly influence model findings.

Given the preceding discussion, for this modeling effort, the following assumptions are applied to model a mixed fleet of autonomous and manually driven vehicles:

1. Manually driven vehicles and autonomous vehicles use the same roadway, including all lanes (i.e., there are no dedicated autonomous vehicle lanes).
2. In mixed traffic, an autonomous vehicle follows similar headway, desired speed, acceleration, and deceleration characteristics as human drivers. For instance, in mixed traffic, autonomous vehicles will not utilize shorter headways (i.e., platooning) due to potential difficulties in manually driven vehicle interaction with these platoons.
3. Autonomous vehicles are highly cooperative; this assumption posits that an autonomous vehicle's safety protocols will prioritize crash avoidance, resulting in the acceptance of high decelerations to avoid crashes. It is also assumed that autonomous vehicles will not attempt to "hold their space" or "box out" vehicles attempting to merge in front. That is, when manually driven vehicles attempt to merge in front of an autonomous vehicle, the autonomous vehicle will always yield due to its collision avoidance safety protocols.
4. Aggressive drivers are more likely to "take advantage" of autonomous vehicles because of the conservative safety behavior of autonomous vehicles, as identified in the prior assumption. This has been referred to as the "bully" phenomenon (Condliffe, J. 2016; Connor S., 2016).

5. Aggressive drivers will attempt to perform necessary lane changes (e.g., at a lane closure or exit ramp) as late as possible where this advances their position on the roadway and an autonomous vehicle is present to enable aggressive lane changing.
6. Aggressive drivers will not display the above aggressiveness when interacting with other manually driven vehicles. Underlying this assumption is a secondary assumption that human drivers can easily distinguish between autonomous and non-autonomous vehicles.

Finally, for these experiments, the simulations do not account for potential benefits derived from communication between autonomous vehicles; future efforts will incorporate this potential expansion. In the simulations, an autonomous vehicle utilizes only information that could be received through onboard sensors such as video and radar.

4.3 METHOD

4.3.1 VISSIM Model Description

Building on the efforts of Chapter 3, the case study model is constructed in VISSIM 5.4. In the remaining text, all references to VISSIM assume VISSIM version 5.4. The core behavior model in VISSIM consists of two major components: the car-following model that captures the psychophysical driver-behavior model developed by Wiedemann in 1974 (*PTV Vision, VISSIM 5.20 User Manual.*, 2009), and the lane-changing model that is developed by Willmann (1978) and Sparmann (1979).

This study focuses on reflecting the interactions between aggressive drivers and autonomous vehicles, and the capacity and travel-time impacts of this interaction, particularly aggressive merges, toward autonomous vehicles. Thus, three types of "drivers" are included in the simulation experiments: normal and aggressive drivers of manually driven vehicles, and autonomous "drivers." The manually driven aggressive vehicle interaction with an autonomous vehicle is implemented using VISSIM application programming interfaces (APIs): the Component Object Model (COM) interface and the External Driver Model (EDM). Initial efforts sought to handle these behaviors solely through parameter calibration using the methodology outlined in Chapter 3. However, as discussed in the next sections of this chapter, the underlying traffic flow model was not amenable to sufficient adjustments through these parameters alone, to adequately capture the assumptions in the preceding section. In particular, the necessity to model different interaction characteristics between aggressive manually driven vehicles with autonomous vehicles and aggressive manually driven vehicles with other manually driven vehicles required the use of APIs. This likely indicates a need to develop more robust and flexible simulation implementations of the underlying car following to reflect the rapid pace of introduction of these disruptive technological innovations.

4.3.2 VISSIM Component Object Model (COM) Interface

The VISSIM program is based on an object-oriented architecture; that is, the program is coded using interacting objects, which represent items such as vehicles, links, input volume, driving behavior parameter sets, routing decisions, etc. The COM interface is a powerful module provided by VISSIM for additional functionality through a built-in scripting and external programming environment (COM Interface Manual, 2009). COM allows automation of VISSIM runs and provides input/output (I/O) access to many of the

VISSIM objects during a simulation run. COM provides greater flexibility in modifying some parameters and accessing objects' properties, allowing model developers to customize simulation modifications not addressed in the standard VISSIM user interface.

Through COM, many properties of traffic objects may be dynamically modified, such as vehicle type, length, color, current lane and desired speed. Critical to this study, COM allows for the generation and tracking of individual traffic. Although parsimony must be exercised in the use of COM, particularly in the identification and tracking of vehicles, as significant computational overhead may be incurred resulting in prohibitive simulation runtimes. In this study, COM is adapted to model the algorithm of lane-changing behavior in aggressive manually driven and autonomous-vehicle interaction.

While COM provides solid and powerful interfaces for customized simulation, there are certain simulation limitations that could not be resolved through the COM interface alone. For instance, the parameter sets in the Wiedemann 99 model and lane-changing model (discussed in Chapter 3) apply to a Vehicle Type. When updating a Vehicle Type parameter during runtime, all vehicle instances of that type will experience the parameter change. The parameter set for a single instance of a Vehicle Type may not be updated in isolation. However, in this model "aggressive" driver behavior is dependent on the vehicle with which they are currently interacting. Aggressive drivers act aggressively only when interacting with an autonomous vehicle, while not displaying aggressive behavior toward other manually driven vehicles. Thus, in the simulation implementation, an aggressive driver Vehicle Type requires one calibrated parameter set when interacting with other manually driven vehicles and a second calibrated parameter set when interacting with autonomous vehicles. Therefore, a capability to modify the parameters for individual vehicles during runtime is required. While not insurmountable through COM, the computational overhead to address this drawback results in prohibitive model run times.

A second COM drawback is constraints in overwriting some critical parameters. While most parameters are accessible through a COM "READ" command during runtime (i.e., script may be generated to read a parameter value while the simulation is running), only a subset of variables allow a "WRITE" command. That is, only a subset of variables may be updated through scripting during runtime. For example, to override a vehicle's internal car-following model the speed and acceleration must be accessed and modified in run-time, yet the acceleration attribute of each individual vehicle in VISSIM COM is read-only. Thus, through COM, behavior changes may not be directly forced (i.e., generate a more aggressive acceleration) for a specific vehicle during a given time step. Another issue relevant to this effort is an inability in COM to transition a vehicle from one lane to an adjacent lane over multiple time steps. COM "WRITE" commands place a vehicle in a single lane; thus, lane changes are instantaneous.

To overcome these limitations of the COM interface, a direct interface with the underlying car-following model is needed. VISSIM provides the EDM API to help address these shortcomings.

