Infrastructure Enablers for Reliable Cooperative Driving Automation (CDA) Phase I: Existing Infrastructure Evaluation

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Metric Conversion

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	M
yd	yards	0.914	meters	M
mi	miles	1.61	kilometers	km
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	G
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC

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16. Abstract

Connected and autonomous vehicles (CAVs) enhance transportation efficiency, reduce costs, and improve safety through cooperative driving automation (CDA), which enables communication and cooperation among vehicles, infrastructure, and road users. However, the existing infrastructure is designed for conventional vehicles and human drivers. The *"Infrastructure Enablers for Reliable CDA"* project addresses this challenge by evaluating the readiness of existing infrastructure. This Phase I report, *"Infrastructure Enablers for Reliable CDA: Existing Infrastructure Evaluation,"* explores CDA sensing technologies, infrastructure features, platooning experiment design guidelines, and co-simulation for testing support.

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Executive Summary

Cooperative driving automation (CDA) enables communication and cooperation between properly equipped vehicles, infrastructure, and other road users. CDA is poised to transform the nation's roads. It is expected to improve transportation efficiency, facilitate freight movement, increase productivity, save billions by reducing the need to increase roadway facilities, and reduce crashes caused by human error to save lives. Despite the promising advantages, efforts are still needed to explore mechanisms to deploy CDA technologies on a large scale, in addition to scarce pilot demonstrations. This project will explore infrastructure-enabled CDA technology to improve the existing infrastructure considering human drivers and connected and autonomous vehicles (CAV).

Section 1 presents a review of state-of-the-art CDA vehicle sensing technologies (cameras, lidar, radar, communication) and infrastructure features (lane markings, signage, traffic lights). A stakeholder alliance with local agencies and industry partners identified gaps in current technologies and infrastructure, with findings presented in a preliminary analysis and discussion.

Section 2 covers the evaluation of CDA vehicle sensing technologies using UWM's lab CAV and seven U.S. brands, including Honda, Ford, Toyota, and Tesla. Direct sensing (cameras, lidar, radar) is examined for infrastructure detection and indirect sensing (C-V2X) for communication. Tests covered diverse scenarios, including freeways, urban arterials, rural roads, adverse weather, and day or night driving. Key findings are summarized in a technical memorandum to guide future CDA technology and infrastructure development.

In section 3, the current infrastructure's compatibility with CDA sensing using UWM's lab CAV and seven commercial vehicles from leading U.S. brands is evaluated. The analysis focused on infrastructure elements like lane markings, static signs (stop, speed limit, yield), and traffic signals across diverse driving environments, including highways, urban arterials, and rural roads, under varying weather and lighting conditions. It identifies infrastructure features that hinder vehicle detection or connectivity and offers recommendations for improvements. These findings aim to guide future CDA technology development and infrastructure upgrades to enhance safety, efficiency, and system compatibility.

Section 4 presents a design guideline for field experiments on freeway vehicle platooning, developed under the Infrastructure Enablers for Reliable (CDA) project. It focuses on platooning formations, V2V and V2I communication integration, and standardized testing methodologies. The guidelines address challenges in mixed traffic conditions and provide recommendations on safety protocols, data management, and regulatory compliance. The section concludes with suggestions for future research on optimizing infrastructure, large-scale platooning deployment, cybersecurity testing, and machine learning verification.

Section 5 explores the integration of advanced simulation and hardware-in-the-loop techniques for CDA systems. In this section of the project, software-in-the-loop co-simulation, combining

traffic, vehicle, and communication simulations with CDA control platforms was covered. A detailed test plan for CDA vehicles in work zone scenarios includes use cases, tested units, operational design domains, performance metrics, test scenarios, and procedures. Results from the co-simulation platform compare traffic and vehicle performance with CDA vehicles and platoons in freeway work zones. The section also examines hardware-in-the-loop simulation, integrating real CDA hardware with virtual environments.

Table of Contents

List of Figures

List of Tables

Abbreviations and Acronyms

3D	Three-Dimensional
ABS	Automatic Braking Systems
ACC	Adaptive Cruise Control
ADAS	Advanced Driver-Assistance Systems
ASCE	American Society of Civil Engineers
BCA	Blind-Spot Collision-Avoidance Assist
BSMs	Basic Safety Messages
CACC	Cooperative Adaptive Cruise Control
CAN	Controller Area Network
CARLA	CAR Learning to Act
CARMA	Cooperative Automation Research for Mobility Applications
CATS	Connected and Autonomous Transportation Systems
CAVs	Connected and Autonomous Vehicles
CDA	Cooperative Driving Automation
CID	Controller Interface Device
CV	Connected Vehicle
C-V2X	Cellular Vehicle-to-Everything
DDT	Dynamic Driving Task
DFoV	Diagonal field of view
DSRC	Dedicated Short-Range Communication
ECU	Electronic Control Unit
FCC	Federal Communications Commission
FDI	False Data Injection
FDOT	Florida Department of Transportation
FHWA	Federal Highway Administration
FOV	Field of Vision
FSD	Full Self-Driving
GNSS	Global Navigation Satellite System
GSM	Global System for Mobile
GPS	Global Positioning System
HIL	Hardware-in-the-Loop
HMI	Human-Machine Interface
HV	Human-driven Vehicles
IEEE	Institute of Electrical and Electronics Engineers

IPG	Inter-Packet Gap
ITS	Intelligent Transportation Systems
JPCP	Jointed Portland Cement Concrete-Surfaced Pavements
LED	Light Emitting Diode
LORA	low-cost long-range
LTE	Long-Term Evolution
MOSAIC	Modular Selection And Identification for Control
MPC	Model Predictive Control
NEMA	National Electrical Manufacturers Association
NHTSA	National Highway Traffic Safety Administration
NS-3	Network Simulator 3
NTCIP	National Transportation Communications for ITS Protocol
OBU	Onboard Unit
ODD	Operational Design Domain
OEM	Original Equipment Manufacturer
OSM	OpenStreetMap
OVs	Objective Vehicles
PER	Package Error Rate
RANCS	Resilient, Autonomous, Networked Control Systems
RGB	Red, Green, and Blue
RMSD	Root Mean Square Deviation
RMSE	Root Mean Square Error
RSU	Roadside Unit
SAE	Society of Automotive Engineers
SIAD	Signalized Intersection Approach and Departure
SIL	Software-in-the-Loop
SNMP	Simple Network Management Protocol
SUMO	Simulation of Urban Mobility
SVs	Subject Vehicles
TDMA	Time-Division Multiple Access
TJET	Ternary Join-Exit-Tree
TLI	Traffic Light Information
TraCI	Traffic Control Interface
TTC	Time To Collision
V2I	Vehicle-to-Infrastructure
V2N	Vehicle-to-Network

V2P	Vehicle-to-Pedestrian
V2V	Vehicle-to-Vehicle
V2X	Vehicle-to-Everything
VIL	Vehicle-in-the-Loop
XIL	Everything-in-the-Loop
XML	Extensible Markup Language
YAML	YAML Ain't Markup Language

1 Literature Review and Preliminary Analysis

1.1 Introduction

The World Health Organization reported on June 21, 2021, that approximately 1.3 million people die yearly from road traffic crashes[1]. In Florida, over 400,000 crashes were reported causing over 240,000 injuries and nearly 3,000 fatalities[2] and over $8 billion is wasted on congestion in major cities in Florida every year[3].

The emergence of cooperative driving automation (CDA) provides essential solutions to these issues (Bai et al., 2022a; Kato et al., 2002; Soualmi et al., 2014). CDA technology is synonymous with connected and autonomous vehicle (CAV) technology (Li et al., 2022). They both refer to vehicles and technologies with automation and connectivity (Chen & Englund, 2016; Li et al., 2020). CAV has been widely used for a long time, yet CDA was proposed more recently with an emphasis on driving cooperation. CDA covers a larger domain, including CAV and infrastructure (SAE International, 2021). It enables communication and cooperation between properly equipped vehicles, infrastructure, and other road users, as shown in Figure 1-1 information shared among CDA participants can directly influence the dynamic driving task (DDT) by one or more nearby vehicles with driving automation feature(s) engaged (R. Xu et al., 2021a). From reducing congestion, collisions, pollution, and energy consumption, to enhancing road user safety, traffic flows, and operational efficiency, CDA is poised to transform the nation's roads. Once deployed, CDA has the potential to improve transportation efficiency, facilitate freight movement, increase productivity, and save billions by reducing the need to increase roadway facilities (Aramrattana et al., 2015). Most importantly, CDA has the potential to reduce crashes caused by human error and save lives (Bai et al., 2022b).

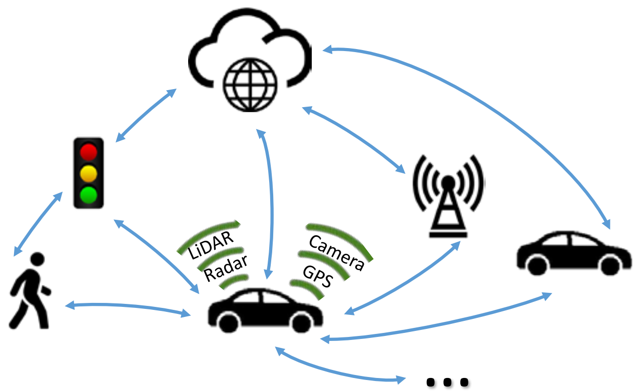


Figure 1-1: CDA technology illustration.

[1] https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries
[2] https://www.flhsmv.gov/resources/crash-citation-reports/
[3] https://www.fdot.gov/docs/default-source/planning/trends/special/flcongestion.pdf

Although CDA technologies have been booming over the past few decades (particularly featuring the successful commercialization of low-level automation), to realize the benefits, CDA technologies with the connected vehicle component are still exploring mechanisms to be deployed at a large scale in addition to scarce pilot demonstrations (Botte et al., 2019).One major hurdle to this process is that enabling devices in the traditional CDA technologies requires costly vehicle and infrastructure upgrades on sensing, communication, computing, and control components, which discourages stakeholders (e.g., vehicle makers, transportation operators) from deploying these innovative technologies (Kargl, et al., 2008; Wolcott & Eustice, 2014a). Whereas cheaper options (e.g., video alone) that are adopted by existing commercial automated vehicles (e.g., Tesla autopilot, lane keep functions by many automakers) may not be reliable and bear substantial safety risks to human drivers (Chavan et al., 2021; Ponn et al., 2020).

This project will explore a new concept of infrastructure-enabled CDA technology to improve the existing infrastructure considering human drivers and CAVs. This new concept aims to design infrastructure features that are easy to detect with low-cost sensors (e.g., video cameras) or received (e.g., with connected vehicles (CVs)) in a mixed traffic environment. The approaches include improving road coatings and surface markings to improve CDA detection rates, adding special static information signages that can transmit relatively complicated information (e.g., curves, grade changes, work zones), and real-time traffic information (queue warning, incident warning) to CDA vehicles with proper CV communications including traditional technologies, e.g., cellular vehicle-to-everything (C-V2X) communications, and low-cost technologies, e.g., visual-based light-code communications and low-cost long-range (LORA) communications (Ghafoor et al., 2020a; Takai et al., 2014).

This project will identify infrastructure features (e.g., lane markings, message signs, traffic lights) to estimate how well CDA vehicles can sense them. The research team will test the CDA technology of mainstream commercial automated vehicles (e.g., Ford, GM, Toyota, Honda) and the lab level 3 CAVs in processing infrastructure features. Field tests will be conducted on test tracks (e.g., SunTrax) and public roads. Further, the research team will report the evaluation performance, such as false positives and negatives, in recognizing these features, delays, and errors. The research team will be able to identify a candidate list of infrastructure features that are challenging existing CDA vehicles (or require expensive sensors). This list will be used to propose corresponding infrastructure treatment measures and estimate their costs and benefits in future implementations. Finally, the research team will build a foundation for investigating the test scenarios and procedures for testing CDA technologies at the SunTrax test tracks. A co-simulation platform with hardware-in-the-loop simulations and field data will be developed to support the testing of CDA technologies at SunTrax.

This project can help the Florida Department of Transportation (FDOT) identify candidate treatments for the existing infrastructure to suit CDA vehicles, estimate the cost of benefits of these treatments, and eventually help design guidelines for roadway design to supplement those for human drivers alone, during rapid federal CDA developments, e.g., cooperative classes defined by Society of Automotive Engineers (SAE) J3216, Cooperative Automation Research for Mobility Applications (CARMA) ecosystem (Geißler & Shi, 2022; Soleimaniamiri et al., 2021). Further, this project can help evaluate the safety and mobility of CDA technologies and potentially recommend modifications to enhance the CDA technologies with simulations and field data.

This section studies state-of-the-art CDA vehicle sensing technologies, such as cameras, lidar, radar, and communication technologies. It investigates existing infrastructure features, such as lane markings, static signage, dynamic message signs, and traffic lights. In addition to the literature review, the research team formed a stakeholder alliance with local agencies and industrial partners. Stakeholder meetings were conducted to identify the gaps in existing CDA vehicle technologies and infrastructure features. Based on the outcomes of the two aspects, this section presents the preliminary analysis and discussion, followed by a summary.

1.2 Literature Review

This section reviews existing literature on CDA technologies and infrastructure features required for CDA vehicle operations.

1.2.1 CDA Technologies

CDA vehicles use emerging technologies to perceive the surrounding environment (e.g. vehicles, bicyclists, pedestrians, traffic lights) to safely and efficiently provide mobility services for society (Van Brummelen et al., 2018). In general, these technologies are divided into sensing and communication.

Representative vehicle sensing technologies include cameras, radars, lidars, and global positioning systems (GPS). Researchers have developed models for different types of sensors for perception and decision-making for CDA vehicles (Daftry et al., 2020; Elbaz et al., 2017; Engelcke et al., 2017; Liang et al., 2018; Meyer et al., 2019; Qi et al., 2018; Ros et al., 2015). Table 1-1 summarizes representative sensors. More details are presented in subsections 2.1.1 to 2.1.5.

Table 1-1 Summary of representative sensors

Sensor	Pros	Cons
Monocular camera	Low cost Different Field of Vision (FOV)	Inability to compute object velocity Constrained by weather and lighting conditions Inability to perform simple distance computations
Stereo camera	Depth computation 3D localization of objects Better object identification	More costly Greater computing requirements Inability to compute object velocity Constrained by weather and lighting conditions
Short-range radar	Broad FOV	Short detecting range Large data package size
Long-range radar	Long detection range High accuracy Small data package size	More data loss Limited FOV at close range
2D Lidar	Simple structure Fast-ranging speed A more stable and reliable system	Limited FOV
3D Lidar	3D object detection	Broad FOV
GPS	Not affected by weather Reliable and efficient	Signal constrained by dense infrastructures

Communication technologies enable information exchanges among vehicles, infrastructure, and other road users. Effective communication technology can expand CDA vehicle perception from the immediate neighborhood to a broader area and enable vehicles to follow prescriptive infrastructure guidance or seek cooperative agreements (Abboud et al., 2016; N. Alam et al., 2011; Maglogiannis et al., 2022) . More details are discussed in subsection 2.1.6.

1.2.1.1 Cameras

Visual information can offer a concise summary of the surrounding objects. Cameras, typically mounted near the rearview mirror or the vehicle's rear, play a crucial role in CDA due to their affordability, wide field of view, and high resolution. However, because regular cameras perform poorly in low-light environments, infrared cameras are required for night detection (Niknejad et al., 2011). Monocular cameras are commonly used for tasks such as lane detection and traffic signal recognition due to their low cost, but they lack depth estimation and velocity computation capabilities (Khatab et al., 2021). Multi-monocular setups address these limitations by combining data from multiple cameras to enhance detection (Ieng et al., 2005). Stereo cameras go further, offering 3D imaging, depth computation, and precise localization, though they are more expensive and computationally demanding (Patel et al., 2013). These advanced systems are used in applications such as parking assistance and pedestrian detection (Nedevschi et al., 2009).

1.2.1.2 Radar

Radar is a key sensor for CDA vehicle object detection, capable of calculating distance, angle, and velocity using radio waves. It performs well in narrow FOV applications but struggles with cross-traffic detection and pedestrian identification (Sivaraman, 2013) (Sivaraman & Trivedi, 2013). Depending on detection range, radar is classified as short-range or long-range. Short-range radar offers a wider FOV but shorter range and is used for blind spot detection, parking aid, and collision avoidance (Khatab et al., 2021)(Murad et al., 2012) . Long-range radar has greater range and accuracy but a limited close-range FOV, making it suitable for speed measurement and highway alerts (Khatab et al., 2021). Advanced algorithms and antenna designs have further enhanced Radar's detection capabilities (Kumari et al., 2018); (Y. Yu et al., 2018). Its resilience to environmental factors and high-range resolution make radar essential for CDA.

1.2.1.3 Lidar

Lidar is widely used for obstacle detection and tracking (Xie et al., 2019) and is increasingly applied in driver assistance systems like adaptive cruise control (Bharmal & Rashid, 2019). Compared to radar, lidar provides clearer measurements and a larger FOV, enabling multi-lane tracking (Sivaraman & Trivedi, 2013), though it is more expensive and sensitive to environmental factors (de Ponte Müller, 2017). Lidar operates as 2D or 3D systems, with 2D lidar excelling in vehicle and pedestrian detection due to its simplicity and stability (Khatab et al., 2021) while 3D lidar offers higher precision for 3D object detection and tracking using advanced algorithms like SVM and Kalman filters (H. Wang & Zhang, 2022). Its high accuracy, fast response, and anti-interference capabilities make lidar indispensable for navigation, obstacle avoidance, and modern transportation systems.

1.2.1.4 GPS

GPS, a global navigation satellite system, enables real-time vehicle tracking and monitoring in various conditions (Ajay, 2015). While highly reliable, its accuracy can be affected near high-rise buildings, tunnels, or dense infrastructure (Ward & Folkesson, 2016). GPS-based systems have been developed for map-matching (Jagadeesh et al., 2004), vehicle routing and monitoring, and car positioning using Global System for Mobile (GSM) communication (Mohol et al., 2014). Advanced methods, such as Bayesian approaches (Rohani et al., 2015), enhance localization accuracy. GPS integration with other sensors improves vehicle state estimation and lateral stability control (Ryu & Gerdes, 2004) ; (Bevly et al., 2000). Combining GPS with deep learning and multimedia data further expands vehicle perception and minimizes blind spots, making GPS indispensable for modern transportation and fleet management.

1.2.1.5 Sensor Fusion

Sensor fusion addresses the limitations of individual sensors by combining data from multiple types, such as radar, camera, and lidar, to enhance perception in CDA systems (Khatab et al., 2021). Common combinations like radar-camera and camera-lidar improve accuracy in object detection, distance estimation, and obstacle avoidance (Yeong et al., 2021); (Premebida et al., 2007). The integration of all three—radar, camera, and lidar—provides the most comprehensive perception but is the most expensive (Cho et al., 2014). This technology is critical for improving vehicle detection, tracking reliability, and the safety of CDA vehicles, driving advancements in commercial applications (Stateczny et al., 2021); (Stateczny et al., 2021).

1.2.1.6 Communication

Researchers have extensively studied Dedicated Short-Range Communication (DSRC) as a connected vehicle communication technology since its approval in recent decades. More recently, C-V2X has emerged as a communication technology enabled by long-term evolution (LTE). It can be easily upgraded to 5G networks, allowing C-V2X to benefit from new high-transmission speeds. The existing communication technology is undergoing drastic changes due to the transition from DSRC to C-V2X (Federal Communications Commission, 2021). Table 1-2 shows the summary of communication technologies.

Table 1-2 Summary of communication technologies

Communication technology	Pros	Cons
DSRC	Well studied Low latency	Signals blocked by buildings Inefficiency caused by the distributed nature Short transmission distance
C-V2X	High dependability Expanded range of transmitted data streams Resolving communication issues caused by high mobility and vehicle density	Delay due to centralized nature Early stage without wide deployment

DSRC enables data transmission between vehicles, infrastructure, and pedestrians within hundreds of meters, supporting applications like collision warnings, blind spot detection, and intersection assistance despite reliability and range limitations (Kenney, 2011). Algorithms and frameworks have been developed to enhance DSRC-based collision avoidance and safety communication (A. Tang & Yip, 2010); (Somak et al., 2011). In contrast, C-V2X offers greater range, reliability, and advanced applications like platooning and lane merging but faces challenges in latency and large-scale commercialization (Miao et al., 2021); (Ghafoor et al., 2020b). As C-V2X matures, transitioning from DSRC will require careful planning to ensure communication effectiveness.

1.2.2 Infrastructure Features

This section reviews efforts to evaluate existing infrastructure features for CDA operations. The anticipated advantages of CDA technologies might be hampered by a lack of an appropriate infrastructure to enable safe and dependable operations.

1.2.2.1 Early Stage of the CDA Technology

In the early stages of CDA technology, maintaining existing infrastructure to support both CDA and human-driven vehicles is crucial, as large-scale changes are not yet feasible (Tafidis et al., 2021). Clear traffic signs and pavement markings are essential for navigation, positioning, and safety systems (Ghafoor et al., 2020b); (Hallmark et al., 2019). Poor road conditions, such as potholes and faded markings, can hinder vehicle stability and sensing accuracy (Nitsche et al., 2014); (Binshuang et al., 2019). Regular maintenance, including improved street lighting, drainage systems, and vegetation management, ensures better road readability and safety for all users (Liu et al., 2019). Since CDA vehicles differ in detection accuracy, high-quality infrastructure is key to reliable operations until standardized sensing performance is achieved (Rana & Hossain, 2023).