4.3.3 VISSIM External Driver Model API

The External Driver Model is an API developed by VISSIM to provide extra flexibility in replacing the internal driver model, including car-following characteristics and lane-changing behavior. In the EDM, acceleration is the critical parameter that determines the traffic-flow characteristics. The EDM also provides a set of interfaces for users to replace the lane-changing logic, if desired. Thus, in each time step of simulation, VISSIM will provide the current state for each vehicle controlled by the external model, such as speed, acceleration, lane change decision, and surrounding vehicles. The EDM then calculates the acceleration and lane-change decision according to user-defined car-following and lane-changing models. These parameters are returned to VISSIM, replacing the VISSIM generated values. If there is no user-defined car-following model, default VISSIM behavior is returned (Fellendorf & Vortisch, 2010). These EDM functionalities compensate for COM's inability to change a vehicle's car-following behavior and lateral movements. Therefore, by combining COM and EDM, VISSIM provides the potential for full control of individual vehicles. A limitation of EDM, however, is that EDM's perception of a vehicle's surrounding is limited to two vehicles in all directions. In contrast, COM provides access to all vehicles within the model. In this effort, a combination of COM and EDM is utilized to model the aggressive driver behavior (Figure 10).

In the architecture in Figure 10, the communication between the COM interface and EDM is required. EDM is compiled as a dynamic link library (DLL) file and linked to a specific vehicle type in VISSIM. As EDM has its own local memory stack in the computer, separate from COM, direct information sharing between the EDM and COM is not readily possible. Another strategy is to use a vehicle attribute that EDM could recognize as a flag to engage or disengage EDM control of a vehicle. This requires the same I/O privilege in both COM and EDM over a vehicle property (i.e., both the COM interface and EDM can read and overwrite the same vehicle property). In this implementation, the color of vehicle is used as the flag for the activation and deactivation of EDM.

The detailed mechanism of how VISSIM runs with COM and EDM is illustrated in the following flowchart.

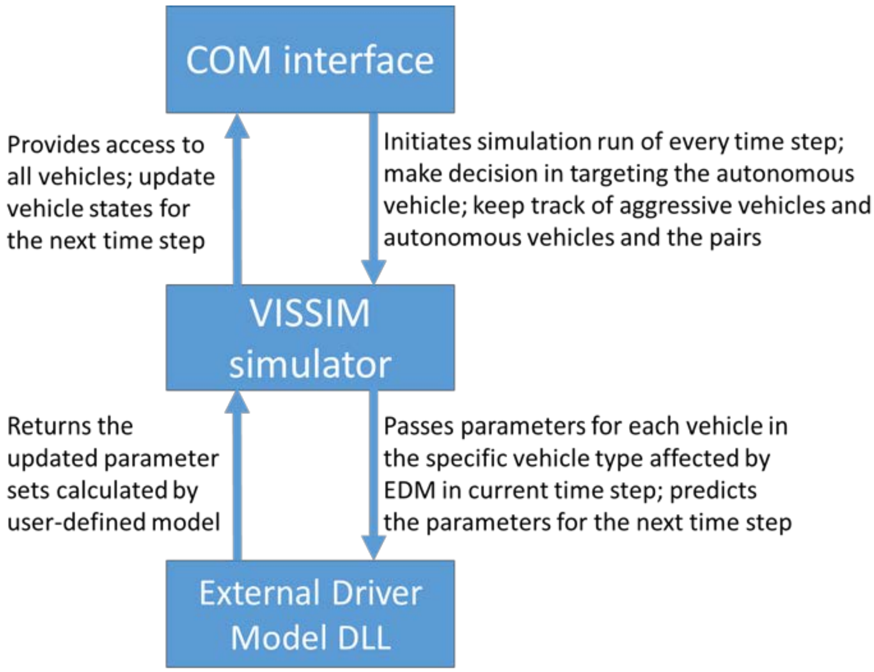


Figure 10. The Internal Mechanism between COM Interface, VISSIM Simulator, and EDM DLL

4.3.4 Simulation Configuration

This example models a single direction of a 1.3-mile freeway segment, two lanes in one direction, with a downstream right-side off-ramp 0.9 miles from the segment start (Figure 11). Upstream of the ramp junction, aggressive manually driven vehicles are in the left lane, autonomous vehicles are assumed to travel in the right lane, and normal manually driven vehicles may select either lane. All aggressive manually driven vehicles have a routing decision to exit the freeway; thus, they must change lanes from the left lane to the right lane, prior to the exit. Normal manually driven vehicles may have either routing decision, to stay on the mainline or to exit the freeway.

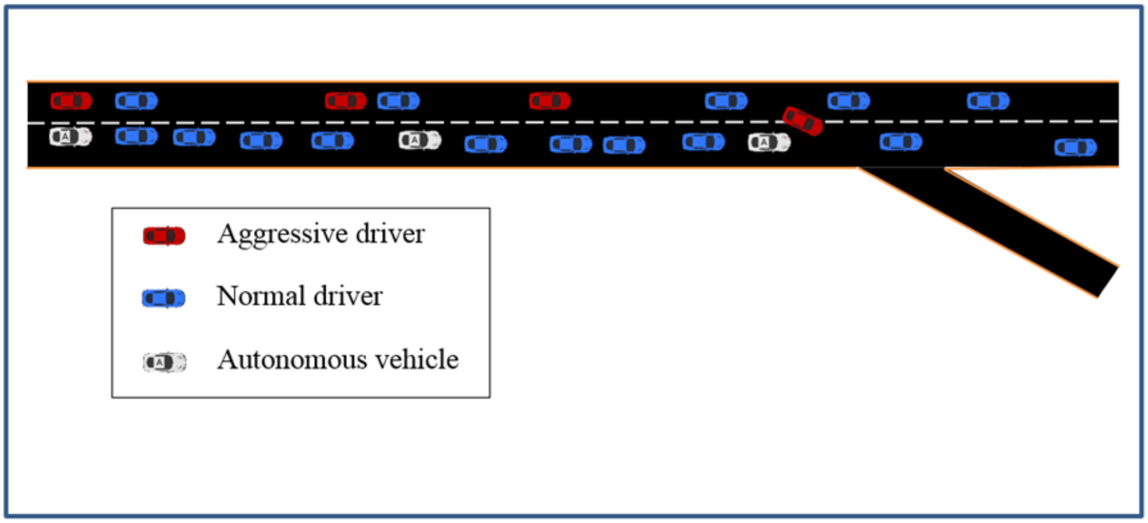


Figure 11. Simulated Study Site with Different Types of Vehicles

The left-lane volume is 500 vehicles per lane per hour; the right-lane volume is 1800 vehicles per lane per hour. The proportion of aggressive vehicles on the left lane ranges from 0 to 100 percent in stepped increases of 25 percent, depending on the simulation run. The proportion of autonomous vehicles in the right lane ranges from 0 to 100 percent with stepped increases of 25 percent, also depending on the simulation run.

Parameters were set according to the outcomes in Chapter 3, manipulating only variables shown to impact the model flow. These parameters are shown in Table 6. For each parameter set of aggressive ratio and autonomous ratio, 10 replicates of different random seeds were utilized for generating the results.