1.2.2.2 Prevailing Mixture of CDA Vehicles and Human-Driven Vehicles

As CDA technology advances, dedicated infrastructure is required to enhance roadway capacity, safety, and fuel efficiency while maintaining traditional infrastructure for human-driven vehicles (Rana & Hossain, 2023). Transition zones and exclusive lanes for CDA vehicles can improve traffic efficiency and safety during mixed traffic stages, requiring features like additional roadside sensors and clear lane markings (Farah et al., 2018); (K. Ma & Wang, 2019). Digital infrastructure, including V2V and V2I communication systems, fiber optic cables, and RSUs, will be essential for seamless communication (Sanusi et al., 2022). Redesigning bridges, pavements, and parking lots to accommodate CDA-specific needs while retaining traditional infrastructure ensures a smooth transition to automation (Liu et al., 2019).

1.2.2.3 Mature Stage of the CDA Technology

In the mature stage of CDA technology, advanced infrastructure can maximize efficiency and safety while simplifying existing components. Slot-based vehicle movement, single communication beacons replacing traffic lights, and streamlined parking layouts are proposed to enhance operations (C. Yu et al., 2018); (Liu et al., 2019). Full automation will reduce the need for traditional infrastructure, improve road capacity, and optimize land use, transforming parking lots and travel hubs (Farah et al., 2018); (McDonald & Rodier, 2015).

1.3 Stakeholder Involvement

The research team formed a stakeholder alliance with local agencies and industrial partners. The research team hosted several stakeholder meetings to identify the gaps in existing CDA vehicle technologies and infrastructure features by discussing critical questions. These questions were developed based on the research tasks of phase 1 in this project.

On November 22, 2022, the research team held the first stakeholder meeting. Participants included stakeholders from FDOT, Connected Wise, Robert Bosch, Florida International University, the University of South Florida, and the University of Wisconsin – Madison. To solicit more feedback, on December 12, 2022, the research team hosted a one-on-one meeting with stakeholders from Locomotion. On December 14, 2022, the research team hosted another one-on-one meeting with stakeholders from Coast Autonomous. Specifically, the following questions were discussed. The research team summarized the feedback and comments below.

Q1. What are your expectations of (CDA) technologies?

Most stakeholders expect CDA to improve traffic mobility, safety, and fuel efficiency in different applications. CDA vehicles without different cooperation classes should impact the traffic system differently. Stakeholders think the future traffic flow should be all-inclusive, harmonizing all vehicles (e.g., CDA vehicles and manually driven vehicles) to work together for better functionality. Some stakeholders also think CDA vehicles should be deployed on existing roads without requiring new infrastructure. Companies should work on CDA technology development targeting this goal. Existing infrastructure will only provide additional useful information to CDA vehicles. CDA vehicle operation will not rely on roadside infrastructure. In addition, stakeholders expect great data quality and cybersecurity associated with CDA.

Q2. What critical infrastructures do CDA vehicles need to identify? What type of infrastructure is difficult to identify and why?

Stakeholders believe any roadway feature must be identified by CDA vehicles to operate safely. Some stakeholders also suggested that warning beacons (e.g., school zones) should be accurately perceived. The following challenges exist.

Communication with roadside equipment is probably difficult since it is still under initial development.

The inconsistency among infrastructure features at different places can make CDA vehicle sensing challenging. A uniform and consistent infrastructure standard is demanded.

Dynamic features can be difficult to identify since they change with time, e.g., work zone.

Intersections, conflict points, mid-block pedestrian crossing, and traffic signals might also be challenges for CDA perceptions.

Stakeholders believe accurate mapping is critical for CDA vehicle perception. It is useful to store basic information like the locations of bridges and the curvature of highways and tunnels in HD maps. Stakeholders also believe appropriate traffic rules and policies are important to facilitate CDA vehicle operation.

Q3. The following technologies can help CDA vehicles identify existing infrastructure, camera, radar, lidar, GPS, and C-V2X. What else? Which ones are the most promising and why?

Most stakeholders believe all these technologies are important and promising. Some stakeholders think the communication between vehicles and infrastructure might be even more critical. Stakeholders brought up the concept of cooperative perception, that is, to integrate the perceptions from various sensors from not only the individual vehicle but also other vehicles and infrastructures. Vehicles will have a more comprehensive perception of the surroundings through cooperative perception. Other stakeholders think GPS is the most promising technology since it is the most popular one and performs well most of the time.

Q4. What are the gaps/limitations of existing CDA vehicle technologies? What modifications/innovations should be made from the infrastructure side to support CDA vehicles? When should these modifications/innovations be made (level of CDA vehicle penetration rate)?

Stakeholders discussed the following limitations of CDA vehicle technologies. The existing CDA technologies are not robust enough to sense various infrastructures in the presence of disturbances, e.g., bad weather and blocked by tree branches. Sensor fusion strategies can be used to enhance the robustness of CDA technologies. Existing infrastructure (e.g., pavement markings and traffic signs) should be clearly visible, consistent, and uniform. Stakeholders also mentioned that the data associated with CDA technologies should be available to everyone. These strategies should be implemented, starting at the current stage. Further, there are only limited roadside units in the current transportation system (especially in rural areas). More units are needed to support CDA vehicle operations. This strategy should be implemented when the CDA vehicle penetration rate reaches a threshold, depending on the deployment agency.

Q5. The research team will evaluate a list of CDA vehicle technologies in different scenarios. What technologies should be evaluated? What scenarios should be tested (e.g., freeway, arterial, daytime, nighttime, adverse weather)? What performance should be measured?

Most stakeholders think all CDA technologies are important and should be evaluated. Stakeholders are interested in evaluating CDA technologies in the worst scenario, e.g., adverse weather in a work zone. Some stakeholders are interested in testing freight management. Vehicle merging and diverging locations are also worth evaluating. Some stakeholders are particularly interested in CDA vehicle operations at the city center or industrial sites. They expect CDA vehicles to operate like a great driver. Some stakeholders provided that there was no real difference between daytime and nighttime regarding CDA vehicle operations. Other stakeholders suggested testing CDA operations in unstable traffic flow and the presence of heavy pedestrian volumes. Stakeholders believed that vehicle perception time should be measured.

Q6. For CDA vehicle platooning in the field, what scenarios should be tested? For example, platoon speed, platoon headway, and road geometry.

Some stakeholders provided that they had been struggling with platoon speed management. Some stakeholders suggested a platoon speed of 65 to 70 miles per hour. Others also indicated that platoon headway is a critical factor that should be tested. One stakeholder suggested half-second time headway based on the literature.

Q7. For CDA vehicle platooning, what scenarios cannot be tested in the real world, and should they be simulated (e.g., large-scale operation, congestion level)?

Based on stakeholders, some microscopic features should be simulated, e.g., reaction time and shockwave characteristics. Risky scenarios that may put anybody in danger should be simulated, e.g., too-close platooning. Also, large-scale platoon operations should be simulated.

Q8. A hardware-in-the-loop simulation investigates real-world CDA vehicle motions with a simulated traffic environment. What are the suggestions?

Stakeholders suggested that the hardware should be components like sensors, controllers, or whole vehicles. Vehicles should be set up in a spacious test environment with other simulated vehicles, e.g., virtual reality or augmented reality. Individual vehicle simulators should be integrated into the traffic simulator to enhance the scalability of the simulation. Some stakeholders also suggested that the simulation be constructed based on real-world situations.

Q9. A software-in-the-loop simulation incorporates a traffic simulation tool, an automated vehicle simulation tool, and a communication simulation tool. What are the suggestions?

Stakeholders suggested that traffic simulation tools be as realistic as possible to mimic real-world traffic operations. Stochastic car-following and lane-changing models may be used to simulate the stochasticity of real-world traffic movements. Sensing delay and inaccuracy should be incorporated into the automated vehicle simulation tool. Vehicle communication delay and inaccuracy should also be considered in the communication tool.

Q10. Original Equipment Manufacturer (OEM): Do you have an implementation plan to introduce CDA technology in your fleet? If so, when could we expect vehicles to debut with CDA technology? Do you have a plan to project a penetration rate for these vehicles?

One company is developing a communication device using C-V2X and testing it on its vehicle fleet. This company has signed contracts for 3120 trucks from four carriers throughout the country. Some private companies intend to introduce CDA technologies in the intermodal facilities, which have 500 or 1500 parking spots for trailers. They also have plans to implement camera detection, which will notify the approaching vehicles of the presence of pedestrians, other vehicles, or anything else. Some other stakeholders are trying to provide an aftermarket solution for older vehicles. The goal is to keep them up to speed for better overall traffic stream operations.

1.4 Preliminary Analysis and Discussion

This section provides a preliminary analysis based on literature review and stakeholder feedback, which generally align. Sensing technologies, such as cameras, radars, lidar, and GPS, enable CDA vehicles to perceive their surroundings and operate safely, though their detection ranges and accuracy vary. Improved sensor accuracy enhances safety, while greater detection range allows better motion planning. However, existing studies lack sufficient analysis of sensor impacts on CDA operations.

Communication technologies like DSRC and C-V2X also play a crucial role. C-V2X, leveraging advancements in 5G, offers higher transmission speeds but faces uncertainties in communication delay and accuracy due to bandwidth limitations set by the FCC (Federal Communications Commission, 2021).

As CDA technology evolves, infrastructure requirements change to support safe and efficient operations. In the early stages, infrastructure should cater to both CDA and human-driven vehicles, emphasizing consistency and visibility. As adoption grows, dedicated infrastructure, such as advanced communication devices, will be necessary to unlock CDA's full potential, including enhanced safety and reduced fuel consumption. In the mature phase, advanced infrastructure can replace or simplify existing components, maximizing benefits.

Stakeholders stressed the importance of maintaining consistent infrastructure and integrating new communication features, noting that environmental factors significantly impact CDA performance. They also encouraged field experiments to evaluate CDA technologies in real-world scenarios, such as platooning and pedestrian interactions, to inform future developments.

2 Evaluation of CDA Vehicle Sensing Technologies

2.1 Introduction

This section explores advanced CDA vehicle sensing technologies, including cameras, lidar, radar, and communication systems like C-V2X, designed to detect environmental features such as lane markings, static signs, dynamic displays, and traffic lights. The study evaluates CDA sensing technologies in UWM's lab CAV and seven prominent U.S. commercial brands, including Honda, Ford, Toyota, and Tesla. The analysis emphasizes direct sensing technologies for detecting infrastructure elements and indirect sensing technologies for vehicle-to-vehicle and vehicle-to-infrastructure communication. Test scenarios cover diverse conditions such as freeways, urban arterials, rural roads, adverse weather, and day/night settings. These findings offer an initial analysis to support the advancement of CDA technology and infrastructure.

2.2 Commercial Vehicle

The research team conducted a study on six brands of commercial vehicles with various CDA sensing technologies, testing all available features in each model. Experiments covered different road types (freeways, urban arterials, and rural roads) and conditions, including daytime, nighttime, rainy, and clear weather. The testing was limited in scope and not exhaustive, providing insights rather than definitive performance measures. For example, detecting lanes in 4 out of 10 tests does not imply 40% accuracy but reflects performance in specific scenarios. Tests involved seven vehicles, with details provided in Table 2-1.

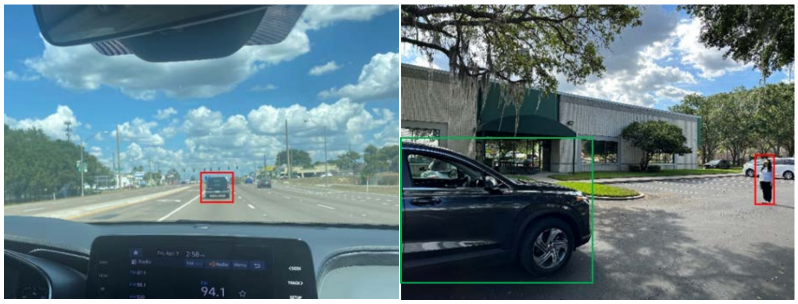
Table 2-1 The vehicles used in the evaluation of CDA vehicle sensing technologies.

Vehicle Number	Brand	Model	Year
Vehicle 1	Toyota	Corolla	2022
Vehicle 2	Hyundai	Santa Fe	2022
Vehicle 3	Ford	Bronco	2022
Vehicle 4	Audi	Q5	2023
Vehicle 5	Honda	Accord	2022
Vehicle 6	Tesla	Model Y	2023
Vehicle 7	Mustang	Electric	2021

Different features of vehicle technologies are used to test the sensing capability of CDA vehicles. This will be discussed as follows.

2.2.1 Pre-collision System

A pre-collision ADAS (Advanced Driver Assistance System) is a safety feature designed to reduce the risk of accidents by detecting potential collisions and taking preventive actions. Using sensors such as cameras, radar, or lidar, the system monitors the vehicle's surroundings, identifies obstacles, and alerts the driver to imminent dangers. In critical situations, it may apply automatic braking or steering assistance to mitigate or avoid collisions, enhancing road safety and reducing driver response time. The typical example of testing of the pre-collision assist scenario is given in the Figure 2-1. The pre-collision system was tested on different vehicles with different conditions (see Table 2-2).



(a) Daytime testing

(b) Nighttime testing

Figure 2-1 Forward collision-avoidance assist testing of vehicle 2[4].

Table 2-2 Pre-collision testing.

Vehicle Brand/Model	Pre-collision system of each vehicle	Conditions	Number of successful detections/ number of tests	
			Vehicle	Pedestrian
Toyota Corolla	Pre-Collision System	Daytime	9/10	9/10
		Nighttime	0/10	-/-
Hyundai Santa Fe	Forward Collision-Avoidance Assist (Sensor Fusion)	Daytime	9/10	9/10
		Nighttime	7/10	6/10
Tesla Model Y	Collision Avoidance Assist/ Pedestrian Warning System	Daytime	10/10	9/10
		Nighttime	9/10	7/10
Ford Bronco	Pre-Collision Assist	Daytime	7/10	
		Nighttime	7/10	
Ford Mustang Mach-E	Pre-Collision Alert	Daytime	12/12	

[4] Green is Vehicle 2, and red is the object.

Table 2-3 presents the testing results for Vehicle 6's Forward Collision Warning (FCW) system, specifically evaluating the distance at which the system detects potential collisions and issues warnings. The tests were conducted under varying conditions, including different speeds

Table 2-3 Vehicle 6 forward collision warning distance testing results.

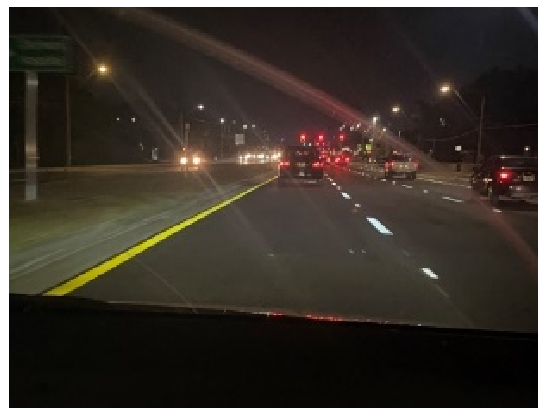
Speed	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Average**	**numbers of successful detections/ Number of tests**
10 mph	19 ft	17 ft	17 ft	22 ft	25 ft	17 ft	17 ft	22 ft	24 ft	20 ft	20.0 ft	10/10
15 mph	30 ft	29 ft	28 ft	33 ft	32 ft	29 ft	31 ft	31 ft	33 ft	31 ft	30.7 ft	10/10
20 mph	42 ft	41 ft	43 ft	40 ft	41 ft	41 ft	43 ft	40 ft	41 ft	41 ft	41.3 ft	10/10

2.2.2 Lane Tracing Assist and Lane Departure Alert

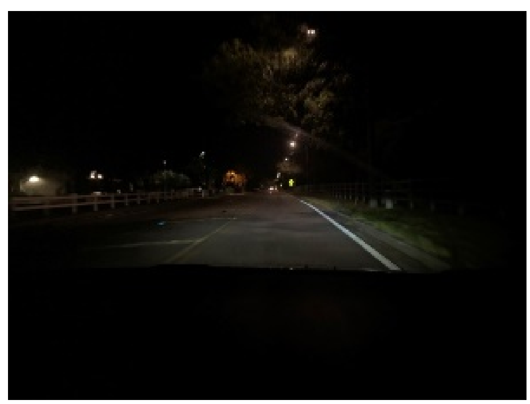
Lane Tracing Assist (LTA) and Lane Departure Alert (LDA) are ADAS features designed to enhance vehicle safety. LTA helps keep the vehicle centered within its lane by providing steering assistance, while LDA alerts the driver when the vehicle unintentionally drifts out of its lane. These systems rely on sensors and cameras to monitor lane markings and vehicle positioning. The typical testing scenario for lane-keeping and lane-tracing assist is illustrated in Figure 2-2. LTA and LDA were tested on various vehicles under different conditions, as detailed in Table 2-3.

Figure 2-2 Lane detection information of Vehicle 1.


(a) Straight and clear lanes at daytime (freeway) (b) Curved and clear lanes at daytime (rural)

(c) Straight and clear lanes at daytime (campus) (d) Straight and clear lanes at nighttime (urban)

(e) Straight and unclear lanes at daytime (rural) (f) Straight and unclear lanes at nighttime (rural)

Figure 2-3 Lane detects testing of Vehicle 1.

Table 2-4 Lane tracing assist and lane departure tests

Vehicle Brand/Model	Lane tracing assist and lane departure of each vehicle	Conditions	Number of successful / Number of tests
Toyota Corolla	Lane Tracing Assist and Lane Departure Alert	Daytime, straight, clear lane	9/10
		Daytime, curved, clear lane	5/10
		Daytime, straight, unclear lane	4/10
		Nighttime, favorable lighting, straight, clear lane	8/10
		Nighttime, poor lighting, straight, clear lane	6/10
		Nighttime, straight, unclear lane	3/10
Hyundai Santa Fe	Lane Keeping Assist & Lane Following Assist	Daytime, straight, clear lane	9/10
		Daytime, curved, clear lane	7/10
		Daytime, straight, unclear lane	6/10
		Daytime, curved, unclear lane	5/10
		Nighttime, straight, clear lane	6/10
		Nighttime, straight, one side unclear lane	4/10
	Lane Keeping System	Daytime, straight, clear lane	9/10
		Nighttime, straight, clear lane	8/10
Ford Bronco		Daytime, curved, clear lane	5/10
		Nighttime, curved, clear lanes	4/10
		Daytime, straight, unclear lane	5/10
		Nighttime, straight, unclear lane	4/10
Audi Q5	Active Lane Assist/Lane Departure Warning	Daytime, straight, clear lane	9/10
		Daytime, curved, clear lane	7/10
		Nighttime, straight, clear lane	4/10
		Nighttime, curved, clear lane	5/10
		Daytime, straight, unclear lane	5/10
		Nighttime, straight, unclear lane	3/10
Honda Accord	Lane Keeping Assist System	Daytime, straight, clear lane	10/10
		Nighttime, straight, clear lane	9/10
		Daytime, curved, clear lane	6/10
		Nighttime, curved, clear lanes	4/10
		Daytime, straight, unclear lane	5/10
		Nighttime, straight, unclear lane	5/10
Tesla Model Y	Lane Assist	Daytime, straight, clear lane	10/10
		Daytime, curved, clear lane	10/10
		Daytime, straight, unclear lane	10/10
		Daytime, curved, unclear lane	10/10
		Nighttime, straight, clear lane	10/10
		Nighttime, straight, one side unclear lane	10/10

Furthermore, the lane-keeping assist of Vehicle 7 was tested. Lane-keeping assist helps Vehicle 7 to stay in the lane by sending a buzzing alert to the driver and provides counter steering aid. This steering aid will position the vehicle back between the lane lines when it is out of the lane.

The camera capability of Vehicle 7 was evaluated through a lane-keeping test. The test description is as follows:

Sensor: Camera

Test location: B Downs Blvd, FL 33612 (for nighttime and daylight tests in dry weather) and 46th St, Tampa, FL 33617 (daytime rainy weather test)

Additionally, a webcam camera was attached to the center of the windshield of Vehicle 7. Then, the lane-keeping driving assist feature was set on (i.e., lane centering with ACC, lane-keeping alert, and lane-keeping aid). While driving the vehicle in the test location, the performance of the lane-keeping feature of Vehicle 7 was observed. The webcam camera recorded this action.

The tests were conducted in four different scenarios.

- Good lane marking in the daytime during dry weather.
- Poor lane marking in the daytime during dry weather.
- Good lane marking in the nighttime during dry weather.
- Poor lane marking in the nighttime during dry weather.
- Good lane marking in the daytime during rainy weather.
- Poor lane marking in the daytime during rainy weather.

The daytime test results show that the Vehicle 7 lane-keeping alert buzzed and kept it within the lane when the vehicle was out of the lane in bad and good lane markings. During the nighttime test, the vehicle's lane-keeping feature was able to detect the good lanes and keep the vehicle within the lane. Meanwhile, in the case of bad lane marking at nighttime, Vehicle 7 was not able to keep its lane.

Furthermore, the effects of rainy weather on camera capability were also tested by observing the performance of the lane-keeping system of Vehicle 7. Due to the light reflection of the wet road surfaces and the water droplets on the surfaces of the camera field of view, lane detection was challenging. It was observed that the lane keeping of Vehicle 7 performed well on good lane marking in the daytime during rainy weather. On the contrary, poor performance was observed in poor lane markings in the daytime for rainy weather.

Lastly, the vehicle did not respond at the intersection of roads where there were no lane markings shown. The research team members were also able to observe the effect of speed on the lane-keeping feature of Vehicle 7 by testing the feature at 20 mph and 40 mph. The lane-keeping feature performed better at higher speeds than at lower speeds.

The images from the webcam camera show the lanes in front of the vehicle when the vehicle tried to keep itself in the lane. The following five steps are taken:

- The color image was changed to a grey image.
- The gray image was changed to a binary image.
- Region masking was added over the binary image.
- The lanes in the binary image were generated.

Finally connecting lines of lane pixels were determined using Hough transforms (the green lines). The above procedures are shown in the following pictures.

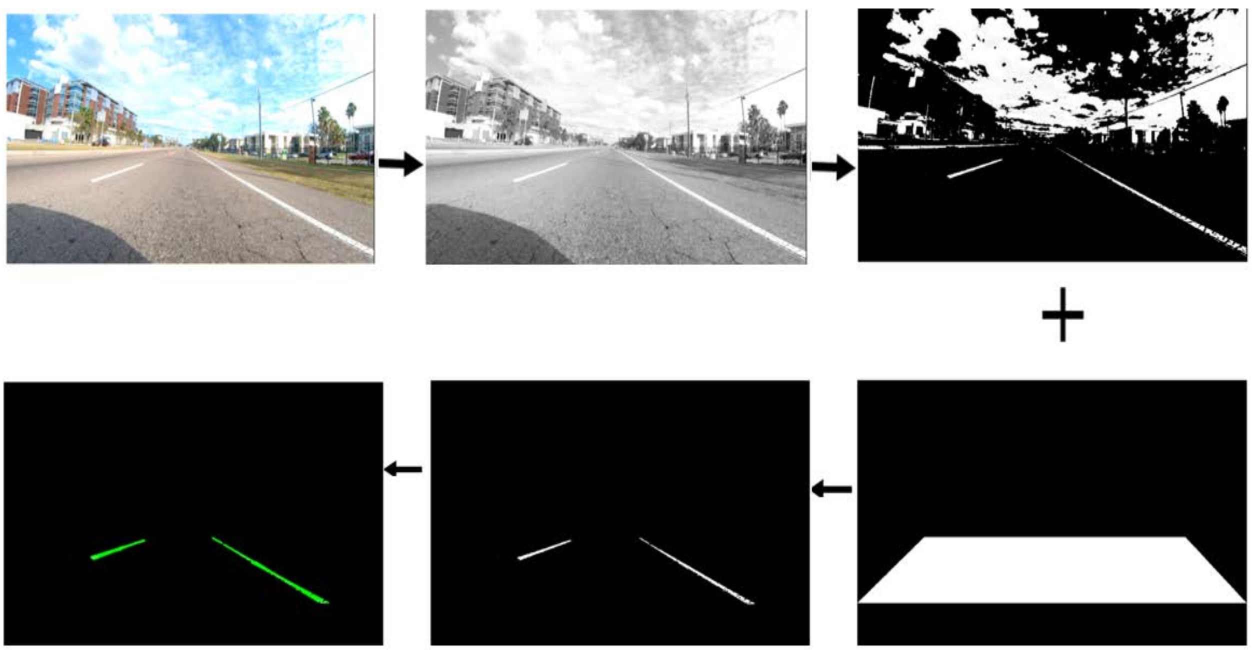


Figure 2-4 Good lane marking test in the daytime during dry weather.

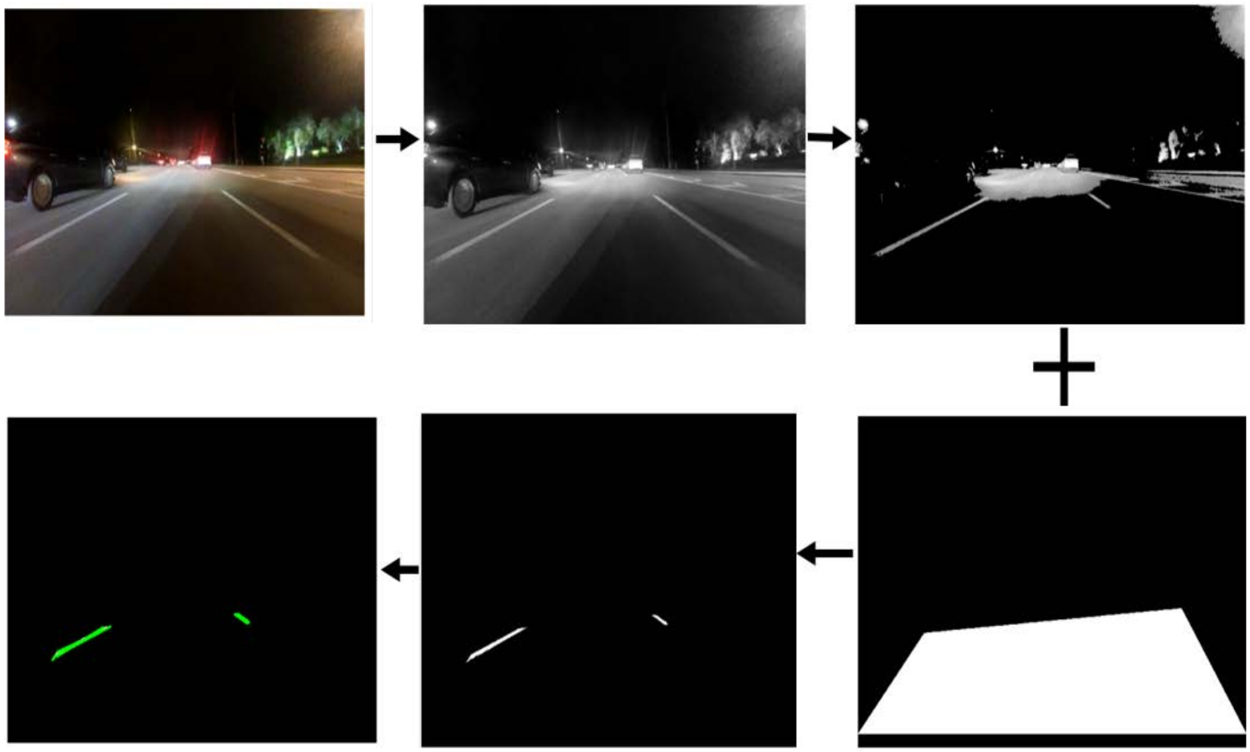


Figure 2-5 Good lane marking test in the nighttime during dry weather

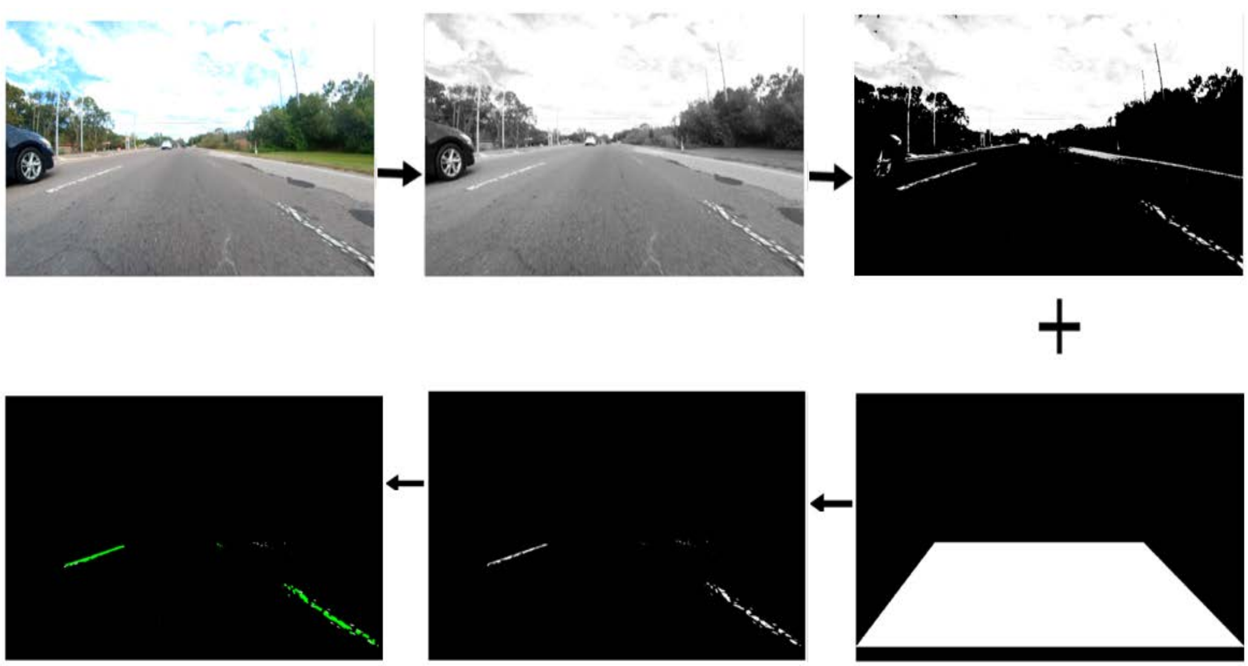


Figure 2-6 Poor lane marking test in the daytime during dry weather

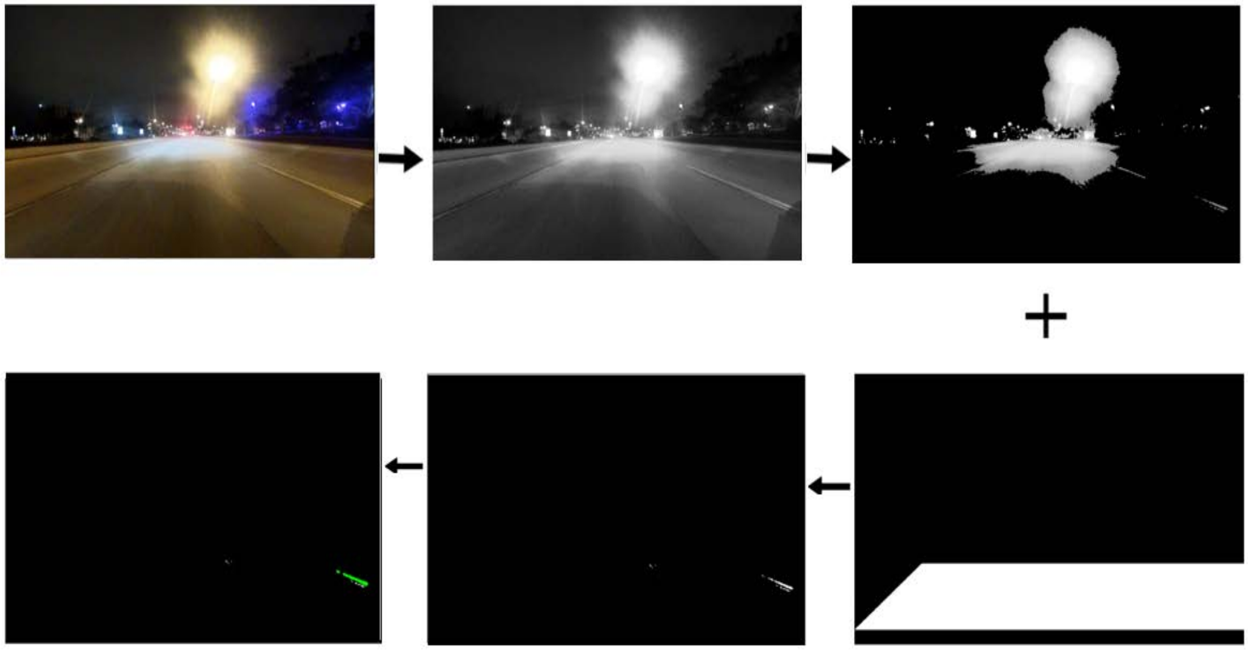


Figure 2-7 Poor lane marking test in the nighttime during dry weather

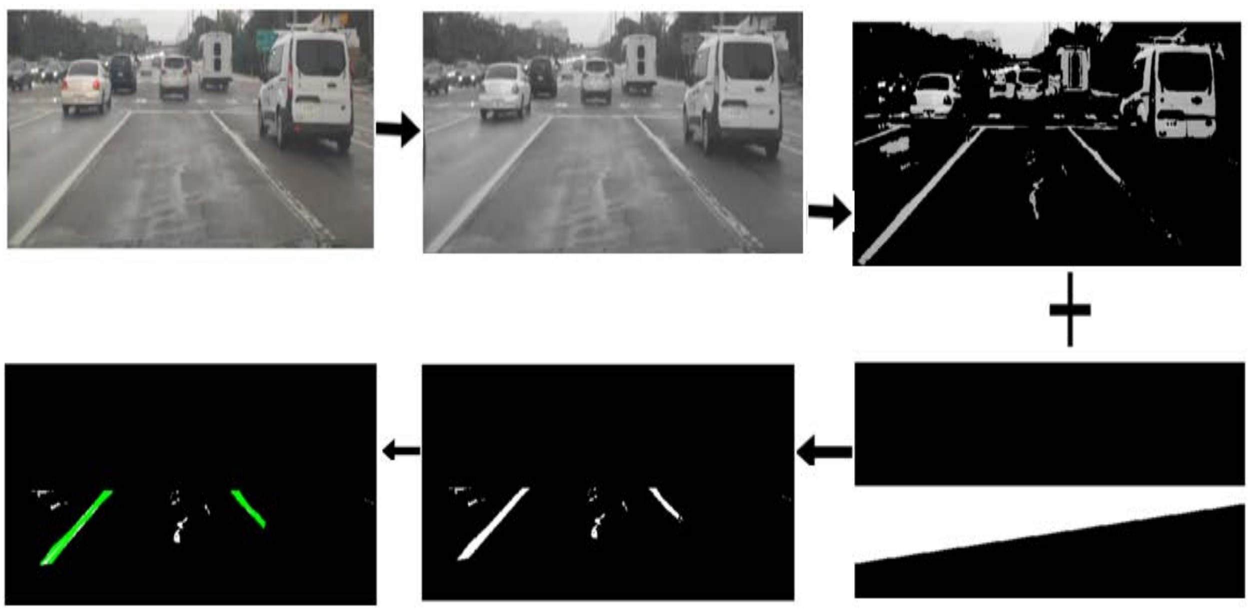


Figure 2-8 Good lane marking test in the daytime during rainy weather.

As shown in all of the above images, the lane that is closer to the vehicle is shorter than the other lane. At this time, the test driver got lane keeping alert for good lane markings. The lane-keeping systems of Vehicle 7 struggled to detect the lanes of poor lane markings at night during dry weather and in the daytime during rainy weather. Thus, Vehicle 7 did not respond to any action under these conditions.

2.2.3 Blind-Spot Collision-Avoidance Assist (BCA)

Blind-Spot Collision-Avoidance Assist (BCA) is an ADAS feature designed to enhance safety by monitoring the vehicle's blind spots and providing alerts or automatic steering/braking to prevent collisions during lane changes. The typical testing scenario for BCA is illustrated in Figure 2-9. This feature was evaluated on various vehicles under different conditions, as detailed in Table 2-5.

(a) Blind-Spot information at daytime (b) Blind-Spot information at nighttime

Figure 2-9 Blind-spot information.

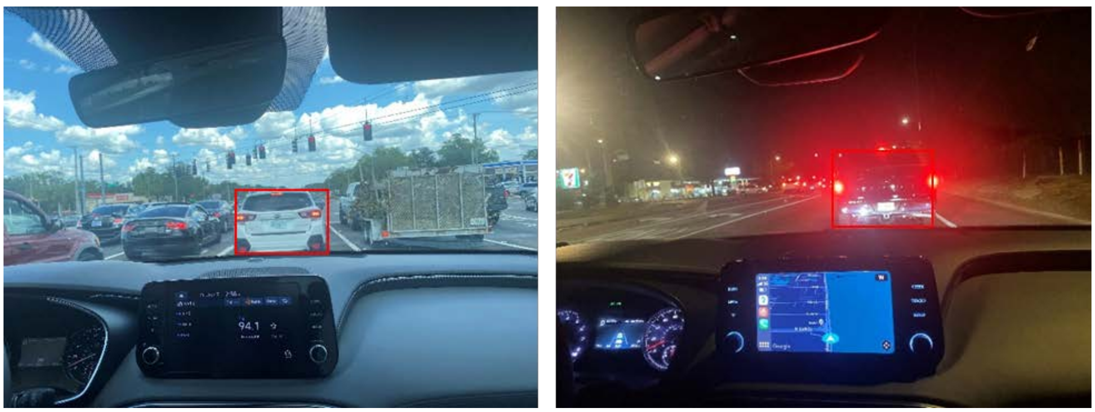
Table 2-5 Blind-spot testing results.

Vehicle Brand/Model	Blind Spot of different vehicles	Conditions	Number of successful detections/ Number of tests
Hyundai Santa Fe	Blind-spot collision-avoidance Assist (BCA)	Daytime	8/10
		Nighttime	8/10
Ford Bronco	Blind Spot Information System	Daytime	8/10
		Nighttime	8/10
Ford Mustang Mach-E	Blind Spot Information	Daytime	12/12

2.2.4 Adaptive and Smart Cruise Control Types

Cruise control systems, including Adaptive Cruise Control (ACC) and Smart Cruise Control (SCC), enhance driving convenience and safety. ACC adjusts the vehicle's speed to maintain a safe following distance, while SCC incorporates advanced features like predictive speed adjustments based on road and traffic conditions. The typical testing scenario for these cruise control types is illustrated in Figure 2-10. They were tested on various vehicles under different conditions, as detailed in Table 2-6.

(a) Vehicle 2 detected and followed the front vehicle



(b) Vehicle 2 followed the front vehicle and stopped with it

Figure 2-10 Vehicle 2 detected and followed the front vehicle [5].

Table 2-6 Cruise control testing.

Vehicle Brand/Model	Cruise control features of the Vehicles	Conditions	Number of successful detections/ Number of tests
Hyundai Santa Fe	Smart Cruise Control	Daytime	7/10
		Nighttime	6/10
Audi Q5	Adaptive Cruise Control (With Stop & Go Function	Daytime	8/10
		Nighttime	7/10

Moreover, adaptive cruise control of Vehicle 7 is tested. The adaptive cruise control feature enables Vehicle 7 to change its reference speed based on the speed of any vehicle in front of it. This feature helps to incorporate the speed information of a vehicle in front of Vehicle 7 into the cruise control system.

[5] Vehicle in red rectangular is the object.

An ACC test was conducted using two vehicles, a leader vehicle, and the follower. The adaptive cruise control was implemented by the follower vehicle, and it adjusted its cruise speed to follow the speed of the leader. The following description elaborates on the ACC test.

- Sensor: Radar mounted on the Vehicle 7
- The leading vehicle: Ford Fusion model owned by the RANCS lab.
- The follower vehicle: Vehicle 7
- Test location: B Downs Blvd, Tampa, FL 33612 (for dry weather) and Interstate 75 Tampa, FL (for rainy weather test).
- The speed and acceleration profiles of the two vehicles are recorded from the Controller Area Network (CAN) bus of both vehicles using built-in CAN interface blocks in MATLAB/Simulink.

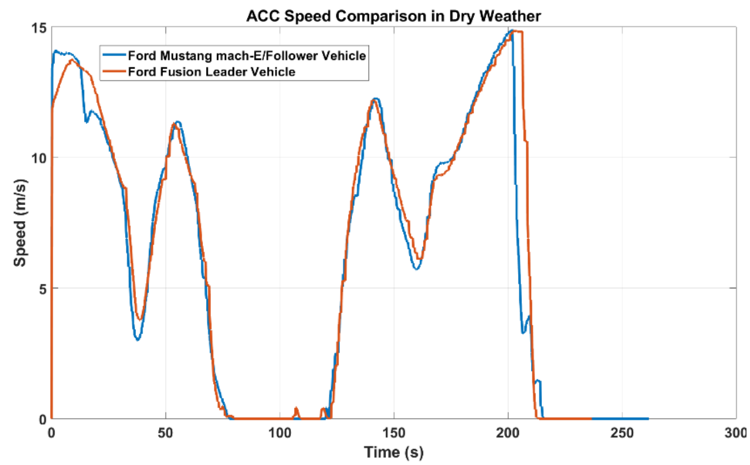


Figure 2-11 Speed profiles of two vehicles used in the ACC test during dry weather

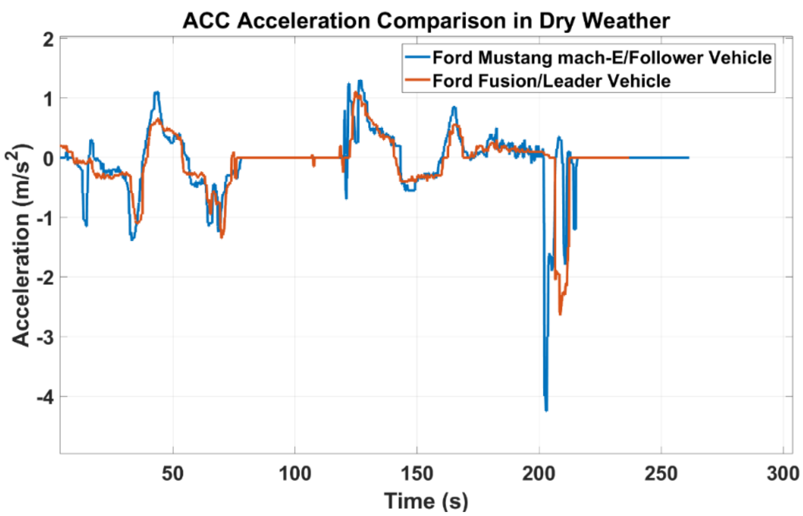


Figure 2-12 Acceleration profiles of two vehicles used in the ACC test during dry weather.