Table 6. Parameter Set Used in Simulation Study of Aggressive and Autonomous Vehicle Interactions

Parameter List	VISSIM Default Vehicles	Aggressive Vehicles	Autonomous Vehicles
CC1 (second)	0.9	0.3	0.9
CC2 (ft)	13.12	13.12	0
Safety distance reduction factor	0.6	0.6	0.1
Maximum deceleration for cooperative braking (ft/s^2)	−9.84	−9.84	−29.53
Desired speed (mph)	60	70	60
Lane change distance (ft)	1312		

4.3.5 Algorithms for Targeting

As stated in the previous section, the modeled user case seeks to determine the potential impact of aggressive drivers who are exiting a freeway seeking additional advantage by "targeting" or "bullying" an autonomous vehicle. As the aggressive vehicle (currently positioned in the left lane) approaches the ramp, it begins to search for downstream autonomous vehicles in the right lane. The aggressive vehicle seeks the greediest merge (i.e., the farthest downstream gap prior to the ramp junction) created by a viable autonomous vehicle. A viable autonomous vehicle is defined as an autonomous vehicle that the aggressive vehicle could overtake prior to reaching the downstream exit. If upon searching, an aggressive vehicle does not find a viable autonomous vehicle downstream, it will default to normal driving characteristics and merge with normal manually driven vehicles in the right lane.

To capture this behavior, one possible algorithm is that an aggressive vehicle will seek the farthest downstream currently viable autonomous vehicle for targeting. However, the dynamic of traffic flow changes makes the viability decision process increasingly uncertain as the distance between the aggressive vehicle and autonomous vehicle increases. Alternatively, this research implemented an incremental advancement approach. In this approach, the aggressive vehicle targets the nearest downstream viable autonomous vehicle. Upon overtaking the target autonomous vehicle, the aggressive vehicle will search to determine if another viable autonomous vehicle is present downstream. If a viable autonomous vehicle is present, the aggressive vehicle will now target that vehicle. If no additional viable autonomous vehicles are present in the traffic stream, the aggressive vehicle will merge in front of the current target vehicle. This process will continue until the aggressive vehicle either must merge into the right lane in order to exit, or no additional viable autonomous vehicles are present. Additional logic is also included to reflect the possibility of the left lane speed dropping below the right lane. In this instance, the aggressive vehicle will aggressively merge in front of an autonomous vehicle that is overtaking it in the right lane.

The architecture of aggressive merging is implemented as follows: each time step, COM iterates through every aggressive vehicle in the system, checking for the nearest downstream autonomous vehicle on the target lane. COM determines whether the aggressive vehicle should aim for the potential target autonomous vehicle by determining if the aggressive vehicle has sufficient distance to overtake the autonomous vehicle (i.e., determining if targeting of the autonomous vehicle is viable), assuming a 10 mph higher speed of the aggressive vehicle and no downstream vehicles blocking the aggressive vehicle’s lane. If a target autonomous vehicle is identified, the aggressive vehicle will accelerate to overtake its target autonomous vehicle. When the aggressive vehicle sufficiently overtakes the autonomous vehicle to allow for an aggressive merge (i.e., the autonomous vehicle could hard-brake to allow the merge, as determined by VISSIM's lane-changing parameters), COM will communicate with EDM to initiate an overwrite of VISSIM's behavioral characteristics of the aggressive vehicle. The aggressive vehicle will take advantage of the safety constraint of the autonomous vehicle by merging into the autonomous vehicle's lane even though the minimum safety requirements as defined in VISSIM are not met. The aggressive vehicle will force its way in front of the autonomous vehicle, triggering the autonomous vehicle's rapid safety braking. After the aggressive lane-change maneuver is finished, EDM will be deactivated for this individual vehicle, and all controls of this vehicle resume the previous behavior settings in VISSIM.

4.4 RESULTS

Figure 12 shows the right lane speed-flow charts with data collected 100 ft upstream of the off-ramp connector. As described previously, the proportion of aggressive vehicles in the left-lane traffic and the proportion of autonomous vehicles in the right-lane traffic are varied from 0 to 100 percent. Each column denotes the aggressive vehicle ratio ranging from 0 to 100 percent. Each row denotes the autonomous vehicle ratio ranging from 0 to 100 percent.

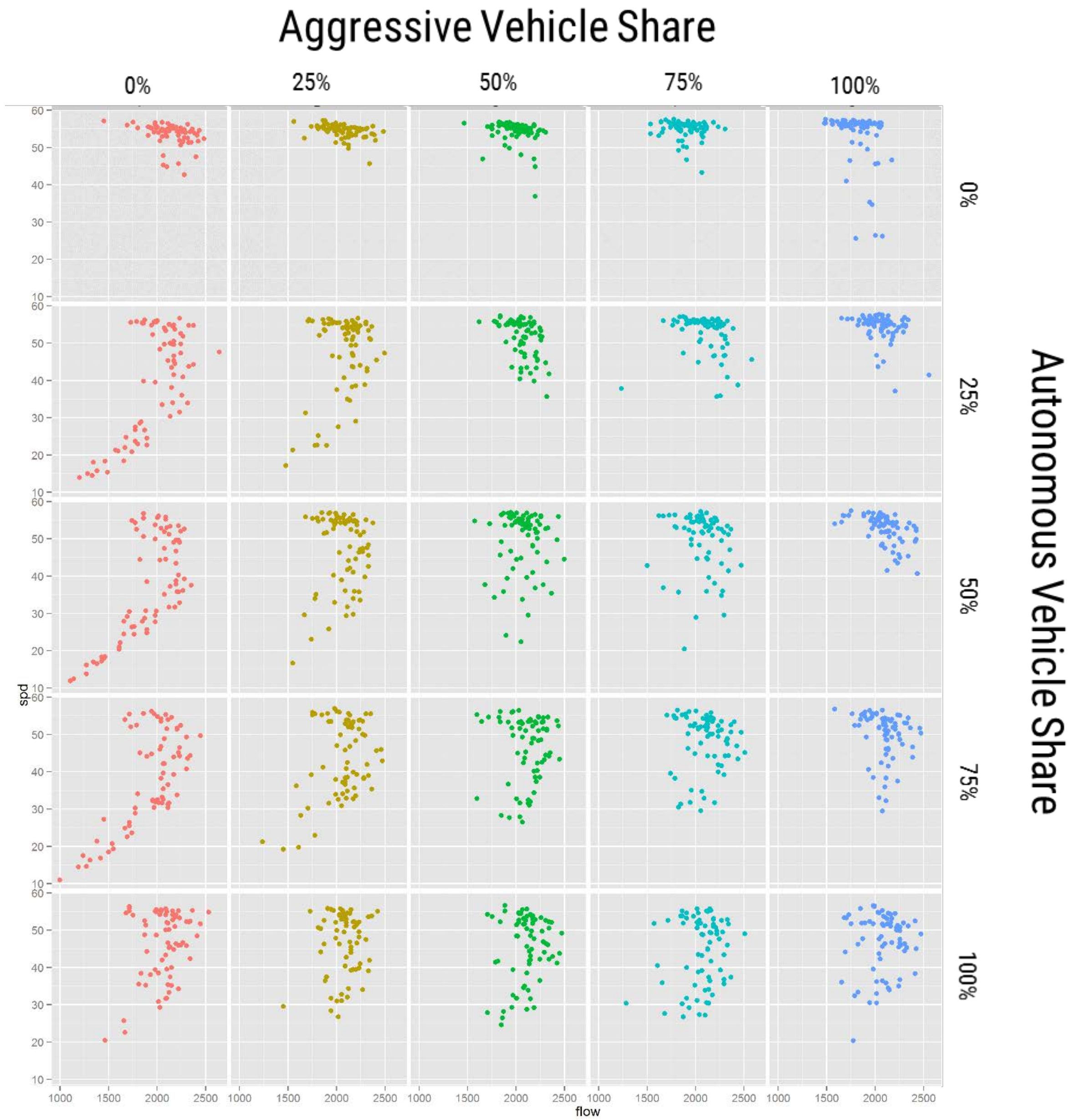


Figure 12. Speed-flow Grid Plots of Aggressive Vehicle Ratio Versus Autonomous Vehicle Penetration

From these diagrams, it is evident that the introduction of autonomous vehicles resulted in additional instability in the traffic flow. There are several possible reasons for this finding. First, the potential for erroneous modeling must be acknowledged. While both COM and EDM were utilized, there is still an aspect of the "black box" phenomenon when using VISSIM. It is possible that the developed scripts did not correctly interact with the VISSIM traffic flow logic, resulting in erroneous behavior. For instance, in reviewing individual vehicle trajectories during merging events the model rarely reflected the hard braking expected for the autonomous vehicles. However, a second underlying reason for the finding is that mixed traffic, manually driven and autonomous, may reasonably result in this behavior. The manually driven vehicles (aggressive and normal), when not in the presence of autonomous vehicles, have similar driving parameters. The demands selected for this experiment were near capacity conditions. When all vehicles have similar characteristics, the flow is homogeneous, likely resulting in optimal flow conditions. By mixing autonomous vehicles into the traffic stream, a heterogeneous flow results, likely leading to breakdown. Of course, the realism of this finding is debatable. When using a single vehicle type, VISSIM may over-estimate flow when compared to the real world that often has significantly more heterogeneous flow, even in the absence of autonomous vehicles. However, this does not negate the potential that a significant introduction of technology may negatively impact traffic flow. If autonomous vehicle technology (as well as other CHVA technology) is introduced by multiple manufacturers with widely ranging characteristics, the aggregate impact may be negative.

Additionally, as the share of aggressive vehicles increases, the traffic flow is seen to improve. This results from an interesting aspect of assumed aggressive manually driven vehicle behavior. It is assumed that the aggressive vehicles stay in the left lane until the last possible advantageous moment to merge right. This had the impact of reducing the demand over much of the right lane, thus improving flow until prior to the exit. It was also observed (not shown) that the aggressive drivers could incorrectly gauge traffic, move too far downstream, and create a breakdown in the left lane when unable to merge successfully. The aggressive vehicles failed to reach their intended target and found themselves trapped in the left lane. Ultimately, in-field calibration efforts are needed to determine if this is a failure of the developed scripts to accurately capture aggressive vehicle behavior or if the behavior would be realized.

To provide some additional insights, example trajectory plots for each vehicle type of the experiment are shown in the following figures (Figure 13 to Figure 15). In these plots, the aggressive vehicle targeting of autonomous vehicles is disabled, although aggressive merging in the presence of autonomous vehicles occurs.