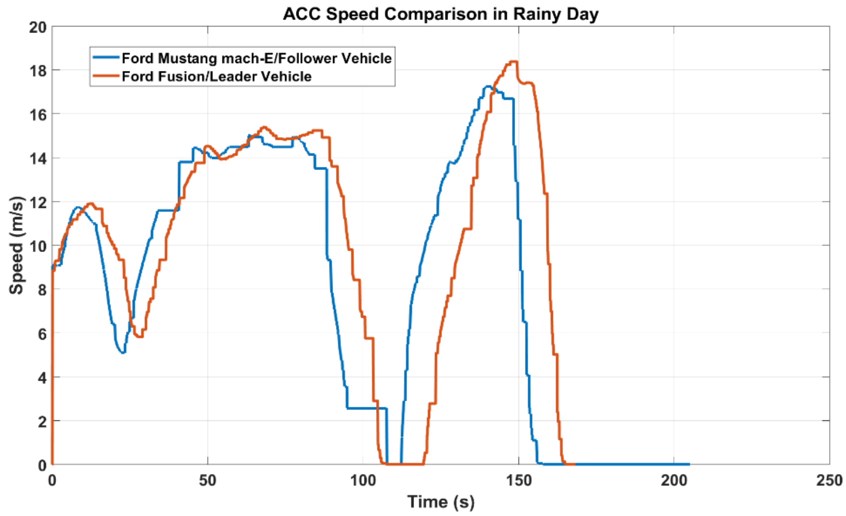


Figure 2-13 Speed profiles of two vehicles used in the ACC test during rainy weather

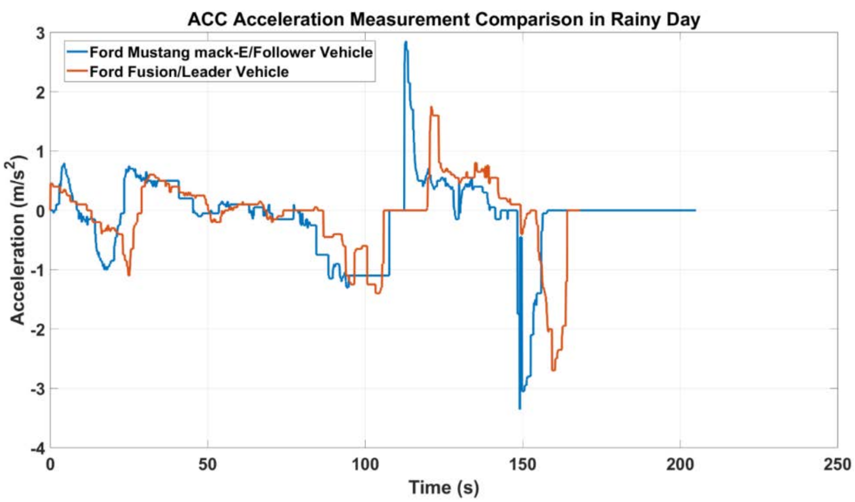


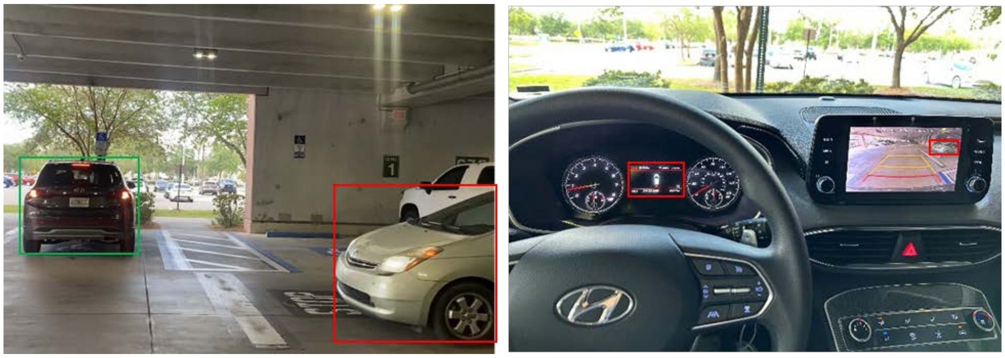
Figure 2-14 Acceleration profiles of two vehicles used in the ACC test during rainy weather

The two-vehicle speed profile plots show that the Mustang Mach-E was able to track the speed of the Ford Fusion vehicle with a little deviation. In addition, the test results show that during rainy weather the ACC performance degraded compared to the dry weather condition. Overall, the adaptive cruise control feature was used to test the Mach-E radar sensor capability, and the plot result shows the sensor capability is good.

2.2.5 Rear Cross-Traffic Collision-Avoidance Assist

Rear Cross-Traffic Assist is an ADAS feature designed to enhance safety by detecting approaching vehicles while reversing, particularly in parking lots or driveways, and providing alerts or automatic braking to prevent collisions. The typical testing scenario for Rear Cross-

Traffic Assist is illustrated in Figure 2-15. This feature was tested on various vehicles under different conditions, as detailed in Table 2-7.



(a) Daytime vehicle testing (outside-vehicle view) (b) Daytime vehicle testing (in-vehicle view)

(c) Nighttime vehicle testing (outside-vehicle view) (d) Nighttime vehicle testing (in-vehicle view)

Figure 2-15 Rear cross-traffic collision-avoidance assist testing of Vehicle 2[6].

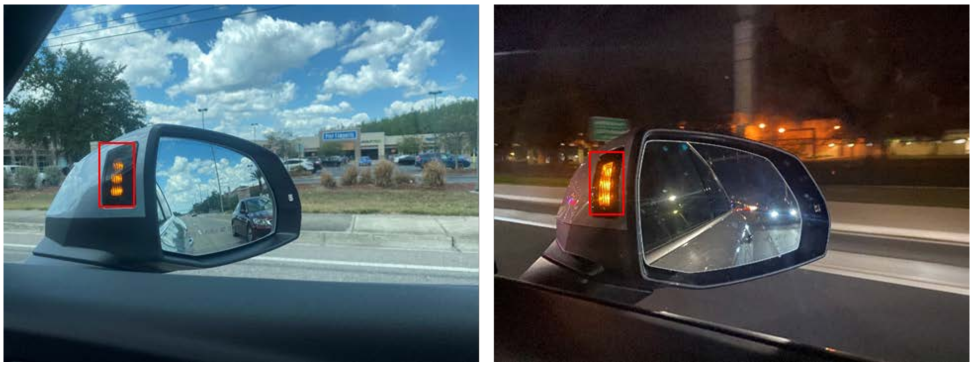
Table 2-7 Vehicle 2 rear cross-traffic collision-avoidance assist testing results.

Vehicle Brand/ Model	**Cross-traffic assist of different vehicles**	**Conditions**	**Number of successful detections/ Number of tests**
Hyundai Santa Fe	Rear Cross-Traffic Collision-Avoidance Assist	Daytime	8/10
		Nighttime	7/10
Ford Bronco	Cross Traffic Alert	Daytime	8/10
		Nighttime	7/10
Audi Q5	Rear-Cross Traffic Assist	Daytime	9/10
		Nighttime	7/10
Ford Mustang Mach-E	Cross Traffic Alert	Daytime	12/12

[6] Green is Vehicle 2, and red is the object.

2.2.6 Side Assist

The Vehicle 4 Side Assist is a lane-changing assistant designed to help drivers when changing lanes at speeds above 9.3 mph. It utilizes two rear-mounted radar sensors (shown in Figure 2-16) with a scanning range of approximately 229.7 ft. When a vehicle is detected in the blind spot or approaching rapidly from behind, an LED warning light illuminates in the housing of the corresponding side mirror. If the driver activates the turn signal, the LED flashes rapidly to provide heightened visibility and alertness.



(a) Side Assist information at daytime (b) Side Assist information at nighttime

Figure 2-16 Side assist information indicator of vehicle 4.

The research team conducted comprehensive tests on the Side Assist feature of Vehicle 4, evaluating its performance in both daytime and nighttime conditions. The results, detailed in Table 2-8, demonstrated that the system exhibited commendable performance in both scenarios.

Table 2-8 Vehicle 4 side assist testing results.

Conditions	Number of successful detections/ Number of tests
Daytime	9/10
Nighttime	7/10

2.2.7 Road Sign Assist and Traffic Sign Recognition System

The RSA system in Vehicle 1 and the Traffic Sign Recognition System in Vehicle 5, both using a front camera, were analyzed for their traffic sign detection capabilities. Vehicle 1 detects stop, speed limit, yield, and "do not enter" signs, displaying alerts on the multi-information display. Vehicle 5 focuses on speed limit signs, showing them on the driver interface and head-up display.

Stop Sign

Vehicle 1 consistently detected stop signs, with performance evaluated at speeds of 5 mph, 15 mph, and 25 mph through 10 tests per speed. Table 2-9 summarizes the first five detection distances. At 5 mph and 15 mph, averages were based on 7 successful detections, while at 25 mph, only 5 successful results were recorded. The longest average detection distance (107.3 ft) occurred at 15 mph, while the shortest (23.9 ft) was at 25 mph. At 5 mph, the average detection distance was 41.7 ft. Results show a correlation between detection range and speed.

Table 2-9 Vehicle 1: stop sign detection distance results.

Speed	1	2	3	4	5	6	7	Average	Number of successful detections/ Number of tests
5 mph	41.0 ft	34.5 ft	40.1 ft	51.6 ft	39.6 ft	52.1 ft	33.0 ft	41.7 ft	7/10
15 mph	106.6 ft	114.1 ft	96.1 ft	111.1 ft	107.3 ft	120.5 ft	95.1 ft	107.3 ft	7/10
25 mph	20.6 ft	26.1 ft	29.7 ft	24.11 ft	19.1 ft	-	-	23.9 ft	5/10

The research team evaluated stop sign detection under daylight with slight, moderate, and severe obstructions, as shown in Figure 2-7. Detailed results are provided in Table 2-10.

Table 2-10 Vehicle 1: stop sign obstructed detection results.

Vehicle Brand/ Model	Technology feature	Conditions	Description of obstruction	Number of successful detections/ Number of tests
		Slight obstruction	Partly or all four letters were slightly blocked but still clearly visible	8/10
Toyota Corolla	Road Sign Assist	Moderate obstruction	Two letters that were almost totally blocked	6/10
		Severe obstruction	All four letters were blocked	2/10

The research team tested stop sign fading on Vehicle 1 (see Table 2-11) and examined lighting effects on detection. In favorable daylight and nighttime lighting (Figure 2-9a), the detection was accurate. However, in poor nighttime lighting (see Figure 2-9b), accuracy declined due to reduced visibility. Detailed results are in Table 2-11.

(a) Slight obstruction

(b) Moderate obstruction

(c) Severe obstruction

Figure 2-17 Examples of obscuring stop signs.

(a) Lightly faded (b) Severely faded

Figure 2-18 Faded stop sign.

(a) Favorable lighting conditions (b) Deteriorated lighting conditions

Figure 2-19 Stop signs at night.

Table 2-11 Vehicle 1: detection results of a stop sign in different light conditions.

Conditions	Number of successful detections/ number of tests
Daytime	7/10
Favorable light at night	6/10
Poor light at night	3/10

In addition, test results showed a decline in Vehicle 1's stop sign detection immediately after turns, day or night, as it adjusted to the front view (see Figure 2-20). Results at 5 mph are in Table 2-12.

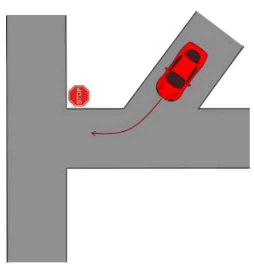


Figure 2-20 Turning scenario.

Table 2-12 Vehicle 1: detection results of a stop sign in a turning scenario.

Conditions	Number of successful detections/ number of tests
Daytime	3/10
Nighttime	2/10

Speed Limit

Vehicle 1 reliably detected speed limit signs, displaying the limit promptly and updating it when encountering new signs. After turns, the display briefly disappeared but reappeared with the next sign. Exceeding the limit triggered a buzzer and accentuated display. Tests with obstructed signs (see Figure 2-21) showed minor obstructions had little impact, while severe obstructions, especially covering both numbers, caused detection failures. Detailed results are in Table 2-13.

Table 2-13 Vehicle 1: speed limit sign obstructed detection results.

Conditions	Detection results	Number of successful detections/Number of tests
Partially obstructing the number "5"	25 mph	10/10
Almost completely obstructing the number "5"	20/ 25 mph	For 20 mph, 4/10 For 25 mph, 2 /10
Partially obstructing the number "2"	25 mph	10/10
Almost completely obstructing the number "2"	25 mph	4/10
Partially obstructing the number "25"	25 mph	10/10
Almost completely obstructing the number "25"	Cannot detect the sign	0/ 10

(a) Partially obstructing the number "5"

(b) Almost completely obstructing the number "5"

(c) Partially obstructing the number "2"

(d) Almost completely obstructing the number "2"

Figure 2-21 Example of obscuring speed limit signs of Vehicle 1.

(e) Partially obstructing the number "25" (f) Almost completely obstructing the number "25"

Figure 2-21 Example of obscuring speed limit signs of Vehicle 1.

The study also examined lighting effects on Vehicle 1's speed limit sign detection. Detection was accurate in daylight but less reliable at night. Under optimal nighttime lighting (Figure 2-22a), accuracy remained high, while poor lighting (Figure 2-22b) reduced performance, highlighting the impact of visibility conditions.

(a) Good lighting conditions (b) Poor lighting conditions

Figure 2-22 Speed limit sign at night.

Similarly, Vehicle 5's traffic sign recognition system is tested for both high-speed and low-speed scenarios. Vehicle 5 excelled in detecting speed limit signs, but performance declined at night, especially with obscured signs. Table 2-14 details the results, and Figure 2-23 illustrates nighttime and obstructed conditions. Detection is affected by lighting and obstructions due to the system's reliance on a camera.

Table 2-14 Vehicle 5: speed limit sign testing results.

Conditions	Number of successful detections/ Number of tests
Daytime	9/10
Nighttime	7/10

Figure 2-23 Example of speed limit signs of Vehicle 5 at nighttime and obscuring it.

Yield Sign

Vehicle 1 detected yield signs less effectively than stop and speed limit signs. The detection distance, as detailed in Table 2-15, increased with speed, which aided timely detection. However, the detection distances were more consistent at 5 mph and 25 mph compared to 15 mph.

Table 2-15 Vehicle 1: yields sign detection distance results.

Speed	1	2	3	4	Average	Number of successful detections/ Number of tests
5 mph	121.1 ft	127.5 ft	—	—	124.3 ft	2/10
15 mph	73.5 ft	218.2 ft	216.5 ft	—	169.4 ft	3/10
25 mph	187.9 ft	188.1 ft	194.1 ft	183.1 ft	188.3 ft	4/10

The research team found that partial obstructions (Figure 2-24a) had little impact on yield sign detection, while significant blockages (Figure 2-24b) reduced accuracy. Results in Table 2-16 align with findings for stop and speed limit signs.

(a) Partially obstructing the yield sign.

(b) Almost completely obstructing the yield sign

Figure 2-24 Example of obstructing yield signs of Vehicle 1.

Table 2-16 Vehicle 1: yield sign obstructed detection results.

Conditions	Number of successful detections/ Number of tests
Slight obstruction	4/10
Severe obstruction	2/10

Dirt-covered yield signs (Figure 2-25a) significantly reduced Vehicle 1's detection accuracy. Nighttime conditions (Figure 2-25b) also impaired detection. Table 2-17 details results, all at 25 mph, highlighting the strong impact of lighting on the camera system's performance.

(a) Yield sign covered with dirt

(b) Yield sign at night

Figure 2-25 Yield sign with dirt and at night.

Table 2-17 Vehicle 1: yield sign with dirt and night detection results.

Conditions	Number of successful detections/ Number of tests
Dirty yield sign	3/10
Nighttime	2/10

Do Not Enter Sign

The research team conducted multiple tests under various conditions, encompassing different times of day and locations, to detect several visible "do not enter" signs. Regrettably, Vehicle 1 consistently failed to detect any of them.

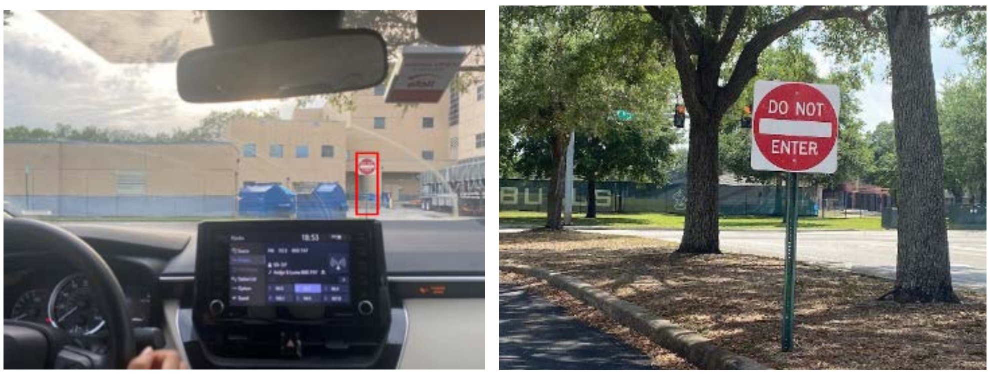


Figure 2-26 Do not enter sign.

2.2.8 Traffic Light Information or Traffic Light and Stop Sign Control

2.2.8.1 Traffic Light Information

Traffic Light Information (TLI) in Vehicle 4 communicates with traffic signals, providing speed recommendations and countdowns. It connects to signal servers for predictive changes, displaying a gray light symbol when data is unavailable. Testing on East Fowler Avenue (see Figure 2-27) showed speed recommendations aligned with limits but didn’t confirm real-time adjustments. Detection was generally accurate, but signal phase errors and fluctuating red-light countdowns occurred, likely due to reliance on connected data and real-time traffic adjustments. Figure 2-28 illustrates Vehicle 4's TLI testing. Vehicle 4’s TLI results are shown in Table 2-18.

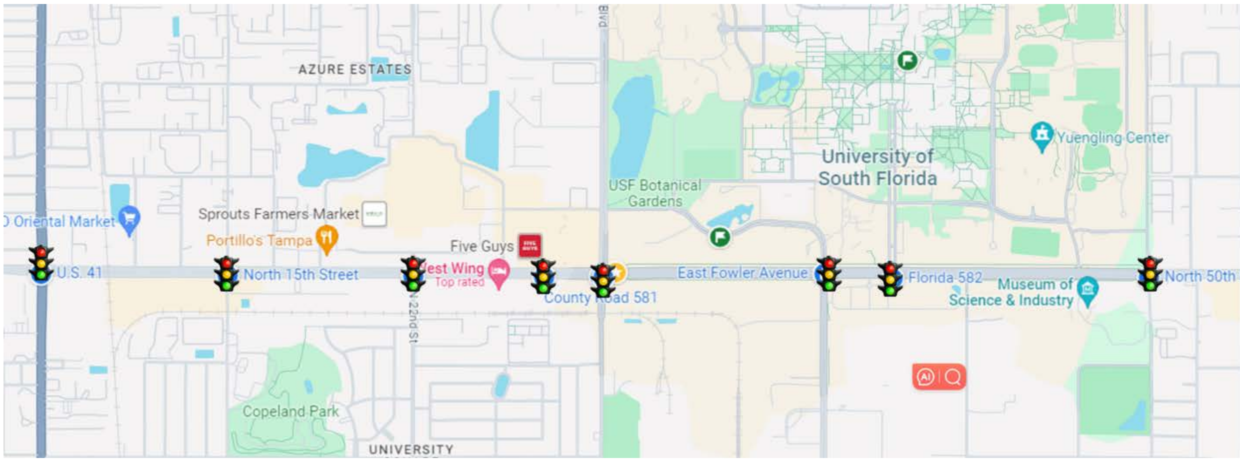
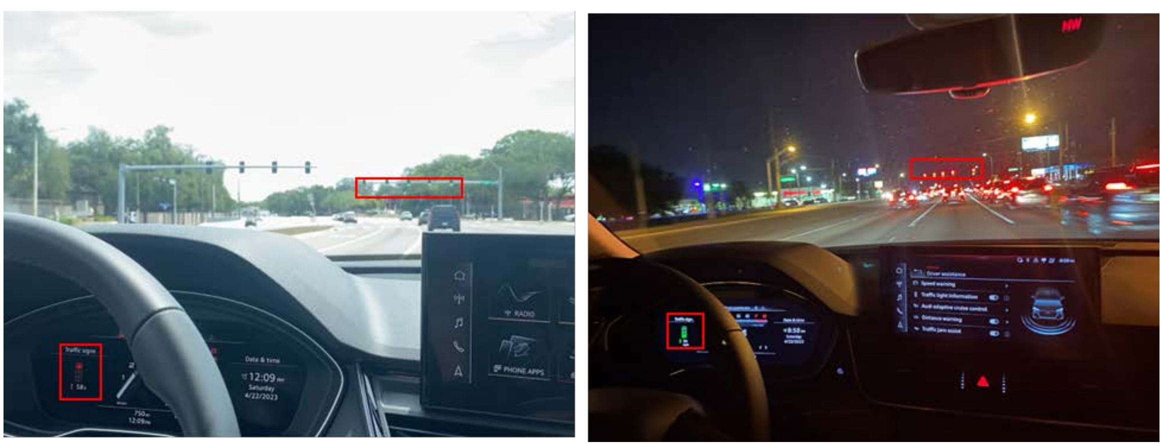


Figure 2-27 Connected intersections map.

(a) Correct phase



(b) Incorrect phase

Figure 2-28 Vehicle 4's traffic light testing.

Table 2-18 Vehicle 4: traffic light testing results.