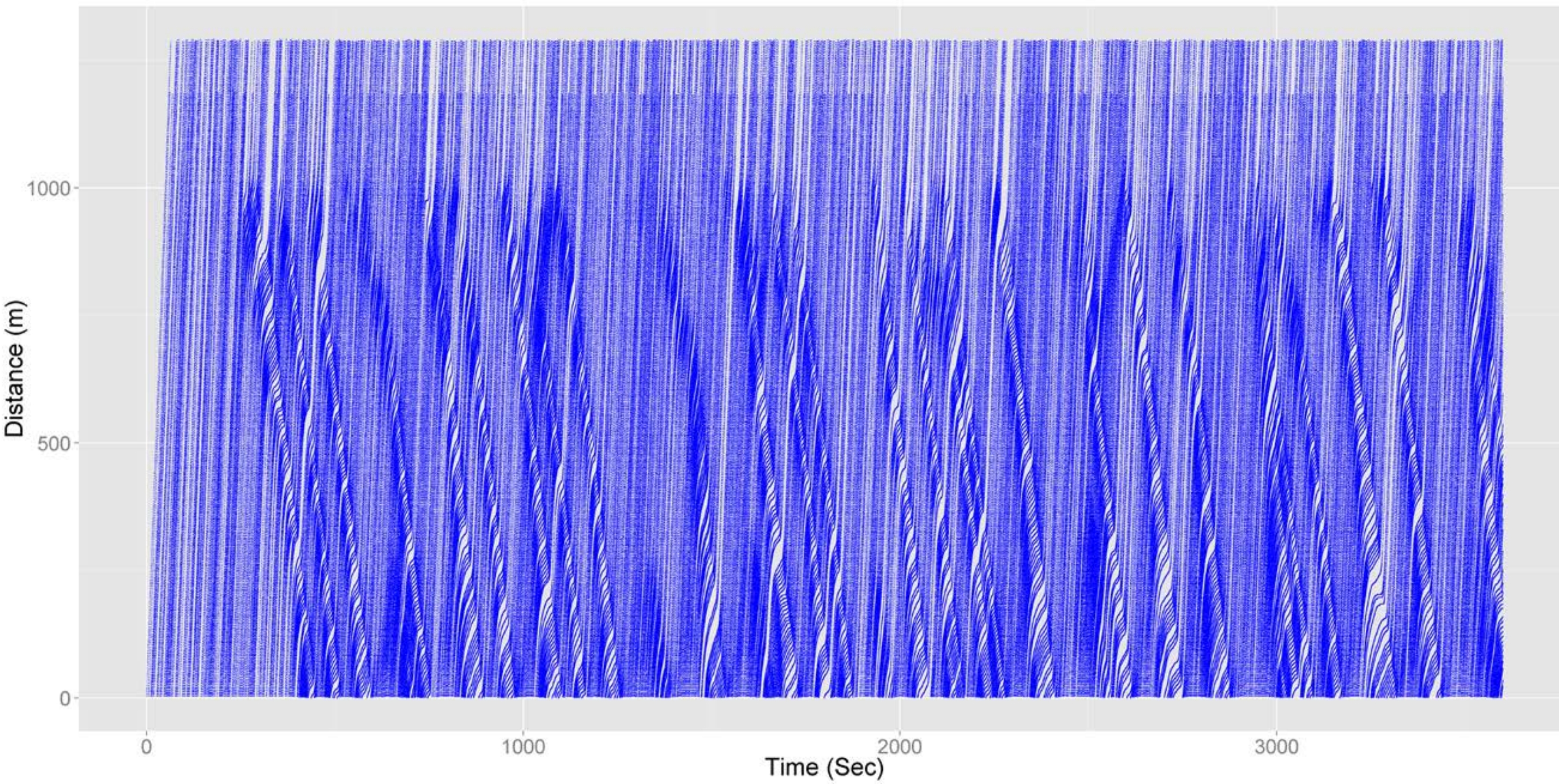


Figure 13. Trajectory Plot for Manually Driven Normal Vehicles

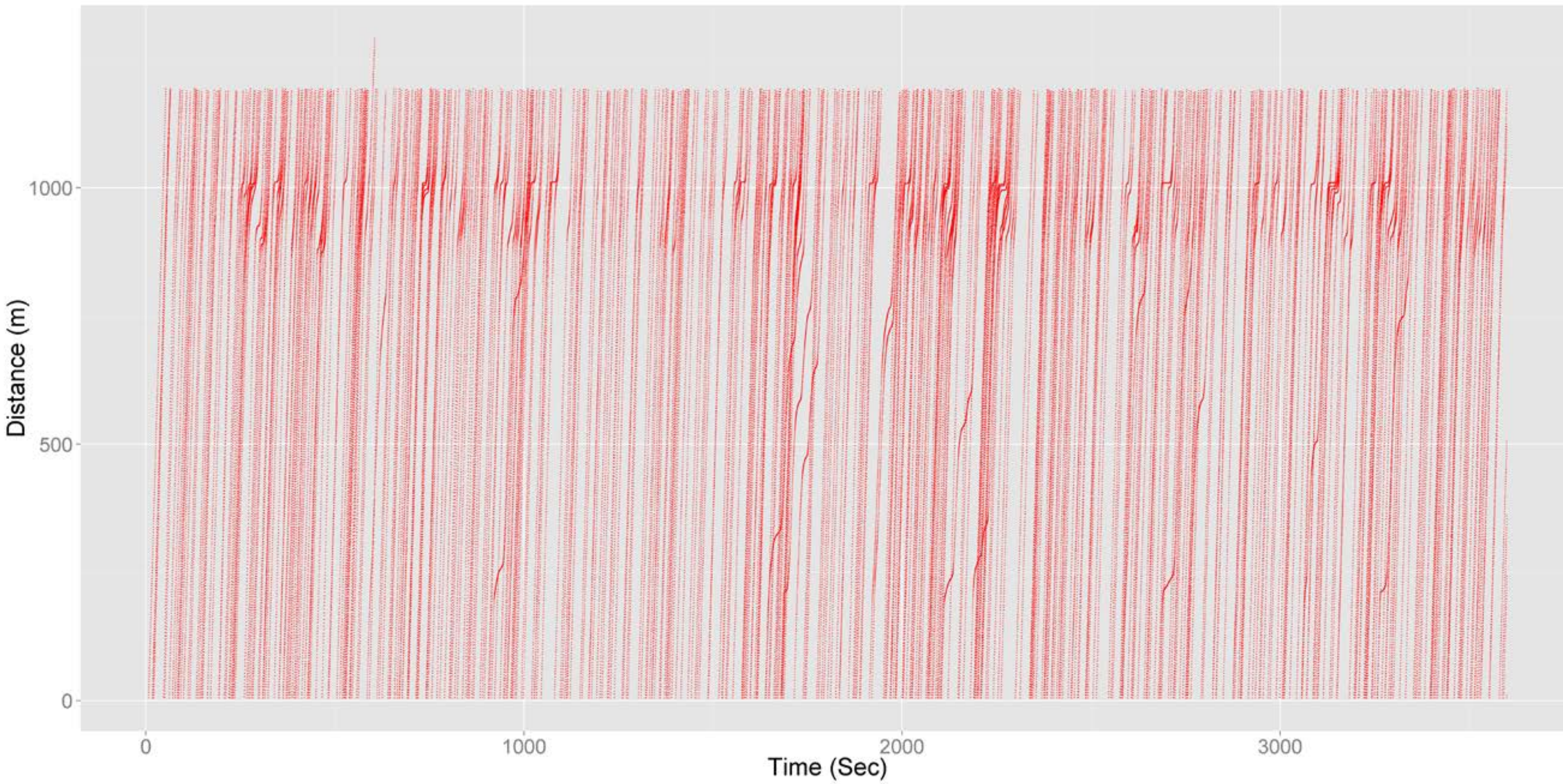


Figure 14. Trajectory Plot for Manually Driven Aggressive Vehicles

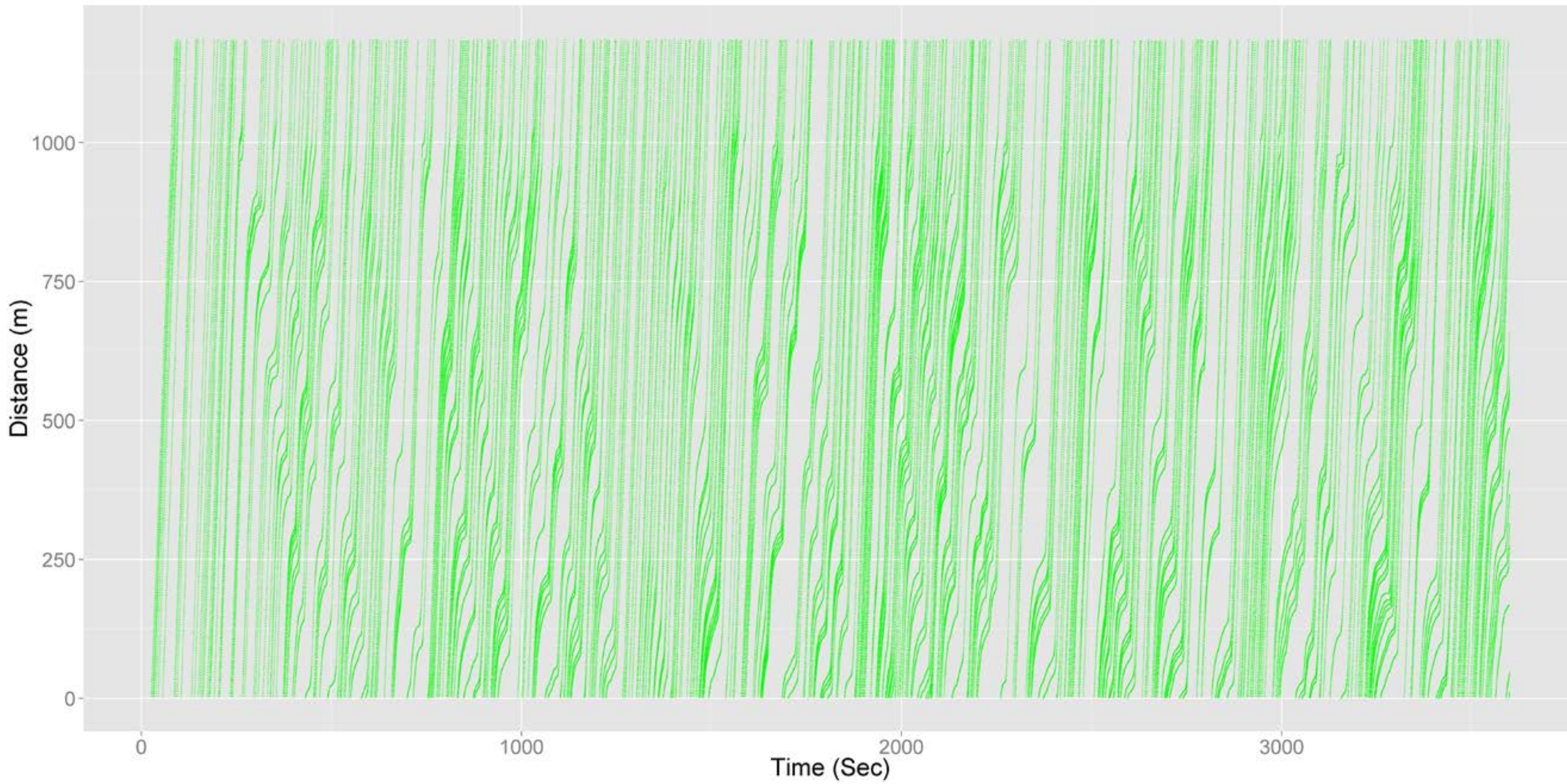


Figure 15. Trajectory Plot for Autonomous Vehicles

Figure 13 presents the normal manually driven vehicle trajectories, Figure 14 represents the aggressive manually driven vehicle trajectories, and Figure 15 represents the autonomous vehicle trajectories. It is clear that the aggressive vehicles are rewarded for their behavior, with minimal speed reduction, only occurring downstream near the ramp exit. The autonomous vehicles experience significant disruption (shock waves) because of the aggressive vehicle merges. This disruption is experienced by the normal manually driven vehicles, as well, as they are in the traffic stream with the autonomous vehicles. In alternatives where the autonomous vehicles are not present and, thus, there is no aggressive merging, this disruption is not witnessed.

5 Conclusions and Recommendations

The past few years have witnessed a rapidly growing market in assistive driving technologies, designed to improve safety and operations by supporting driver performance. Often referred to as cooperative vehicle–highway automation systems, these assistive technologies commonly use radar, LiDAR, or other machine-vision technologies, as well as vehicle-to-vehicle and vehicle-to-infrastructure technology, to obtain surrounding roadway and traffic data. Extensive research has been conducted on CVHA technology since the late 1990s. Findings have been generally positive, including potential safety benefits, high potential acceptance rates, and reductions in driver workload. Operations and capacity impacts have been mixed, depending on the technology. In addition, numerous opportunities for further advancement in traffic control strategies that leverage V2V and V2I have been identified and are under development.

A key finding from this study is related to the underlying modeling approach to study many of these potential technologies. It is clear that current simulation models are not capable of readily modeling cooperative assist technologies or autonomous vehicles. A critical component in the determination of the impact of many of these technologies is the human interaction with the technology, including both those individuals inside the equipped vehicle and those driving other vehicles that interact with the vehicle. Currently, it is not clear how individuals will interact with this technology on a wide scale, particularly when considering autonomous vehicles. To a significant degree this lack of information is not unexpected. Current in-vehicle technologies are in a state of continual flux, both within and across manufacturers. The “driving” characteristics of an autonomous vehicle are not yet known. Potentially dozens of autonomous vehicles are under development, each with its own logic, algorithms, etc. Pilot tests and constant updating govern the foreseeable future of development. More importantly, as highlighted in Chapter 4, it is not known how other drivers will interact with autonomous vehicles or other CVHA technology. Most previous studies have assumed a generally "well-behaved" interaction. However, should drivers choose to "bully" these vehicles, taking advantage of their safety protocols, traffic and safety improvements become much less certain.

Thus, it is necessary to view simulation through a new lens. To date, commercial simulation packages have built-in driver behavior for traffic flow models. These models contain a limited number of calibration parameters, and a limited range of potential behaviors. For instance, Chapter 3 shows that while 16 parameters had significant impact on the model performance, only four likely influenced the modeling of autonomous vehicles. However, in Chapter 4 the use case revealed that even with these parameters, significant additional efforts were required in the attempt to capture driver behavior outside of that reflected by the default modes.

As the definitions of vehicles and drivers enter a constant state of change, this will no longer be sufficient. The key finding from this effort is that to reflect CVHA it is necessary to design a new simulation and modeling approach, likely from an agent-based simulation point of view, where the vehicle types, behaviors, and abilities may be readily updated. Specific behaviors should not be "hard coded" into a model. Instead, models must provide easily acceptable interfaces, allowing for data exchange with new agents. Modelers must have an ability to create agents (i.e., new drivers, vehicles, etc.) with diverse potential characters and behaviors. From such a modeling tool, analysis of the ever-changing technological environment may then be efficiently conducted.

6 References

2014 Cadenza Features & Specs. (2014). Retrieved from http://www.kia.com/us/en/vehicle/cadenza/2014/features

2014 Lincoln MKS. (2014). Retrieved from http://www.lincoln.com/cars/mks/features/#page=FeatureCategory4

2014 LS Features - Safety. (2014). Retrieved from http://www.lexus.com/models/LS/features/

2014 Q70 Features. (2014). Retrieved from http://www.infinitiusa.com/sedan/q70/highlights/safety.html

2014 RLX Features. (2014). Retrieved from http://www.acura.com/Features.aspx?model=RLX

2014 Taurus Features. (2014). Retrieved from http://www.ford.com/cars/taurus/features/#page=FeatureCategory3

2014 XTS Sedan Trims & Specifications. (2014). Retrieved from http://www.cadillac.com/xts-luxury-sedan/features-specs/standard-optional-equipment.html

2015 K900 Features & Specs. (2015). Retrieved from http://www.kia.com/us/en/vehicle/k900/2015/features

2015 Volvo V60 Features & Options. (2015). Retrieved from http://www.volvocars.com/us/all-cars/volvo-v60/details/pages/default.aspx#/?category=2dd7a937-46d5-4251-8015-12939a77a480

Alkim, T. P., Schuurman, H., & Tampere, C. M. J. (2000). Effects of External Cruise Control and Co-operative Following on Highways : an Analysis with the MIXIC Traffic Simulation Model. *Proceedings of the Intelligent Vehicles Symposium*, (Mi), 474–479.

Arnaout, G. M., & Bowling, S. (2014). A Progressive Deployment Strategy for Cooperative Adaptive Cruise Control to Improve Traffic Dynamics. *International Journal of Automation and Computing*, *11*(1), 10–18. https://doi.org/10.1007/s11633-014-0760-2

Audi Traffic Jam Assistant Photos. (2014).

Ayapana, E. (2013a). First Look: 2015 Mercedes-Benz C-Class. Clearly Grown Up. Retrieved from http://www.motortrend.com/roadtests/sedans/1312_2015_mercedes_benz_c_class_first_look/

Ayapana, E. (2013b). First Look: 2015 Mercedes-Benz C-Class. Clearly Grown Up.