Vehicle Brand/Model	Traffic light detection features of the vehicles	Conditions	The number of successful shows the phase/ Number of tests
Audi Q5	Traffic Light Information	Daytime	5/10
		Nighttime	5/10

Note: Even if the phase can be recognized correctly, the red-light countdown still has an error of a few seconds.

2.2.8.2 Traffic Light and Stop Sign Control

Vehicle 6's Traffic Light and Stop Sign Control uses cameras and GPS to detect and slow traffic lights, stop signs, and road markings.

Traffic Light

Vehicle 6 displays a slowdown notification at intersections, stopping if not confirmed. Testing showed consistent traffic light detection but occasional phase errors, especially at night, sometimes causing unnecessary stops. A map-road mismatch in one test led to a poor left-turn lane choice. Figure 2-29 shows traffic light testing, and Table 2-19 details phase errors and detection distances.

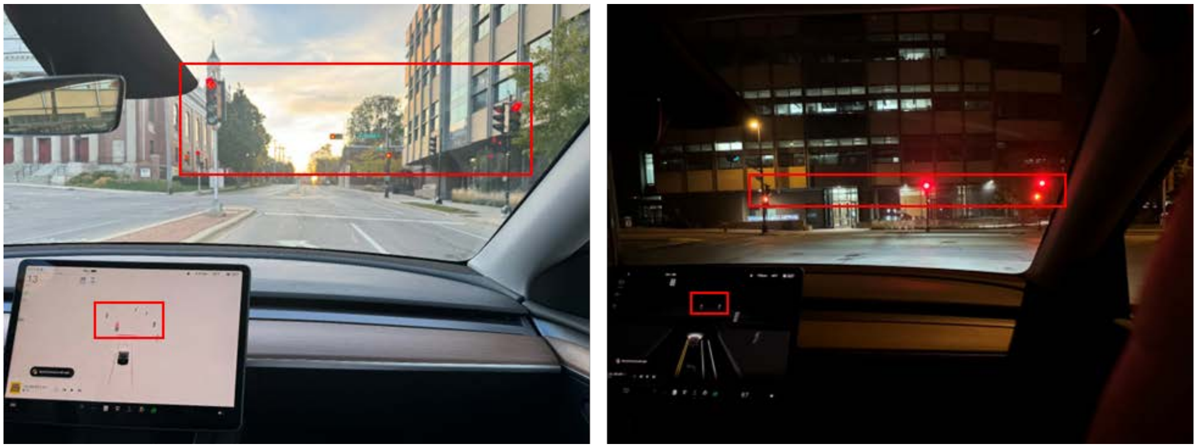


Figure 2-29 Traffic light testing of Vehicle 6.

Table 2-19 Vehicle 6 traffic light phase error times and average detect distance.

Conditions	Error times/Number of tests	Average detect distance
Daytime	3/85	About 1000 ft
Nighttime	4/85	About 1500 ft

Stop Sign

Vehicle 6 reliably stopped at the red stop line for intersections with stop signs and resumed driving when using Full Self-Driving. Testing showed excellent stop sign detection in all lighting conditions. Table 2-20 indicates that lower speeds enabled earlier stop sign detection.

Table 2-20 Vehicle 6's stop sign detection distance results.

Speed	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Average**	**numbers of successful detections/Number of tests**
5 mph	140 ft	135 ft	155 ft	160 ft	154 ft	153 ft	166 ft	142 ft	145 ft	144 ft	149 ft	10/10
10mph	125 ft	122 ft	110 ft	123 ft	105 ft	102 ft	110 ft	135 ft	133 ft	126 ft	119 ft	10/10
15 mph	95 ft	99 ft	96 ft	105 ft	90 ft	109 ft	95 ft	101 ft	112 ft	102 ft	100 ft	10/10

Obstructions like trees had little impact (see Figure 2-30 and Figure 2-31) on stop sign detection distance, but Vehicle 6 detected stop signs from farther away when unobstructed. The Stop sign occlusion test result of Vehicle 6 is provided in Table 2-21.

(a) Severe obstruction (b) Moderate obstruction

Figure 2-30 Simulate tree occlusion.

(a) Severe obstruction

(b) Moderate obstruction

Figure 2-31 Simulate occlusion by other objects.

Table 2-21 Stop sign occlusion test result of Vehicle 6.

Scenario	Occlusion by tree			Occlusion by other objects		
Speed	5 mph	10 mph	15 mph	5 mph	10 mph	15 mph
Severe obstruction	87 ft	54 ft	44 ft	112 ft	94 ft	82 ft
Moderate obstruction	110 ft	110 ft	90 ft	94 ft	84 ft	79 ft
No obstruction	150 ft	120 ft	100 ft	150 ft	120 ft	100 ft

During testing, Vehicle 6 stopped before right turns despite a "Right Turn No Stop" sign. It detected stop signs after turns but did not always come to a full stop.

Figure 2-32 Stop sign with “Right Turn No Stop”.

2.2.9 Full Self-Driving (Beta)

Vehicle 6's Full Self-Driving (Beta) (FSD), also known as Autosteer on City Streets, navigates intersections, turns, roundabouts, and highways using multiple cameras and real-time environmental modeling. FSD operates below 85 mph and provides dynamic on-screen visualizations, highlighting system-controlled elements in blue. It manages lane changes, turns, ramps, and road forks while maintaining speed and following distance relative to the leading vehicle. The system responds to traffic lights, stop signs, pedestrians, and cyclists. The research team tested FSD on a 76-mile route (see Figure 2-33). The FSD test results are provided in Table 2-22. The system showed aggressive driving, including abrupt acceleration, lane changes, and braking. A near-collision occurred when it misjudged an oncoming vehicle, requiring human intervention.

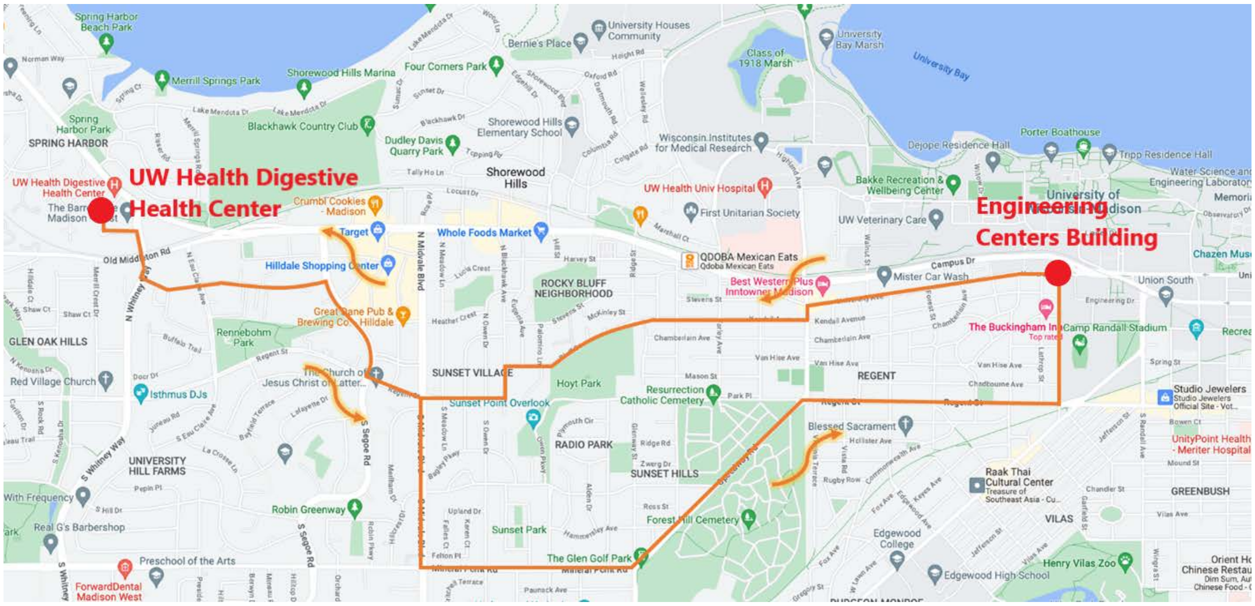


Figure 2-33 Testing map of Vehicle 6

Table 2-22 FSD road testing results.

	# of traffic light	Success rate	# of a stop sign	Success rate	# of speed limit sign	Success rate	Lane detection	Success rate
Daytime	85	100%	55	98.2%	120	95.8%	76 miles	100%
Nighttime		100%		100%		98.3%		100%

Vehicle 6's speed limit sign detection was most effective within close range, with 90% of signs recognized within 14 feet but only 10% detected at 50 feet. The system consistently failed to identify speed limit signs when a yellow “school” sign was placed above them, regardless of lighting conditions. However, when a white “end school zone” sign was positioned below the speed limit sign, detection was unsuccessful during the day but fully accurate at night.

Vehicle 6 exhibited strong car-following performance, successfully handling 58 instances during the day and all 40 at night (see Table 2-23). This consistency indicates reliable detection and response across different lighting conditions.

Table 2-23 Car following testing results of Vehicle 6.

Conditions	Number of successful detections/Number of tests
Daytime	58/58
Nighttime	40/40

2.2.10 Summary of Testing Commercial CDA Vehicle Sensing Technologies

Vehicle 1's Road Sign Assist performed well but failed to detect "Do Not Enter" signs, with performance affected by obstructions, poor lighting, and vehicle speed due to reliance on a front-mounted camera. The Pre-Collision System uses both a camera and radar; the camera struggled in low-light conditions, while the radar provides fixed-distance object detection. Lane detection is also camera-dependent and suffers in unclear or curved lane conditions.

Vehicle 2 was tested for forward collision-avoidance assist, lane keeping assist & lane following assist, blind-spot collision-avoidance assist (BCA), smart cruise control, and rear cross-traffic collision-avoidance assist. The smart cruise control demonstrated outstanding performance, smoothly adapting to traffic like an experienced driver. Forward collision-avoidance assist outperformed Vehicle 1, especially at night. Lane-keeping assist & lane following assist matched Vehicle 1 but showed minor detection limitations in curved or unclear lane conditions due to camera reliance. The BCA system, using a front-view camera and rear-corner radar, performed exceptionally. The rear cross-traffic collision-avoidance assist excelled in both day and night conditions, making Vehicle 2’s safety features highly effective in various scenarios.

Vehicle 3 was tested for a lane-keeping system, blind spot information system, cross-traffic alert, and pre-collision assist. The lane-keeping system performed similarly to Vehicles 1 and 2, with detection limitations in unclear, curved lanes, and poor lighting due to camera reliance. The collision avoidance system showed comparable effectiveness to Vehicle 2.

Vehicle 4 was tested for active lane assist/lane departure warning, ACC with stop & go, traffic light information (TLI), side assist, and rear cross-traffic assist. It features a TLI system using C-V2X technology, which predicts traffic signal changes through server connections and machine learning. However, tests revealed time discrepancies, incorrect light phase displays, and abrupt red-light countdown changes. The ACC with stop & go performed smoothly like Vehicle 2's Smart Cruise Control but showed abrupt acceleration when no leading vehicle was present, potentially causing discomfort. Other features were comparable to those in other vehicles.

Vehicle 5 was tested for the traffic sign recognition system and lane-keeping assist system, with performance largely consistent with other vehicles. The Traffic Sign Recognition System was designed to detect speed limit signs but struggled in nighttime conditions or when signs were obscured, similar to Vehicle 2. Lane detection was also affected by poor lighting, curved lanes, and unclear markings.

Vehicle 6 was tested for FSD capability, traffic light and stop sign control, pedestrian warning system, lane assist, and collision avoidance assist. It primarily relies on cameras for environmental perception and demonstrates exceptional detection and visualization capabilities, especially on the touchscreen interface. The FSD feature outperformed other vehicles but still required driver attention. Notably, it showed superior detection of stop signs and speed limit signs at night, unlike other vehicles. It also excelled in lane and traffic light detection under all lighting conditions, likely due to onboard mapping data and camera-based detection. However, it was more prone to misinterpreting traffic light phases at night.

Vehicle 7 was evaluated for sensor capabilities using radar, camera, and short-range proximity (ultrasonic) sensors across five ADAS features. Radar performed well in all weather conditions, while ultrasonic sensors excelled in short-range detection. However, camera performance was highly affected by lighting and weather, deteriorating in rain, glare, reflections, and low-light conditions. The research team suggested that night vision cameras and AI-based perception software could help improve performance in adverse conditions.

2.3 CATS Lab's Connected and Autonomous Vehicle

The Connected & Autonomous Transportation Systems Laboratory (CATS lab) vehicle was a full-scale CAV as illustrated in the Figure 2-34. This CAV was retrofitted from a 2016 Lincoln MKZ hybrid with various sensors (e.g. lidars, Cameras, Mobileye, NovAtel navigation units), a by-wire control platform, a Savari DSRC on-board unit (OBU) for CV communication, and a computation and data storage platform. The vehicle also had several portable OBUs (which could be plugged into other regular vehicles to convert them into CVs and Road Side Units. The camera, lidar, and the V2X system of the CATS lab’s vehicle were evaluated in this test.

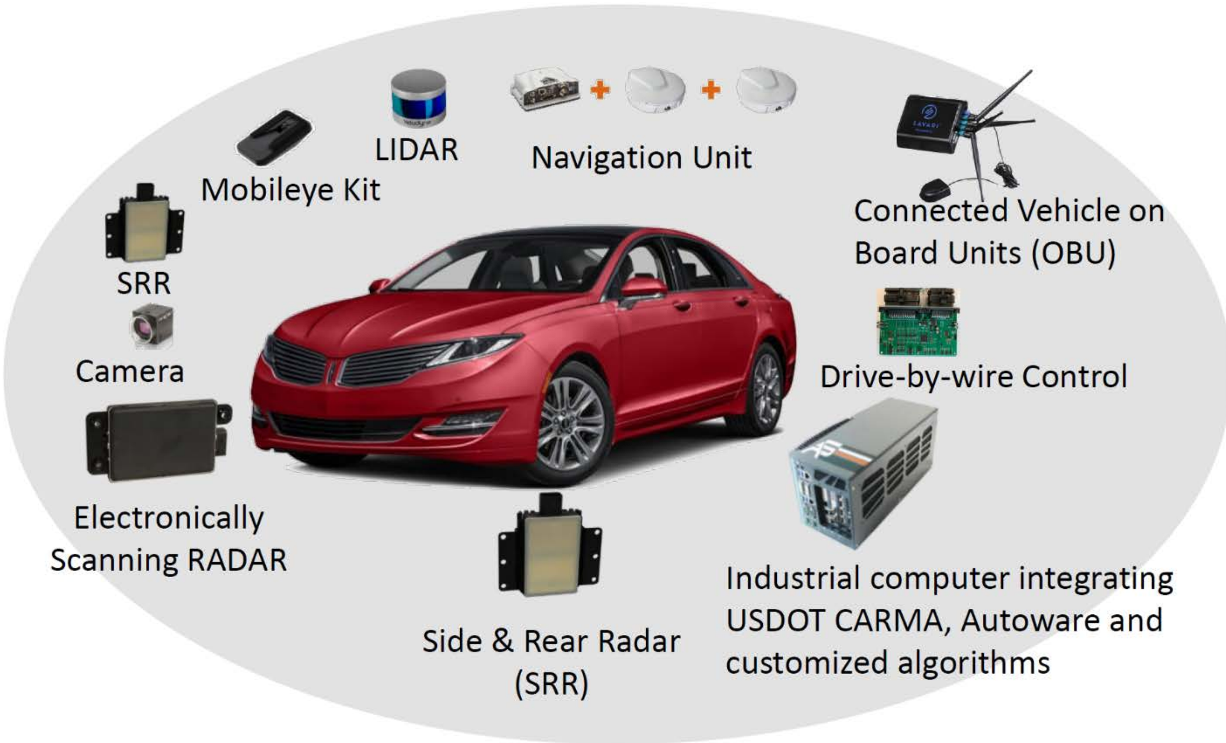


Figure 2-34 The CATS lab's CAV system

2.3.1 Camera

The detection performance of the CATS lab vehicle's camera and YOLO V3 recognition algorithms was evaluated using traffic lights and stop signs, as speed limit signs were not supported by the algorithm. Performance indicators included detection accuracy, and the distance required for object detection, considering factors like weather, lighting, and sign obstructions. The tests were conducted along a predefined route shown in Figure 2-35, covering 10 round trips between the University of Wisconsin Health Digestive Health Center and the Engineering Centers Building. Each round trip spanned 7.6 miles, with 17 traffic lights and 11 stop signs, resulting in a total test distance of 76 miles. This route provided a comprehensive assessment of the camera's capabilities.

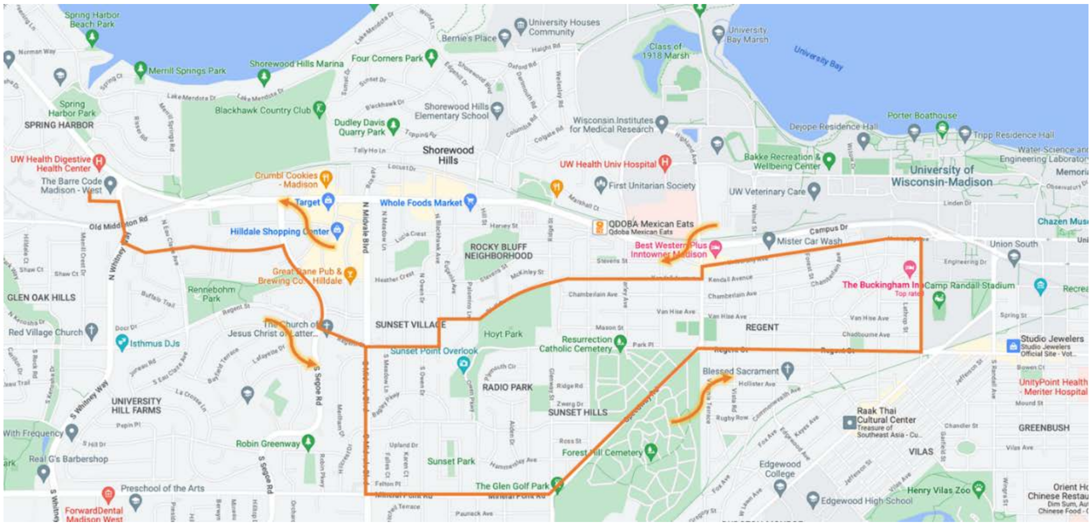


Figure 2-35 Testing route of CATS lab's CAV

(1) Traffic light

The camera's precision in detecting traffic lights was tested during sunny daytime, rainy daytime, and nighttime, with 5, 2, and 3 round trips, respectively, as shown in Figure 2-36. Detection accuracy served as the evaluation metric, and the results are summarized in Table 2-24.

During sunny and rainy daytime tests, the camera achieved a perfect 100% detection accuracy, demonstrating exceptional performance even under adverse weather conditions. However, during nighttime testing, the detection accuracy slightly declined to 96%, with two failed detections out of 51 traffic lights. This reduction was attributed to light interference, which affected the camera's performance and recognition algorithm.

In conclusion, the CATS lab vehicle's camera demonstrated outstanding precision in detecting traffic lights under clear and rainy daytime conditions, with slight limitations in nighttime performance, highlighting the need for system enhancements to address low-light challenges.

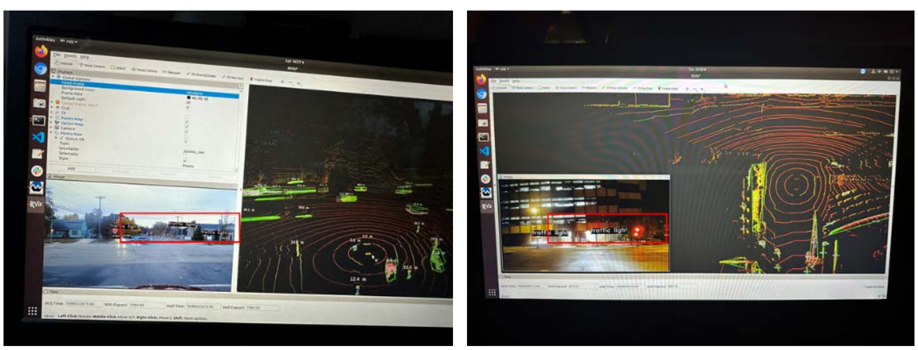


Figure 2-36 Camera's precision test in the detection of traffic lights.

Table 2-24 Test results of the camera's precision in the detection of traffic lights.

Conditions	Success tests / Number of tests	Detection accuracy
Sunny daytime	85/85	100%
Rainy daytime	34/85	100%
Nighttime	49/51	96%

(2) Stop sign

The camera's precision in detecting stop signs was tested under sunny, rainy, and nighttime conditions, with 5, 2, and 3 round trips, respectively, as shown in Figure 2-37. Detection accuracy, summarized in Table 2-25, was 100% during sunny and rainy daytime tests, demonstrating robust performance. However, accuracy dropped to 91% at night, with four missed detections out of 33 stop signs due to reduced ambient lighting.

Table 2-26 summarizes the distance required for the camera to detect stop signs at various cruising speeds and occlusion levels. Figure 2-38 provides an illustration of different levels of obstruction on the stop signs, which significantly impacted detection performance. Higher speeds and severe obstructions reduced detection distances, while lower speeds and minimal obstructions allowed longer recognition distances.

In summary, the CATS lab's camera exhibited excellent precision in detecting stop signs during daytime conditions, with minor accuracy reductions at night. The study highlights the influence of speed, obstructions, and lighting conditions on detection distances, offering insights for improving camera systems in autonomous vehicles.