Baber, J., Kolodko, J., Noel, T., Parent, M., & Vlacic, L. (2005). Cooperative Autonomous Driving: Intelligent Vehicles Sharing City Roads. *Robotics &*

Automation Magainze, IEEE, *12*(1), 44–49.

Bergenhem, C.; Hedin, E.; Skarin, D. (2012). Vehicle-to-Vehicle Communication for a Platooning System. *Procedia Social and Behavioral Sciences*, 11.

Biester, L., & Bosch, R. (2005). The Concept of Cooperative Automation in Cars: Results from the Experiment "Overtaking on Highways." *Proceedings of the 3rd International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design*, 342–348.

Boeriu, H. (2013). Parking Assistant and Driving Assistant Plus including Traffic Jam Assistant.

Boeriu, H. (2014). CES 2014: BMW unveils M235i with automated driving, new control and assistance systems.

Brookhuis, K. A., Van Driel, C. J. G., Hof, T., Van Arem, B., & Hoedemaeker, M. (2009). Driving with a Congestion Assistant; mental workload and acceptance. *Applied Ergonomics*, *40*(6), 1019–25. https://doi.org/10.1016/j.apergo.2008.06.010

Calvert, S. C., van den Broek, T. H. a, & van Noort, M. (2012). Cooperative driving in mixed traffic networks — Optimizing for performance. *2012 IEEE Intelligent Vehicles Symposium*, 861–866. https://doi.org/10.1109/IVS.2012.6232138

Davis, L. C. (2004). Effect of adaptive cruise control systems on traffic flow. *Physical Review E*, *69*(66110), 1–8. https://doi.org/10.1103/PhysRevE.69.066110

Davis, L. C. (2007). Effect of adaptive cruise control systems on mixed traffic flow near an on-ramp. *Physica A: Statistical Mechanics and Its Applications*, *379*(1), 274–290. https://doi.org/10.1016/j.physa.2006.12.017

Driver Assistance. Drive smarter, safer and with confidence. (2014). Retrieved from http://www.bmwusa.com/standard/content/innovations/bmwconnecteddrive/connecteddrive.aspx?from=/Standard/Content/Innovations/BMWConnectedDriveRD.aspx&return=/Standard/Content/Innovations/BMWConnectedDriveRD.aspx#dassist

Elefteriadou, L., Martin, B., Simmerman, T., & Hale, D. (2011). *Using Microsimulation to Evaluate the Effects of Advanced Vehicle Technologies on Congestion*. Department of Civil and Coastal Engineering, University of Florida. Center for Multimodal Solutions for Congestion Mitigation. Project 2009-006.

Equipment highlights of the new Audi A8. (2015). Retrieved from http://www.audi.de/de/brand/de/neuwagen/a8/a8/motor/benzin.html#page=/de/brand/de/neuwagen/a8/a8/ausstattung.html

Eriksson, L., Bolling, A., Alm, T., Andersson, A., Ahlstrom, C., Blissing, B., & Nilsson, G. (2013). Driver acceptance and performance with LDW and rumble strips assistance in unintentional lane departures. *Visual Prototyping and Assessment by Simulation (ViP)*, *4*.

Fancher, P., Ervin, R., Sayer, J., Hagan, M., Bogard, S., Bareket, Z., … Haugen, J. (1998). *Intelligent Cruise Control Field Operational Test (Final Report)* (Vol. I). Washington, DC: The University of Michigan Transportation Research Institute. Sponsored by NHTSA, US DOT. Report No. DOT HS 808 849.

Fellendorf, M., & Vortisch, P. (2010). Microscopic traffic flow simulator VISSIM. In *International Series in Operations Research and Management Science* (Vol. 145, pp. 63–93). https://doi.org/10.1007/978-1-4419-6142-6_2

Flemisch, F., Kelsch, J., Löper, C., Schieben, A., & Schindler, J. (2008). Automation spectrum , inner / outer compatibility and other potentially useful human factors concepts for assistance and automation. *Human Factors for Assistance and Automation*, 1–16.

Flemisch, F., Kelsch, J., Loper, C., Schieben, A., Schindler, J., & Heesen, M. (2008). Cooperative Control and Active Interfaces for Vehicle Assistance and Automation. *FISITA World Automotive Congress*.

Ford's New Active Park Assist Aims to Curb Stress. (2009).

Ford Develops "Traffic Jam Assist" and New Parking Technology to Help Address Future Mobility Challenges. (2012).

Forkenbrock, G., Snyder, A., Heitz, M., Hoover, R. L., O'Harra, B., Vasko, S., & Smith, L. (2011). *A Test Track Protocol for Assessing Forward Collision Warning Driver-Vehicle Interface Effectiveness*. National Highway Traffic Safety Administration (NHTSA). Report No. DOT HS 811 501.

Hammerschmidt, C. (2012). Technology News: Volvo announces traffic jam assistant for semi-autonomous driving.

Hoeger, R.; Amditis, A.; Kunert, M.; Hoess, A.; Flemish, F.; Krueger, H., Bartels, A.; Beutner, A. . (2008). Highly Automated Vehicles for Intelligent Transport: HAVEit Approach. In *ITS World Congress* (p. 10). NY.

Hoogendoorn, S. P., & Minderhoud, M. M. (2001). ADAS Impact Assessment by Micro-Simulation. *European Journal of Transport and Infrastructure Research*, *1*(3), 255–275.

Hoogendoorn, S. P., & Minderhoud, M. M. (2002). Motorway Flow Quality Impacts of Advanced Driver Assistance Systems. *Transportation Research Record: Journal of the Transportation Research Board*, *1800*(2), 69–77.

Johnson, L. (2012). Fed Wants More Car Safety Tech.

Jones, S. (2013). *Cooperative Adaptive Cruise Control : Human Factors Analysis*. Science Applications International Corporation. Sponsored by FHWA. Report No. FHWA-HRT-13-045.

Kesting, A., Treiber, M., Schönhof, M., & Helbing, D. (2007). Extending Adaptive Cruise Control to Adaptive Driving Strategies. *Transportation Research Record*, *2000*(1), 16–24. https://doi.org/10.3141/2000-03

Kesting, A., Treiber, M., Schonhof, M., Kranke, F., & Helbing, D. (2007). Jam-Avoiding Adaptive Cruise Control (ACC) and its Impact on Traffic Dynamics. *Traffic and Granular Flow '05*.

Leading through Innovation. (2014). Retrieved from https://www.mbusa.com/mercedes/benz/innovation

Lee, J., Park, B. (Brian), Malakorn, K., & So, J. (Jason). (2011). Safety Assessment of Cooperative Vehicle Infrastructure System-Based Urban Traffic Control. *3rd International Conference on Road Safety and Simulation*, *c*, 1–11.

Lieberman, J. (2013a). First Drive: 2014 Mercedes-Benz S550. Ruling the Ruling Class.