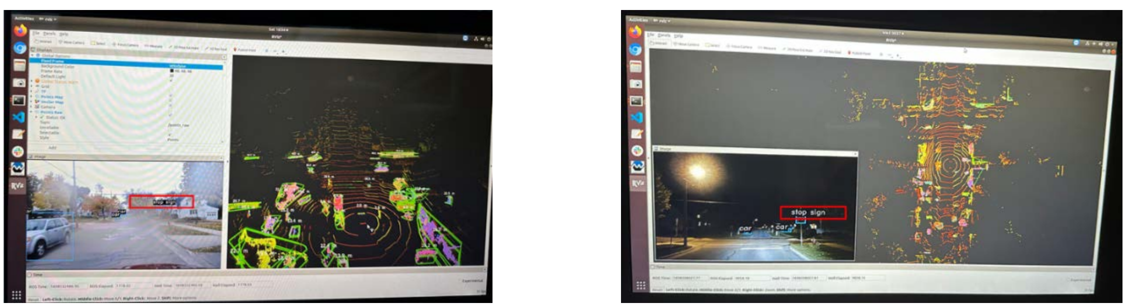


Figure 2-37 Camera's precision test in the detection of stop signs.

Table 2-25 Test results of the camera's precision in the detection of stop signs.

Conditions	Success tests / Number of tests	Detection accuracy
Sunny daytime	55/55	100%
Rainy daytime	22/22	100%
Nighttime	30/33	91%

Figure 2-38 Illustration of different levels of obstruction on the stop signs.

Table 2-26 The distance required for the camera to detect the stop sign at various cruising speeds and occlusion levels of stop signs.

Speed	No obstruction	Moderate obstruction	Severe obstruction
5 mph	92 ft	78 ft	64 ft
10 mph	90 ft	65 ft	55 ft
15 mph	78 ft	55 ft	42 ft
20 mph	51 ft	52 ft	33 ft

2.3.2 Lidar

The detection performance of the lidar sensor on the CATS lab's vehicle was evaluated using traffic lights and stop signs as detection objects. Detection accuracy was the primary performance metric, with weather and lighting conditions considered environmental factors. The evaluation used the same test route as the camera's test, shown in Figure 2-37. A total of 10 round trips were conducted, covering 7.6 miles per trip, with 17 traffic lights and 11 stop signs on each round trip.

(1) Traffic light

Lidar’s precision in detecting traffic lights was tested during sunny daytime, rainy daytime, and nighttime with 5, 2, and 3 trips, respectively, as shown in Figure 2-39. The results, summarized in Table 2-27, showed a 90% detection accuracy, with 10% of traffic lights being detected.

The undetected lights shared common traits: elevated positions and greater distances from the stop line, exceeding lidar's sensing angle and distance parameters. These findings emphasize the need to adjust lidar configurations to improve the detection of traffic lights positioned higher or farther from the road, enhancing overall performance under various conditions.

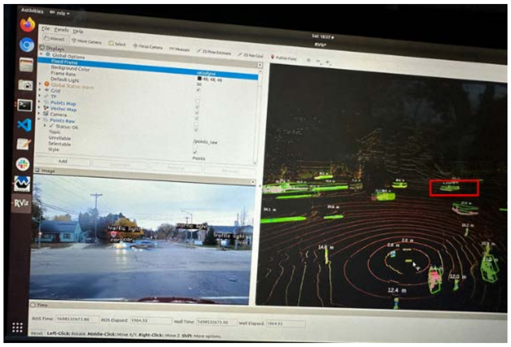


Figure 2-39 Precision test of lidar detection.

Table 2-27 Test results of lidar's precision in the detection of traffic lights.

Conditions	Success tests / Number of tests	Detection accuracy
Sunny daytime	52/55	95%
Rainy daytime	20/22	91%
Nighttime	30/33	91%

(2) Stop sign

Lidar's precision test in the detection of stop signs was also conducted in sunny daytime, rainy daytime, and nighttime with 5, 2, and 3 rounds of trips respectively. The test process is shown in Figure 2-40, and the test results are summarized in Table 2-28.

The lidar system equipped on the CATS lab's vehicle consistently and effectively detected all stop signs across 10 tests with different settings and conditions. This robust performance underscores the reliability and precision of lidar technology in recognizing stop signs in various environmental and operational contexts, further validating its suitability for autonomous vehicle applications, and enhancing road safety.

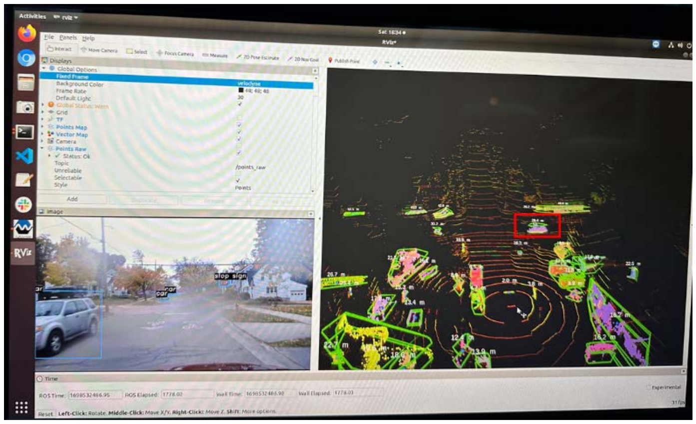


Figure 2-40 Lidar's precision test in the detection of stop signs

Table 2-28 Test results of lidar's precision in the detection of stop signs.

Conditions	Success tests / Number of tests	Detection accuracy
Daytime	55/55	100%
Daytime & rain	22/22	100%
Nighttime	33/33	100%

2.3.3 C-V2X

V2X is an advanced technology enabling communication among vehicles, infrastructure, pedestrians, and networks, encompassing V2V, V2I, V2P, and Vehicle-to-Network (V2N) communication types. The research team focused on testing the more advanced C-V2X technology, which operates on LTE and can seamlessly transition to 5G, offering higher transmission speeds and improved communication reliability. Compared to DSRC, C-V2X provides an extended data transmission range, enabling early hazard detection, improved safety, and traffic efficiency while addressing challenges related to high mobility and dense traffic.

The tests were conducted on University Ave, a major arterial in Madison (see

Figure 2-41), using RSUs (see Figure 2-42) mounted on traffic poles (see Figure 2-43).

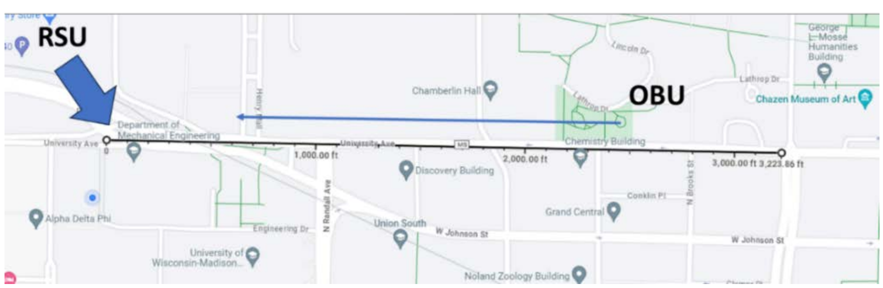


Figure 2-41 The testing road

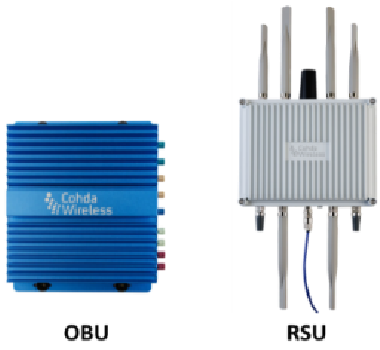


Figure 2-42 The OBU and RSU

Figure 2-43 The RSU used in this test

Table 2-29 The performance matrix of C-V2X.

Distance	PER	IPG
59m	2/(472+2)=0.4%	200 ms
109m	6/(692+6)=0.8%	310 ms
257m	12/(592+12)=1.9%	310 ms
408m	40/(40+615)=6.1%	504 ms
598m	16/(16+932)=1.6%	220 ms
755m	13/(13+765)=1.6%	1900 ms

Data collection involved static OBUs, with team members monitoring the environment and communicating via walkie-talkies for safety and emergency stops. Performance metrics included the Package Error Rate (PER), calculated as the ratio of erroneous packets to total packets received, and the Inter-Packet Gap (IPG), representing the maximum duration between consecutive packets. GPS signals from Google Maps determined distances between the RSU and OBU. Results showed a general increase in PER with distance, though not consistently linear (e.g., PER dropped from 6.1% at 408m to 1.6% at 598m and 755m). IPG also increased with distance but exhibited outliers, such as 1900 ms at 755m, and no clear correlation between PER and IPG was found. Variations in packet numbers across distances added complexity to the analysis.

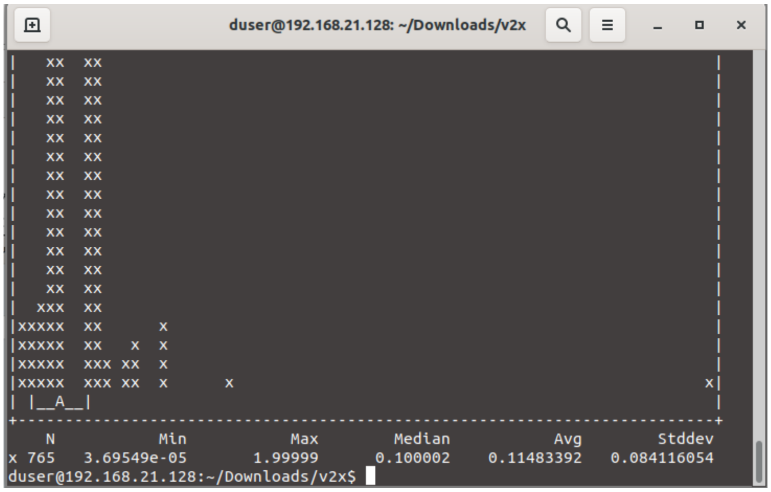


Figure 2-44 The IPG Calculation at 755 m.

The testing revealed challenges, including limited parking affecting distance accuracy and road grades impacting IPG values, particularly at 598 meters on a crest. Environmental factors like trees, buildings, road conditions, and traffic also influenced IPG. The team noted that eliminating vertical curves could improve range and reduce occlusion between the RSU and OBU, emphasizing the need for further data collection to better understand the relationships between PER, IPG, and distance.

2.3.4 Summary of CATS Lab's Vehicle

This test comprehensively evaluated the CATS lab vehicle's camera, lidar, and C-V2X systems. The camera achieved 100% accuracy in traffic light and stop sign detection during sunny and rainy daytime conditions, with slight reductions at night (96% and 91%, respectively) due to light interference. Detection performance was also influenced by cruising speeds and obstructions. C-V2X testing highlighted challenges in the relationship between distance, PER, and IPG, emphasizing further refinement. IPG measures latency, with shorter gaps indicating better performance, while PER assesses reliability by tracking lost packets. These findings provide insights to enhance AV detection capabilities and road safety.

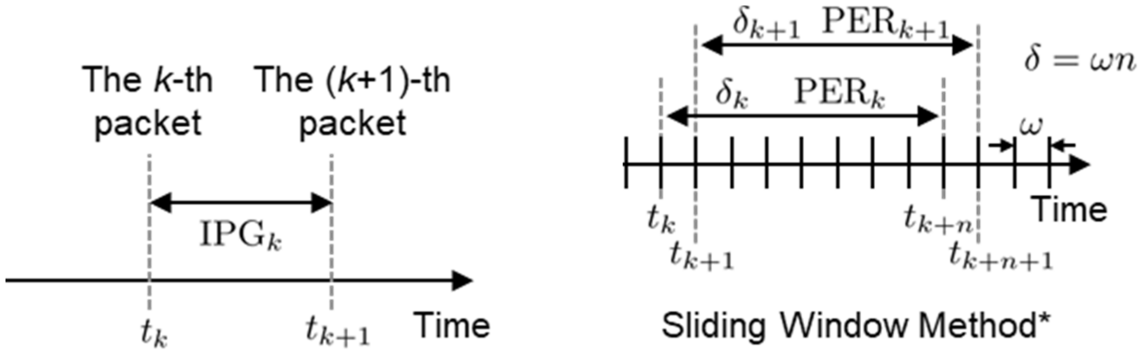


Figure 2-45 The IPG and PER evaluation metrics.

3 Evaluation of Infrastructure Features for CDA Sensing

3.1 Introduction

Section 3 focuses on assessing the compatibility of current infrastructure with CDA sensing, leveraging test data acquired in Section 2. It examines infrastructure elements that impede effective vehicle detection or connectivity and proposes specific modifications or enhancements to improve the integration and functionality of CDA technologies across various scenarios. These recommendations aim to optimize safety and operational efficiency, ensuring smooth integration into both existing and future transportation networks while emphasizing the importance of adapting infrastructure to support advancements in CDA technology.

3.2 Lane and Pavement Markings

Lane markings are vital for vehicle safety, enabling systems like lane keeping and lane following to help drivers stay within their lanes. The research team tested the lane marking detection capabilities of seven commercial vehicles under various conditions, including clear and unclear markings, straight and curved lanes, daytime and nighttime, merging and diverging lanes, and sunny and rainy weather. Complex scenarios with compounded adverse conditions were also evaluated, with ten tests conducted per vehicle in each scenario to record successful detections.

3.2.1 Clear, Moderate Clear, and Unclear Lane Markings

This study classified lane markings into three categories based on their suitability for CDA sensing. Clear markings have high visibility, contrast, and continuity and closely resemble newly painted lines. Moderate markings show some fading or color change, reducing their visibility, contrast, and continuity. Unclear markings have low visibility, contrast, and continuity, leaving only faint traces of the original lines. Testing across multiple vehicles revealed a consistent decline in detection performance when encountering unclear markings regardless of brand or model. These findings highlight the importance of maintaining clear and visible lane markings to ensure the reliability and safety of lane detection systems under various driving conditions. Figure 3-1 shows the example of clear, moderate clear, and unclear lane markings.

(a) Clear (b) Moderate clear (c) Unclear

Figure 3-1 Examples of clear, moderate clear, and unclear lane markings.

The research team evaluated the lane detection performance of six vehicles under clear, moderately clear, and unclear lane conditions, as presented in Table 3-1. Vehicles 1 to 5 exhibited similar results, effectively detecting lanes when markings were clear but with reduced accuracy under moderately clear conditions and nearly failing in unclear scenarios. This highlights the critical dependence of lane detection systems on the clarity and visibility of lane markings, emphasizing the need for regular maintenance and improvements such as high-contrast, reflective, or illuminated markings to enhance detection. Vehicle 6 showed an advantage, successfully detecting lanes in clear and moderately clear conditions, with less performance decline in unclear scenarios due to onboard map data integration, which supplements physical markings and aids detection when markings are compromised (Tesla, 2024). These findings underscore the importance of combining advanced technologies like onboard mapping with improved lane markings to enhance the reliability of autonomous navigation systems.

Table 3-1 Clear, moderate clear, and unclear lanes detection testing results of each vehicle.

Vehicle No.	Number of tests/ numbers of successful detections		
	Clear, straight lane markings during the daytime	**Moderate clear, straight lane markings during the daytime**	**Unclear, straight lane markings during the daytime**
1	10/9	10/4	10/0
2	10/9	10/6	10/0
3	10/9	10/5	10/0
4	10/9	10/5	10/1
5	10/10	10/5	10/0
6	10/10	10/10	10/5

3.2.2 Straight and Curve Lanes

The research team also discovered that, in comparison to straight lanes, the detection performance of nearly all the vehicles decreases when encountering curved lanes. This trend is evident across different brands and models. The geometry of curve lanes presents a more complex visual pattern for vehicle detection systems, which are typically optimized for straight-line recognition. This complexity can lead to delays or inaccuracies in lane detection, particularly in sharp curves or at higher speeds where the detection systems have less time to react. Examples of straight and curved lanes are shown in Figure 3-2.

(a) Straight and clear lanes at daytime (b) Curve and clear lanes at daytime

Figure 3-2 Example of straight and curved lanes.

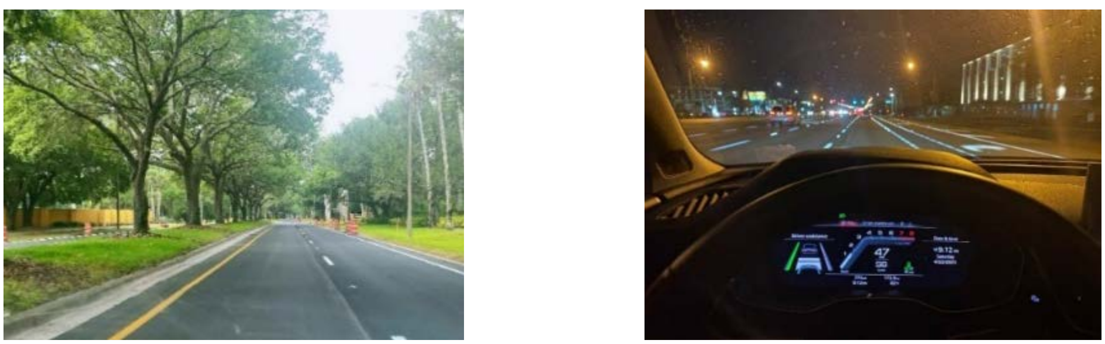
The research team tested six vehicles for lane detection on straight and curved lanes, as shown in Table 3-2. Vehicles 1 to 5 detected straight lanes effectively but struggled with curved lanes at high speeds due to reliance on front-mounted cameras. Suggested improvements include denser lane markings on curves, broader or reflective markings, illuminated curve-specific signage, and enhanced visibility through embedded sensors or retroreflective materials. Sharing lane data from high-quality vehicle-mounted cameras could further improve detection accuracy and mitigate challenges like glare, enhancing safety and reliability in challenging scenarios. Interestingly, Vehicle 6 consistently detects both straight and curved lanes with high accuracy, likely due to its integration of onboard map data. This additional layer of information complements front-mounted cameras, enhancing the vehicle's ability to navigate complex road geometries like curves. The combination of camera-based detection and map data significantly improves safety and efficiency in CDA driving systems. (Tesla, 2024).

Table 3-2 Straight and curve lane detection testing results of each vehicle.

Vehicle No.	Number of tests/ numbers of successful detections	
	Straight, clear lanes during the daytime	Curve, clear lanes during the daytime
1	10/9	10/5
2	10/9	10/7
3	10/9	10/5
4	10/9	10/7
5	10/10	10/6
6	10/10	10/10

3.2.3 Daytime and Nighttime

The research team tested six vehicles for lane detection during daytime and nighttime, finding reduced performance at night due to reliance on camera-based systems. Figure 3-3 highlights this difference. Solutions include higher-contrast or reflective lane markings, smart roadway lighting, and integrating thermal or infrared technologies to enhance detection and improve safety in low-light conditions.



(a) Straight and clear lanes at daytime   (b) Straight and clear lanes at nighttime

Figure 3-3 Example lanes in the daytime and nighttime.

The research team tested the lane detection performance of six vehicles during day and night, with results in Table 3-3. Vehicles 1 to 5 performed better during the day, as their camera-based systems rely on well-lit conditions for effective detection. Suggested improvements include high-contrast reflective lane markings, LED-embedded road surfaces, smart lighting, infrared reflective signage, and V2X-supported roadside beacons. Regular maintenance of markings and adaptive traffic signals can further enhance night-time detection. Vehicle 6 performed consistently well in both conditions due to its integration of onboard map data, which supplements camera systems for high accuracy even in low-light conditions (Tesla, 2024).

Table 3-3 Lanes detection testing results of each vehicle in the daytime and nighttime.

Vehicle No.	Number of tests/ numbers of successful detections	
	Straight, clear lanes during the daytime	Straight, clear lanes at nighttime
1	10/9	10/6
2	10/9	10/6
3	10/9	10/8
4	10/9	10/4
5	10/10	10/9
6	10/10	10/10

3.2.4 Merging and Diverging Lanes

The study observed reduced lane detection performance on merging and diverging lanes compared to straight lanes, particularly at high speeds. This challenge likely arises from cameras struggling to adapt to rapidly changing lane configurations, affecting safe navigation in high-speed scenarios. Figure 3-4 shows the example of merging and diverging lanes. The tests about merging and divergence were conducted on I-275 (FL) and I-94 (WI).

(a) Merging lanes [7]

(b) Diverging lanes[8]

Figure 3-4 Example of merging and diverging lanes.

Testing on six vehicles reveals reduced detection performance in merging and diverging lanes, similar to challenges in curved lanes, especially at higher speeds. Except for Vehicle 6, which

[7] https://streetsurvival.info/merge/
[8] https://www.crosscountryroads.com/photos/florida/fl-i275sb

performs consistently well, other vehicles struggle with these complex configurations, showing a clear decline compared to straight lanes, as detailed in Table 3-4. Enhancing lane markings, deploying advanced signage, and utilizing V2X communication can improve detection and assist vehicles in navigating these scenarios more effectively.

Table 3-4 Continuous straight, merging, and diverging lanes detection testing results of each vehicle.

Vehicle No.	Number of tests/ numbers of successful detections		
	Continuous straight, clear lanes during the daytime	Merging, clear lanes during the daytime	Diverging, clear lanes during the daytime
1	10/9	10/5	10/5
2	10/9	10/7	10/6
3	10/9	10/6	10/5
4	10/9	10/6	10/7
5	10/10	10/7	10/6
6	10/10	10/10	10/10

3.2.5 Dry and Rainy Weather

Tests were conducted under three conditions: daytime sunny, daytime rainy, and nighttime dry, using a Mustang Mach-E from the RANCS lab. Lane markings were evaluated based on the vehicle's lane-keeping assist performance, which includes lane detection and keeping features. A webcam on the windshield recorded rainy weather tests, while a wide-angle camera on the front bumper captured dry weather tests, as detailed in Table 3-5. Video recordings were analyzed using OpenCV and MATLAB, showing that lane-keeping assist performs well with good lane quality and declines with poor markings.

Table 3-5 Camera specifications used in rainy and dry weather

Camera type	Dimension	Technical specification
WebCam	Height: 43.3 mm, Width: 94 mm, Depth: 71 mm, Cable length: 1.5 m, Weight: 162 g	Max Resolution: 1080 p/30 fps - 720p/ 30 fps Camera megapixel: 3 Focus type: Autofocus Lens type: Glass Built-in mic: Stereo Mic range: Up to 1 m Diagonal field of view (DFoV): 78° Tripod-ready universal mounting clip fits laptops, LCD, or monitors
Wide-angle (Fishye) camera	Width: 4.62 cm, Height: 11.30 cm, Depth: 2.98 cm	360^0 view : 5.7K/30fps, 25fps, 24fps 4K/50fps, 30fps 3K@100fps Wide Angle (Steady Cam Mode): 2560x1440@50fps, 30fps 1920x1080@50fps, 30fps

Lane detection was evaluated by measuring the test vehicle's position relative to the left and right lanes, using a reference value of 0.71 meters within a standard 3.5-meter lane. Figure 3-5 and Figure 3-6 illustrate good lane detection and slight deviations caused by sunlight glare during the day. Despite these minor issues, the vehicle consistently detected lane markings well due to their high quality.

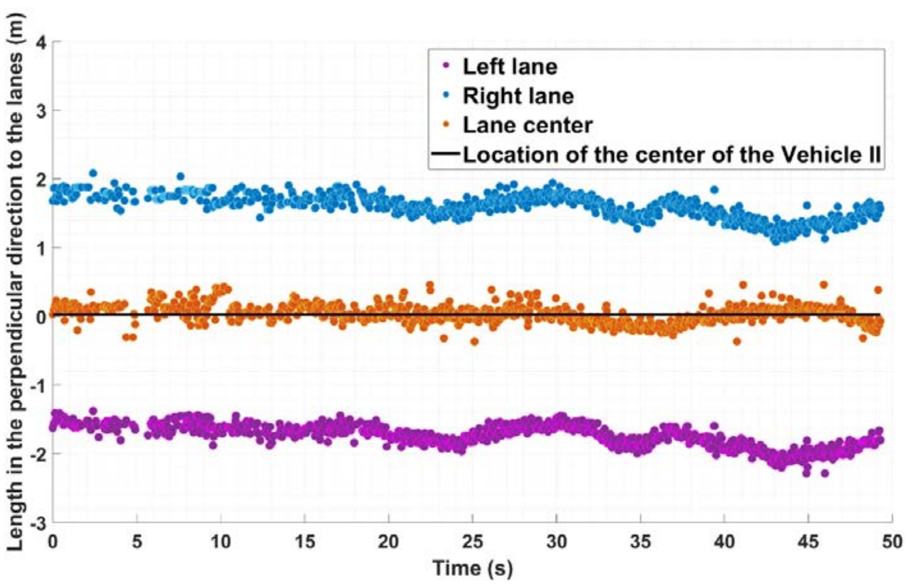


Figure 3-5 Daytime, rainy test lane deviation

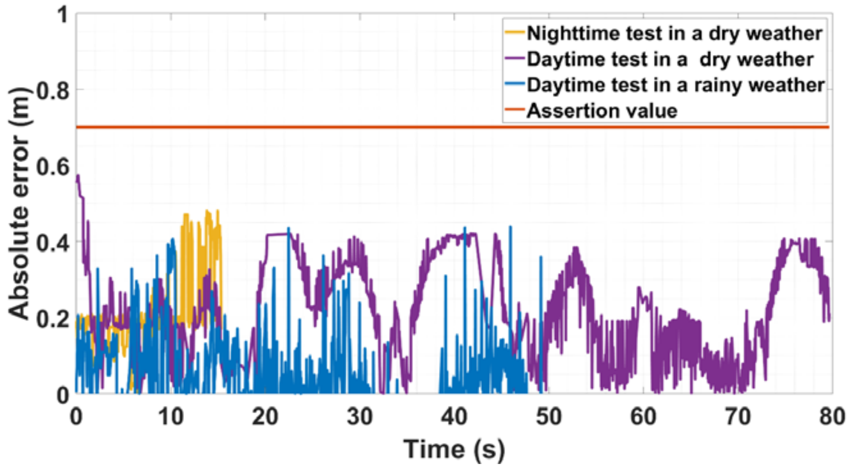
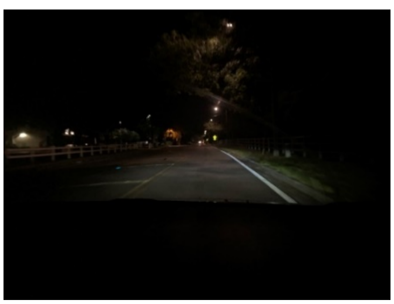


Figure 3-6 Vehicle deviation from the lane center.

3.2.6 Complex Composite Scenarios

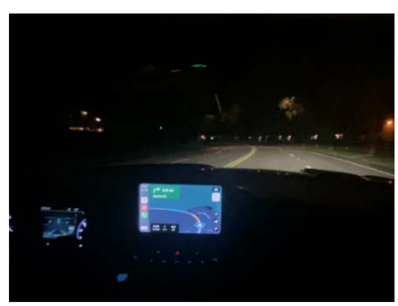
Testing reveals reduced vehicle detection performance in complex composite scenarios, such as navigating curved lanes at night, due to low visibility and challenging road geometries. These scenarios, shown in Figure 3-7, help evaluate system robustness under demanding conditions, guiding improvements to enhance safety and reliability.



(a) Straight and unclear lanes at nighttime

(b) Curve and clear lanes at nighttime

(c) Curve and unclear lanes at daytime



(d) Curve and right side moderately unclear lanes at nighttime

Figure 3-7 Example of lanes in complex composite scenarios.

The research team tested vehicle detection on straight, unclear lanes at night, with results detailed in Table 3-6. Most vehicles, except Vehicles 5 and 6, showed reduced detection performance compared to daytime and clear-lane scenarios, highlighting challenges posed by low-light conditions and unclear markings. These findings emphasize the need for advanced detection technologies, improved lane markings, and robust sensor fusion to enhance performance in complex driving conditions.

Table 3-6 Lanes detection testing results of each vehicle in the complex composite scenario.

Vehicle No.	Number of tests/ numbers of successful detections
	Straight, unclear lane at nighttime
1	10/3
2	10/4
3	10/4
4	10/3
5	10/5
6	10/10

3.2.7 Lane and Pavement Marking on Asphalt and Concrete Roads

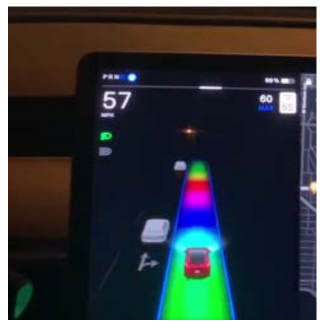
The research team did a test to compare the effect of concrete and asphalt on the vehicle's capability to detect lanes and pavement markings. Vehicle 9 (Tesla Model 3) is used for this test. It is observed that the road type does not affect the detection capability of the vehicle. The test vehicle detects lane markings and pavement markings well in the daytime and nighttime.

Table 3-7 Daytime and nighttime tests on asphalt vs. concrete roads

Marking	Number of tests/ numbers of successful detections			
	Concrete		Asphalt	
	Nighttime	Daytime	Nighttime	Daytime
Lane Marking	10/10	10/10	10/10	10/10
Straight arrow	10/10	10/10	10/10	10/10
Left arrow	10/10	10/10	10/10	10/10
Right arrow	10/10	10/10	10/10	10/10
Straight and left arrow	10/10	10/10	10/10	10/10
Straight and right arrow	10/10	10/10	10/10	10/10

(a) Asphalt road (b) Concrete road

Figure 3-8 Daytime test



(a) Asphalt road (b) Concrete road

Figure 3-9 Nighttime test

3.2.8 Lane Detection in Narrow Shoulders

Narrow shoulder lanes in a construction site or other situations are common on different roads. Vehicle 7 (Mustang Mach-E) and Vehicle 9 (Tesla Model 3) are used for this test. The research team did 10 tests on lane detection on narrow shoulders using Mustang Mach-E. The test vehicle's automatic lane detection and keeping system alarms the driver about the disengagement of this system and disengages 8 times and only the system works well 2 times. In addition, 5 tests are conducted using vehicle 9 on lane detection in narrow shoulders using a Tesla Model 3. The test vehicle's automatic lane detection and keeping system alarms the driver about the disengagement of this system and disengages 3 times and only the system works well 2 times.

Table 3-8 Test results of lane detection in a narrow shoulder

Vehicle	Number of tests/ numbers of successful detections
Vehicle 7 (Mustang Mach-E)	10/2
Vehicle 9 (Tesla Model 3)	5/2

3.3 Static Message Sign

Tests showed that while sensor-based technologies like cameras and lidar help vehicles detect static message signs (stop, speed limit, yield), only a few U.S. vehicle models are equipped with these detection features. This highlights a growth opportunity for enhancing vehicle detection systems to improve road safety. The research team tested three commercial vehicles and a lab CAV, adjusting experimental setups for each sign type due to varying recognition capabilities.

3.3.1 Stop Sign

A stop sign ensures traffic regulation, safety, and accident prevention by clearly indicating where drivers must yield. Accurate stop sign detection is vital for AVs to navigate safely and comply with traffic rules. Tests revealed that two commercial vehicle brands and the research team's CAV, equipped with lidar and camera systems, could detect stop signs. The lab vehicle used a ZED 2 stereo camera, offering high-definition 3D video and neural depth perception. The technical specifications for this camera are listed as follows:

Camera	
Output Resolution	2x (2208x1242) @15fps 2x (1920x1080) @30fps 2x (1280x720) @60fps 2x (672x376) @100fps
Field of View	Max. 110°(H) x 70°(V) x 120°(D)
Interface	USB 3.0/2.0 Integrated 1.2m cable (3.97ft)
Depth Range	0.3 m to 20 m (0.98ft to 65.61ft)
Depth Accuracy	< 1% up to 3m (9.84ft) < 5% up to 15m (49.21ft)

Sensors	
Motion	Gyroscope, Accelerometer, Magnetometer
Environmental	Barometer, Temperature

Physical	
Dimensions	174.9 x 29.8 x 31.9mm (6.89 x 1.18 x 1.25")
Weight	164g (0.36 lb.)
Op. Temp.	-10 °C to +45°C (14°F to 113°F)
Power	380 mA / 5V USB Powered

Figure 3-10 Camera and sensor specifications.

The lab vehicle used the Velodyne VLP-32C lidar, capable of generating 1.2 million 3D points per second with a 200-m range and a 360° horizontal field of view (Velodyne Acoustics Inc., 2018). Tests evaluated detection performance under obstructions, poor lighting, varying speeds, faded signs, and rainy conditions.

(1) Obstruction

The research team evaluated stop sign detection under varying levels of obstruction to understand its impact on accuracy. Scenarios included no obstruction, where signs are fully visible as shown in Figure 3-11 (a), moderate obstruction, with partial visibility due to branches or roadside elements as shown in Figure 3-11 (b) and Figure 3-12 (a), and severe obstruction, where signs are heavily obscured, challenging both humans and detection systems as illustrated in Figure 3-11 (c) and Figure 3-12 (b). Clear and unobstructed sign placement is essential for reliable CDA navigation.

(a) No obstruction (b) Moderate obstruction (c) Severe obstruction

Figure 3-11 Simulate trees obstructing stop signs.

(a) Moderate obstruction (b) Severe obstruction

Figure 3-12 Simulate other objects obstructing the stop sign.

The research team tested stop sign detection under three obstruction levels, with results in Table 3-9 showing decreased performance as obstructions increased. Ensuring clear placement, regular maintenance, high-reflectivity materials, advanced detection technologies, GPS integration, and V2X communication can improve detection and enhance the safety and reliability of CDA systems.

Table 3-9 Stop sign obstructed detection results.

Vehicle No.	Number of tests/ numbers of successful detections		
	No obstruction	**Moderate obstruction**	**Severe obstruction**
1 (commercial vehicle with camera)	10/10	10/6	10/2
2 (commercial vehicle with camera)	10/10	10/9	10/6
3 (lab CAV with camera)	10/10	10/9	10/7
3 (ab CAV with lidar)	10/9	10/8	10/6

(2) Daytime and nighttime

During the testing process, the research team identified that variations in lighting conditions also influence the effectiveness of vehicle detection systems for stop signs. To simulate different lighting scenarios, the research team conducts separate tests to assess vehicle detection performance under two distinct conditions: during the daytime (as illustrated in Figure 3-13 (a)) and at nighttime (as shown in Figure 3-13 (b)). The results of these tests are presented in Table 3-10.

(a) Stop sign during the daytime

(b) Stop sign at nighttime

Figure 3-13 Stop signs in the daytime and nighttime.

Table 3-10 Stop sign testing results of each vehicle in the daytime and nighttime.

Vehicle No.	Number of tests/ numbers of successful detections	
	Stop sign during the daytime	Stop sign at nighttime
1 (commercial vehicle with camera)	10/8	10/3
2 (commercial vehicle with camera)	55/54	55/55
3 (lab CAV with camera)	55/55	33/30
3 (lab CAV with lidar)	55/55	33/33

Tests reveal that Vehicle 1 and the lab CAV with camera perform better in detecting stop signs during the day due to improved visibility and contrast, while detection accuracy declines significantly at night. In contrast, Vehicle 2, tested in Tampa, maintains strong nighttime performance, possibly due to infrared cameras. The lab CAV with lidar shows consistent detection regardless of lighting, highlighting its robustness. Enhancements such as high-reflectivity materials, supplementary lighting, GPS integration, and sensor fusion can improve stop sign detection and ensure safer navigation across varying lighting conditions.

(3) Different speed

The research team analyzed the relationship between vehicle speed and stop sign detection distance, finding that higher speeds reduce detection distances due to limited response time, while lower speeds allow for longer detection distances. Vehicles 2, the lab CAV with a camera, and the lab CAV with lidar exhibit this trend, highlighting the need for early detection to ensure safe navigation. Interestingly, Vehicle 1 shows better detection performance at 15 mph, suggesting unique system characteristics. These findings stress the importance of adaptive detection systems, advanced technologies, and well-designed stop signs with high-visibility materials and strategic placement to enhance detection across varying speeds.

Table 3-11 Vehicles' stop sign detection distance results for different speeds.

Vehicle No.	Speed (mph)	Distance (ft)											Number of tests/ numbers of successful detections
		1	2	3	4	5	6	7	8	9	10	Average	
1 (commercial vehicle with camera)	5	41	35	40	52	40	39	38	40	52	45	42.2	20/14
	15	107	114	96	111	107	110	115	92	108	105	106.5	20/14
	25	21	26	30	24	19	20	22	31	25	20	23.8	20/10
2 (commercial vehicle with camera)	5	140	135	155	160	154	153	166	142	145	144	149.4	10/10
	15	95	99	96	105	90	109	95	101	112	102	100.4	10/10
	25	75	72	60	73	55	52	60	75	73	66	66.1	10/10

Table 3-11 continued

3 (lab CAV with camera)	5	92	95	95	101	104	98	99	103	98	95	98.0	10/10
	15	70	68	66	65	55	59	65	71	62	62	64.3	10/10
	25	45	40	42	50	43	42	39	45	41	42	42.9	10/10
3 (lab CAV with lidar)	5	110	115	125	110	113	113	118	112	115	121	115.2	10/10
	15	83	89	85	85	80	79	84	81	82	85	83.3	10/10
	25	55	52	50	61	65	52	55	52	53	49	54.4	10/10

(4) Unfading and fading

The research team examined the impact of stop sign fading on Vehicle 1's detection performance, categorizing fading into three levels: no fading, where signs retain their vibrant red; moderate fading, with a lighter red but still recognizable; and severe fading, where the red nearly blends with the white text, making detection difficult, as shown in Figure 3-14. This study highlights the limitations of current detection systems under varying sign conditions caused by sunlight, weather, or material quality. It emphasizes the importance of adaptive detection technologies and regular maintenance to ensure signs remain visible, supporting road safety and effective traffic communication.

(a) No fading (b)Moderately fading (c) Severely fading

Figure 3-14 Example of a fading stop sign.

The evaluation shows that Vehicle 1 performs well with moderately fading stop signs, similar to non-fading signs, as detailed in Figure 3-14. However, performance declines significantly with severely fading signs, as the front-facing camera struggles to distinguish the faded color from the white text. This underscores the need for high-quality, fade-resistant materials and regular maintenance to ensure stop sign visibility. Enhancements like reflective materials, additional illumination, GPS integration, and advanced sensor fusion can further improve detection capabilities, ensuring safer navigation under real-world driving conditions.

Table 3-12 Stop sign fading detection results.

Vehicle No.	Number of tests/ numbers of successful detections		
	No fading	**Moderately fading**	**Severely fading**
1 (commercial vehicle with camera)	10/8	10/8	10/2

(5) Sunny day and rainy day

The research team conducts a series of tests on the lab's CAV to understand the impact of rain conditions on the vehicle's ability to detect stop signs. The test scenarios are shown in Figure 3-15. The results of these tests are presented in Table 3-13. This observation indicates that the CAV, whether utilizing camera-based detection systems or lidar, demonstrates proficient detection capabilities both on sunny days and during rainy conditions. This indicates that moderate rainfall does not impair the vehicle's ability to detect stop signs.

(a) Sunny day (b) Rainy day

Figure 3-15 Example of stop signs on sunny and rainy days.

However, it is important to note that the testing period does not encounter heavy rainfall, which means the effects of more severe weather conditions on detection capabilities remain untested. Therefore, while the findings suggest that moderate rain does not adversely affect stop sign detection, the possibility of different outcomes under heavy rain conditions cannot be discounted. Further research and testing under a broader range of weather conditions, especially during heavy downpours, would be necessary to fully understand the impact of extreme weather on the reliability of stop sign detection by vehicles.

Table 3-13 Stop sign in sunny and rainy days detection results.

Vehicle No.	Number of tests/ numbers of successful detections	
	Sunny daytime	**Rainy daytime**
1 (lab CAV with camera)	55/55	22/22
1 (lab CAV with lidar)	55/55	22/22

3.3.2 Yield Sign

Yield sign detection enhances road safety by facilitating smoother traffic flow and preventing conflicts at intersections. Among the tested vehicles, only one could detect yield signs. The research team evaluated detection performance under various conditions, including obstructions, poor lighting, high speeds, and dirty signs. These findings underscore the importance of designing and maintaining visible, unobstructed, and well-kept yield signs to ensure accurate and reliable vehicle detection, contributing to safer navigation.

(1) Obstruction

The research team investigated the impact of obstructions on yield sign detection, categorizing obstructions into three levels. In the no-obstruction scenario, the sign is fully visible, offering ideal detection conditions, as shown in Figure 3-16 (a). Moderate obstruction partially blocks parts of the red portion or letters, though they remain recognizable, as illustrated in Figure 3-16 (b). Severe obstruction completely blocks the sign, making detection difficult for both humans and systems, as shown in Figure 3-16 (c). These findings highlight the importance of proper placement and obstruction-free yield signs to ensure safety and clear communication on roads.

(a) No obstruction (b) Moderate obstruction (c) Severe obstruction

Figure 3-16 Simulate tree obstruct yield sign.

The research team's testing, detailed in Table 3-14, shows that vehicle detection performance for moderately obstructed yield signs is comparable to signs with no obstruction, while severe obstructions significantly reduce detection accuracy. This highlights the importance of placing yield signs in unobstructed locations and maintaining their visibility through regular trimming and removal of obstructions. Enhancing infrastructure with high-visibility materials, and advanced lighting, and integrating detection technologies like GPS and digital mapping can further improve sign detection. A holistic approach combining strategic placement, maintenance, and advanced systems ensures reliable CDA operation and promotes road safety.

Table 3-14 Yield sign obstructed detection results.

Vehicle No.	Number of tests/ numbers of successful detections		
	No obstruction	**Moderate obstruction**	**Severe obstruction**
1 (commercial vehicle with camera)	10/4	10/4	10/2

(2) Daytime and nighttime

The research team conducts a series of tests on yield sign detection during both daytime and nighttime. The test scenarios are depicted in Figure 3-17 and the results are detailed in Table 3-15. The findings reveal that Vehicle 1 exhibits a decrease in detection performance during nighttime compared to daytime. This reduction in performance is likely attributed to the diminished effectiveness of the vehicle's camera-based detection system under low-light conditions. This observation brings to light the challenges faced by detection systems during nighttime and underscores the necessity for enhancements to improve yield sign detection. To address these challenges, improving the visibility of yield signs themselves is essential. This can be achieved by using high-reflectivity materials for the signs, ensuring that they remain visible in various lighting conditions. Additionally, installing supplementary lighting around yield signs can enhance their visibility during nighttime, aiding the vehicle's detection system.

(a) Yield sign during the daytime (b) Yield sign at nighttime

Figure 3-17 Example of yield sign in the daytime and nighttime.

Table 3-15 Yield sign testing results of each vehicle in the daytime and nighttime.