Lieberman, J. (2013b). First Drive: 2014 Mercedes-Benz S550. Ruling the Ruling Class. Retrieved from http://www.motortrend.com/roadtests/sedans/1306_2014_mercedes_benz_s550_first_drive/

Liu, R., & Tate, J. (2004). Network effects of intelligent speed adaptation systems. *Transportation*, *31*, 297–325. https://doi.org/10.1023/B:PORT.0000025394.78857.13

Liu, Y., Dion, F., & Biswas, S. (2006). Safety Assessment of Information Delay on Performance of Intelligent Vehicle Control System. *Transportation Research Record*, *1944*(1), 16–25. https://doi.org/10.3141/1944-03

Max, J. (2012). Driver's Dashboard: Volvo to introduce new traffic jam assistance system.

Miersma, S. (2014). We demo Audi's Traffic Jam Assistant tech on the road [w/ video].

Milanés, V., Shladover, S. E., Spring, J., & Nowakowski, C. (2014). Cooperative Adaptive Cruise Control in Real Traffic Situations. *IEEE Transactions on Intelligent Transportation Systems*, *15*(1), 296–305.

Minderhoud, M. M., & Bovy, P. H. L. (1999). Impact of Intelligent Cruise Control on Motorway Capacity. *Transportation Research Record: Journal of the Transportation Research Board*, *1679*, 1–9.

Nowakowski, C., Shladover, S. E., & Cody, D. (2010). *Cooperative Adaptive Cruise Control : Testing Drivers ' Choices of Following Distances*. University of California PATH. Report No. UCB-ITS-PRR-2010-39.

PTV Vision, VISSIM 5.20 User Manual. (2009).

Reimer, B., Mehler, B., & Coughlin, J. F. (2010). *An Evaluation of Driver Reactions to New Vehicle Parking Assist Technologies Developed to Reduce Driver Stress*. Cambridge, MA: New England University Transportation Center, MIT.

Rim, H., Oh, C., Kang, K., & Kim, S. (2011). Estimation of Lane-Level Travel Times in Vehicle-to-Vehicle and Vehicle-to-Infrastructure-Based Traffic Information System. *Transportation Research Record: Journal of the Transportation Research Board*, *2243*, 9–16. https://doi.org/10.3141/2243-02

Shladover, S. E. (2008). *Assessment of the Applicability of Cooperative Vehicle-Highway Automation Systems (CVHAS) to Bus Transit and Intermodal Freight: Case Study Feasibility Analyses in the Metropolitan Chicago Region*. University of California PATH, Sponsored by CALTRANS. Report No. CA04-0494.

Shladover, S. E. (2012a). *Literature Review on Recent International Activity in Cooperative Vehicle – Highway Automation Systems*. University of California PATH Program & Cambridge Systematics, Inc. Sponsored by FHWA. Report No.

FHWA-HRT-13-025.

Shladover, S. E. (2012b). *Recent International Activity in Cooperative Vehicle – Highway Automation Systems*. University of California PATH Program & Cambridge Systematics, Inc. Sponsored by FHWA. Report No. FHWA-HRT-12-033.

Shladover, S. E., Su, D., & Lu, X.-Y. (2012). Impacts of Cooperative Adaptive Cruise Control on Freeway Traffic Flow. *Transportation Research Record: Journal of the Transportation Research Board*, *2324*, 63–70. https://doi.org/10.3141/2324-08

Silberg, G., Wallace, R., Matuszak, G., Plessers, J., Brower, C., & Subramanian, R. (2012). *Self-driving cars : The next revolution*. KPMG LLP & the Center for Automotive Research (CAR).

Stertz, B. (2012). Driver Assistance Systems.

Timmins, B. (2012a). Ford To The Future: A Taste of Self-Driving, Self-Parking Cars to Come. Retrieved from http://www.automobilemag.com/features/news/ford-to-the-future-a-taste-of-self-driving-self-parking-cars-to-come-150671/

Timmins, B. (2012b). Ford To The Future: A Taste of Self-Driving, Self-Parking Cars to Come.

Tingwall, E. (2014). 2015 Hyundai Genesis: New Looks, Same Engines. Emphasizing reeling in the Germans. Retrieved from http://www.caranddriver.com/news/2015-hyundai-genesis-photos-and-info-news

Toledo, T., Albert, G., & Hakkert, S. (2007). Impact of Active Speed Limiters on Traffic Flow and Safety: Simulation-Based Evaluation. *Transportation Research Record: Journal of the Transportation Research Board*, *2019*, 169–180. https://doi.org/10.3141/2019-20

Udy, J. (2014). First Look: 2015 Hyundai Genesis Sedan. A Renewed Beginning. Retrieved from http://www.motortrend.com/roadtests/sedans/1401_2015_hyundai_genesis_sedan_first_look/

van Arem, B., van Driel, C. J. G., & Visser, R. (2006). The Impact of Cooperative Adaptive Cruise Control on Traffic-Flow Characteristics. *IEEE Transactions on Intelligent Transportation Systems*, *7*(4), 429–436. https://doi.org/10.1109/TITS.2006.884615

Van Driel, C. J. G. (2007). *Driver Support in Congestion: An Assessment of User Needs and Impacts on Driver and Traffic Flow*. Ph.D Thesis. University of Twente, Netherlands.

Van Driel, C. J. G., Hoedemaeker, M., & Van Arem, B. (2007). Impacts of a Congestion Assistant on driving behaviour and acceptance using a driving simulator. *Transportation Research Part F: Traffic Psychology and Behaviour*, *10*(2), 139–152. https://doi.org/10.1016/j.trf.2006.08.003

Van Driel, C. J. G., & Van Arem, B. (2008). Traffic Flow Impacts of a Congestion Assistant. *TRB 2008 Annual Meeting CD-ROM*, (November 2007), 1–14.

Wang, J., & Rajamani, R. (2004). The impact of adaptive cruise control systems on highway safety and traffic flow. *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, *218*(2), 111–130. https://doi.org/10.1243/095440704772913918

Wang, M., Daamen, W., Hoogendoorn, S. P., & van Arem, B. (2014). Rolling horizon control framework for driver assistance systems. Part II: Cooperative sensing and cooperative control. *Transportation Research Part C: Emerging Technologies*, *40*, 290–311. https://doi.org/10.1016/j.trc.2013.11.024

Wille, M.; Röwenstrunk, M.; Debus, G. (2008). KONVOI: Electronically Coupled Truck-Convoys. In *Human Factors for Assistance and Automation* (pp. 243–256).

Wu, G., Boriboonsomsin, K., Zhang, W.-B., Li, M., & Barth, M. (2010). Energy and Emission Benefit Comparison of Stationary and In-Vehicle Advanced Driving Alert Systems. *Transportation Research Record: Journal of the Transportation Research Board*, *2189*, 98–106. https://doi.org/10.3141/2189-11

Yeo, H., Shladover, S. E., Krishnan, H., & Skabardonis, A. (2010). Microscopic Traffic Simulation of Vehicle-to-Vehicle Hazard Alerts on Freeway. *Transportation Research Record: Journal of the Transportation Research Board*, *2189*, 68–77. https://doi.org/10.3141/2189-08