Vehicle No.	Number of tests/numbers of successful detections	
	Yield sign during the daytime	**Yield sign at nighttime**
1 (commercial vehicle with camera)	10/4	10/2

(3) Clean and dirty

Additionally, the research team conducts tests to compare the detection performance of clean versus dirty yield signs, with the test scenarios illustrated in Figure 3-19 and the results presented in Table 3-16. Table 3-16 Clean and dirty stop sign testing results of each vehicle. The findings indicate a slight decrease in the detection performance of Vehicle 1 when the yield sign is dirty. This suggests that dirt and grime can have an impact on a vehicle's ability to detect signs. Consequently, this emphasizes the importance of regular maintenance to ensure that signs remain clean and visible. Regular cleaning of yield signs can prevent the accumulation of dirt and maintain their visibility, thereby enhancing the detection capabilities of vehicle systems and ensuring the safe and efficient operation of traffic.

(a) Clean yield sign (b) Dirty yield sign

Figure 3-18 Example of a clean and dirty yield sign.

Table 3-16 Clean and dirty stop sign testing results of each vehicle.

Vehicle No.	Number of tests/ numbers of successful detections	
	Clean sign	**Dirty sign**
1 (commercial vehicle with camera)	10/4	10/3

(4) Different speed.

The research team also explores how different speeds affect a vehicle's ability to detect yield signs, with the findings detailed in Table 3-17. Interestingly, the results reveal that higher speeds enable the vehicle to detect yield signs from a greater distance, a finding that contrasts with the results for stop signs. This discrepancy can potentially be attributed to differences in the detection algorithms used for yield signs versus stop signs, leading to this divergent outcome. The vehicle's detection system may employ distinct strategies or prioritize different visual cues for each type of sign, resulting in varying detection behaviors at different speeds. Understanding these nuances in detection algorithms is crucial for optimizing the performance of vehicle detection systems and ensuring their reliability across different driving scenarios.

Table 3-17 Vehicle’s yield sign detection distance results for different speeds.

Vehicle No.	Speed (mph)	Distance (ft)											Number of tests/ numbers of successful detections
		1	2	3	4	5	6	7	8	9	10	Average	
1 (commercial vehicle with camera)	5	121	128	—	—	—	—	—	—	—	—	124.5	10/2
	15	74	218	217	—	—	—	—	—	—	—	169.7	10/3
	25	188	188	194	183	—	—	—	—	—	—	188.3	10/4

3.3.3 Speed Limit Sign

The research team tested speed limit sign detection across four vehicles with camera-based systems under various conditions. Tests evaluated performance in optimal daytime lighting, low nighttime lighting, varying levels of obstruction, and, for one vehicle, rainy versus clear weather. Results highlight the impact of lighting, obstructions, and weather on detection accuracy, emphasizing the need for resilient detection systems to ensure adherence to traffic laws and enhance road safety.

(1) Daytime and nighttime.

The research team tested speed limit sign detection during daytime and nighttime, as shown in Figure 3-19and detailed in Table 3-18. Vehicles 1 and 2 showed reduced detection at night due to the limitations of their camera systems in low-light conditions, emphasizing the need for high-visibility materials, proper illumination, and regular maintenance of signs. Vehicle 3 demonstrated improved nighttime performance, likely due to infrared cameras, while Vehicle 4 maintained consistent detection in all conditions by using GPS-based navigation with updated maps, highlighting the potential of integrating GPS and mapping for reliable speed limit recognition.

(a) Speed limit sign during the daytime

(b) Speed limit sign at nighttime

Figure 3-19 Examples of speed limit signs in the daytime and nighttime.

Table 3-18 Speed limit sign testing results of each vehicle in the daytime and nighttime.

Vehicle No.	**Number of tests/ numbers of successful detections**	
	Speed limit sign during the daytime	**Speed limit sign at nighttime**
1 (commercial vehicle with camera)	10/10	10/7
2 (commercial vehicle with camera)	10/9	10/6
3 (commercial vehicle with camera)	120/115	120/118
4 (commercial vehicle with GPS)	10/10	10/10

(2) Obstruction

The research team evaluated Vehicle 1's detection capabilities under daytime conditions by deliberately obscuring sections of speed limit signs, with results shown in Figure 3-20. When the number "5" was partially obscured (a), the system occasionally detected 25 mph, and when almost entirely obscured (b), it inconsistently detected 20 or 25 mph. Nearly fully obscuring the number "2" (c) led to inconsistent detection of 25 mph, while minor obstructions (d) did not significantly impact detection. Slight partial obstructions of both numbers (e) allowed accurate detection, but when both numbers were nearly fully obscured (f), the sign went undetected.

(a) Partially obstructing the number "5" (b) Almost completely obstructing the number "5"

(c) Partially obstructing the number "2" (d) Almost completely obstructing the number "2"

(e) Partially obstructing the number "25" (f) Almost completely obstructing the number "25"

Figure 3-20 Example of obscuring speed limit signs of Vehicle 1.

These results, detailed in highlights how Vehicle 1's reliance on camera-based detection is impacted by obstructions, leading to missed or incorrect speed limit sign detections. Like obstructed stop signs, obstructions reduce detection accuracy. Ensuring signs remain unobstructed through regular maintenance, such as clearing trees, and strategically placing signs to avoid blockages, is essential for maintaining clear visibility. These measures enhance vehicle detection performance, promoting safer and more efficient road navigation.

Table 3-19, highlights how Vehicle 1's reliance on camera-based detection is impacted by obstructions, leading to missed or incorrect speed limit sign detections. Like obstructed stop signs, obstructions reduce detection accuracy. Ensuring signs remain unobstructed through regular maintenance, such as clearing trees, and strategically placing signs to avoid blockages, is essential for maintaining clear visibility. These measures enhance vehicle detection performance, promoting safer and more efficient road navigation.

Table 3-19 Vehicle 1’s speed limit sign obstructed detection results.

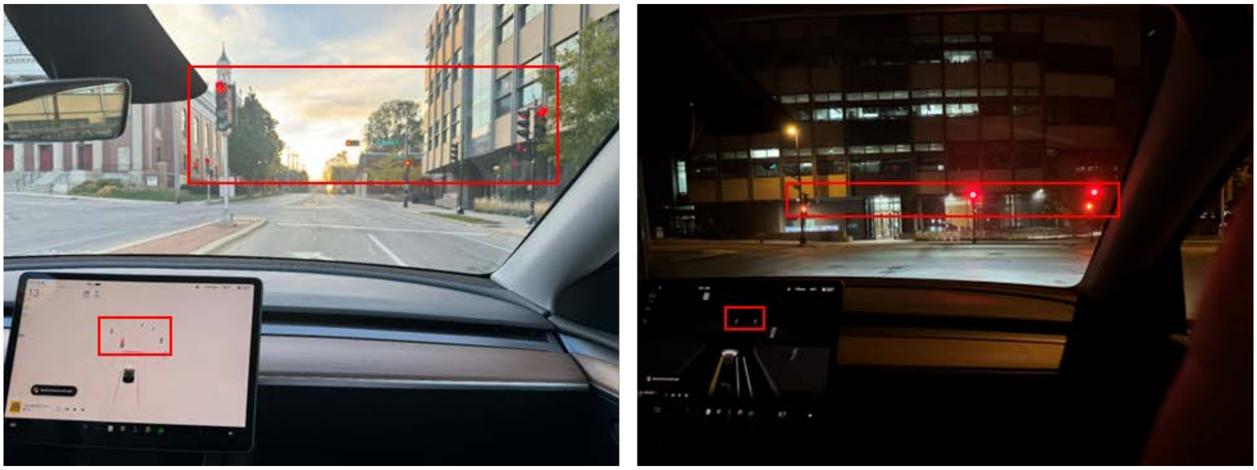
Conditions	Detection results	Number of tests/ numbers of successful detections
Partially obstructing the number "5"	25 mph	10/10
Almost completely obstructing the number "5"	20/ 25 mph	10/ 4 (20 mph)/ 2 (25 mph)
Partially obstructing the number "2"	25 mph	10/10
Almost completely obstructing the number "2"	25 mph	10/4
Partially obstructing the number "25"	25 mph	10/10
Almost completely obstructing the number "25"	Cannot detect the sign	10/ 0

3.4 Traffic Signal

`Vehicles' ability to detect traffic signals is essential for safe navigation, particularly for AVs at signal-controlled intersections. Traffic signal detection remains complex, with only a few advanced commercial vehicles and lab CAVs equipped with this functionality. The research team tested two commercial vehicles and a lab CAV, categorizing them into two groups based on their technology. The first group relies on sensor-based detection using cameras or lidar to visually interpret signals, while the second group uses V2I technology to receive real-time traffic signal updates. Due to differences in technology and functionality, the team tailored experimental setups for each vehicle.

3.4.1 Sensor-based Traffic Signal Detection

The research team tested sensor-based vehicles, including commercial vehicles and lab CAVs using cameras and lidar, for traffic signal detection during both daytime and nighttime, as shown in Figure 3-21. Nighttime tests posed additional challenges due to low visibility and interference from streetlights, headlights, and commercial signage. These tests revealed how well the systems discern traffic signals amidst dynamic lighting, highlighting their adaptability and sensitivity. The findings emphasize the need for continuous innovation in sensor technology to enhance reliability and safety in complex urban environments.



(a) Daytime (b) Nighttime

Figure 3-21 Example of traffic signal testing at daytime and nighttime.

Table 3-20 Sensor-based traffic signal testing results of each vehicle in the daytime and nighttime.

Vehicle No.	The number of tests/ numbers of successful shows the phase	
	Daytime	**Nighttime**
1 (commercial vehicle with camera)	85/82	85/81
2 (lab CAV with camera)	85/85	51/49
2 (lab CAV with lidar)	55/52	33/30

Table 3-20 presents traffic signal detection results for vehicles during daytime and nighttime. Camera-based systems showed reduced accuracy at night due to limited visibility and interference from environmental lighting, such as streetlights and vehicle headlights. To address this, improving traffic signal illumination with LED lights, optimizing signal placement, using retroreflective backplates, and integrating V2I communication can enhance detection reliability.

Lidar-based systems failed to detect about 10% of signals, particularly those positioned higher or farther from the stop line, exceeding the system's predefined sensing parameters. Adjusting lidar settings to accommodate varying signal heights and distances can improve detection accuracy, ensuring better performance under diverse environmental conditions

3.4.2 Connected-based Traffic Signal Interpretation

Traffic signals equipped with V2I technology transmit real-time traffic signal data. The vehicle's V2I system receives this data and can translate it into visual or audible alerts for the driver or use the information directly for autonomous vehicles. This allows for a more informed driving experience, promoting adherence to traffic regulations and improving overall road safety. For section 3, within the group of vehicles utilizing communication technology, one commercial vehicle and a lab CAV employed V2I technology to facilitate communication between the vehicle and traffic signals, thereby transmitting information about the phase of the traffic signals.

(1) Commercial vehicle

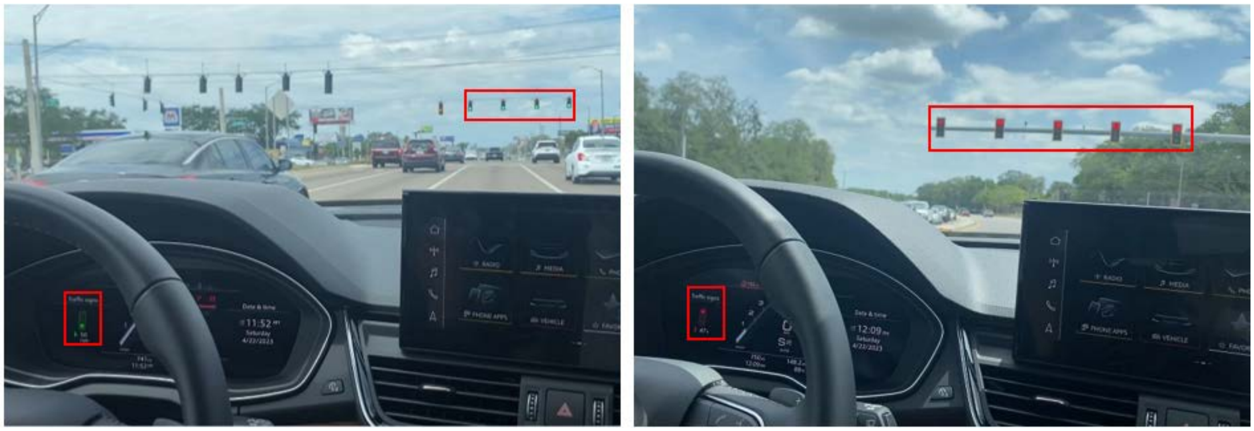
The research team tested a communication-based commercial vehicle's V2I technology for traffic signal detection during both daytime and nighttime. As shown in Figure 3-22 , the results were consistent across both periods, demonstrating the system's robustness. However, the overall success rate in accurately detecting traffic signal phases remains low, indicating that the technology is still in development. Further improvements are needed to enhance accuracy and reliability, ensuring safe and efficient navigation through intersections.

Table 3-21 Connected-based traffic signal testing results of Vehicle 1 in the daytime and nighttime.

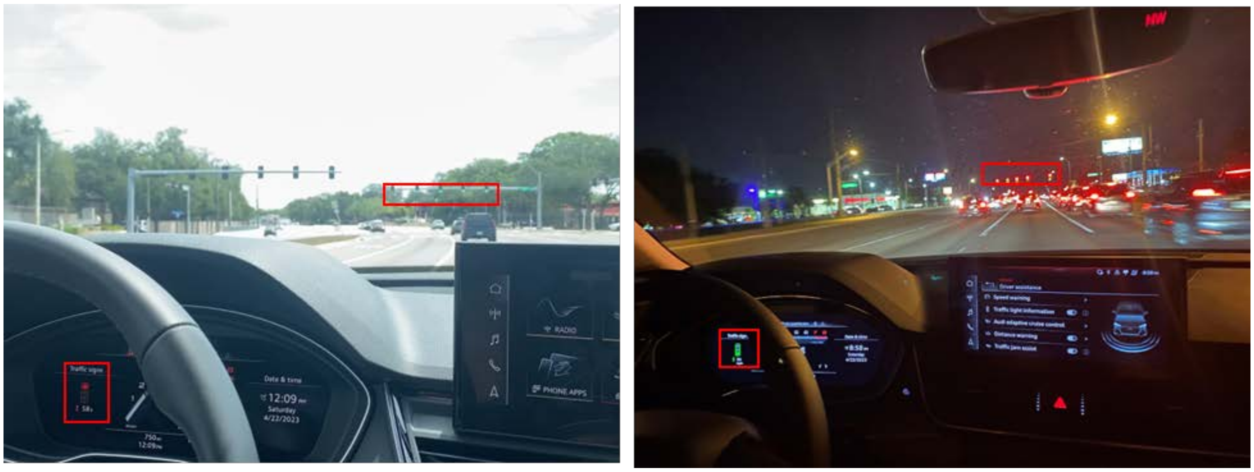
Vehicle No.	**The number of tests/ numbers of successful shows the phase**	
	Daytime	**Nighttime**
1 (commercial vehicle with V2I technology)	10/5	10/5

Note: Even if the phase can be recognized correctly, the red-light countdown still has an error of a few seconds.

Figure 3-22 illustrates test results from the commercial vehicle, revealing instances of traffic signal phase misidentification and inconsistent red-light countdowns, with a discrepancy of about 4 seconds and occasional fluctuations. While the vehicle generally detects upcoming signals, its speed recommendations often match existing road speed limits, raising questions about its ability to generate real-time recommendations based on signal distance and green light duration. These issues stem from data delays and dynamic traffic signal adjustments in connected systems. The findings emphasize the need for refining communication technologies and data processing to improve the accuracy and reliability of traffic signal information systems.



(a) Correct phase



(b) Incorrect phase

Figure 3-22 Traffic signal testing of commercial vehicle

(2) Lab CAV

The research team tested a lab CAV equipped with C-V2X technology for vehicle-to-traffic signal communication. The OBU in the vehicle exchanges signals with the RSU, enabling two-way communication with traffic signals to share real-time status and updates. This process enhances traffic flow, road safety, and driving conditions. Figure 2-42 and Figure 2-43 show the OBU and RSU used in this test respectively. GPS signals from Google Maps determined the distance between the OBU and RSU, with performance measured by PER (packet error rate) and IPG (inter-packet gap). The results are summarized in Table 3-22.

Table 3-22 The performance matrix of C-V2X.

Distance	PER	IPG
59m	2/(472+2)=0.4%	200 ms
109m	6/(692+6)=0.8%	310 ms
257m	12/(592+12)=1.9%	310 ms
408m	40/(40+615)=6.1%	504 ms
598m	16/(16+932)=1.6%	220 ms
755m	13/(13+765)=1.6%	1900 ms

The analysis of the relationships between distance, PER, and IPG reveals several key insights. While PER generally increases with distance between the RSU and OBU, the trend is not strictly linear, as shown by a PER drop from 6.1% at 408 meters to 1.6% at 598 and 755 meters. IPG tends to rise with distance but is inconsistent, with an outlier of 1900 milliseconds at 755 meters. No clear correlation exists between PER and IPG, and varying data packet numbers add complexity. Testing challenges include the impact of road grade and environmental factors like trees, buildings, and traffic, which influence IPG values. For instance, IPG values improve on segments without vertical curves, as highlighted in Figure 2-44, which calculates the IPG at 755m.

4 Platooning Field Experiment Design Guideline

4.1 Introduction

4.1.1 Background

In conventional transportation systems, vehicles work independently following the traffic rules and regulations. However, this conventional approach does not maximize the safety and efficiency of transportation systems. There is no coordination between the vehicles and infrastructure, leading to a higher risk of accidents, traffic congestion, increased fuel consumption, inefficient traffic flow, and environmental impact. Platooning (see Figure 4-1), which involves coordinated driving between vehicles and infrastructure, is a common strategy to address these issues. Platooning in CDA refers to a strategy where a group of vehicles, often equipped with automated driving systems, travel closely together in a coordinated manner.

Recent reports from the National Highway Traffic Safety Administration (NHTSA) highlight the ongoing issue of traffic accidents and fatalities in the USA (NHTSA, 2024b). In 2022, there were 42,514 fatalities in motor vehicle traffic crashes, representing a slight decrease from previous years. The NHTSA report indicates that preliminary fatality estimates for 2023 are 40,990, reflecting a 3.6% decrease compared to 2022. The reduction in fatalities corresponds with a significant rise in vehicle miles travel, which increased by 67.5 billion miles (2.1 %) in 2023. The fatality rate per 100 million VMT also decreased to 1.26 in 2023 from 1.33 in 2022. These statistics reflect the effectiveness of ongoing safety measures and technological advancements to reduce road fatalities. Additionally, distracted driving remains a critical issue, with 3,308 fatalities and nearly 290,000 injuries reported in 2022 due to distracted drivers (NHTSA, 2024a).

Platooning has the potential to significantly enhance road safety and efficiency by reducing fuel consumption (Hardes & Sommer, 2019) and travel time and addresses safety in dense traffic (Thormann et al., 2022a). These potential benefits could be seen from the perspective of traffic flow and fuel usage efficiency, reduced emissions, and improved safety.

Traffic congestion in urban areas leads to longer commutes (Afrin & Yodo, 2020), higher fuel use, and more emissions (Arti et al., 2022). Without coordinated movement, each driver must gauge their speed and follow distance individually, leading to inconsistent gaps, bottlenecks, and slower overall traffic flow.

Conventional transportation systems contribute significantly to increased fuel consumption due to factors such as traffic congestion, inefficient driving patterns, and high vehicle ownership rates. Implementing platooning can mitigate these issues by reducing aerodynamic drag and improving traffic flow (Hussein & Rakha, 2022).

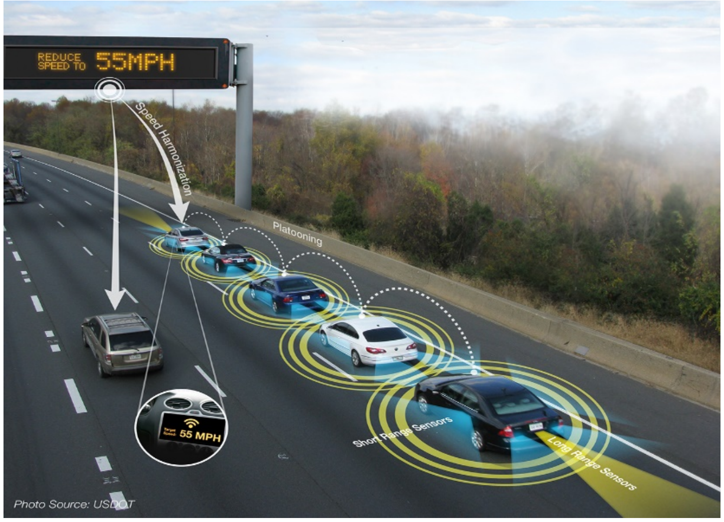


Figure 4-1 Vehicle platooning

4.1.2 Benefits of Platooning

Platooning offers numerous benefits that address many inefficiencies of conventional transportation systems. Platooning offers numerous advantages for modern transportation systems, encompassing improvements in road safety, traffic flow, fuel efficiency, and emissions reduction.

- **Enhanced Safety**: The use of automated driving systems and V2V communication in platooning enhances road safety by reducing accidents caused by human error. Properly managed platoons have been shown to significantly reduce the risk of accidents (Imad et al., 2021). Automated systems in platooning vehicles can react faster and more accurately than human drivers, reducing the risk of accidents caused by factors such as distraction, fatigue, or misjudgment. Advanced sensors and communication technologies enable platooning vehicles to detect and respond to potential hazards more effectively. For instance, if the lead vehicle brakes suddenly, the following vehicles can react almost instantaneously, preventing rear-end collisions. Automation in platooning thus not only enhances safety but also contributes to smoother and more efficient transportation systems overall.
- **Traffic Flow Improvement**: Platooning significantly improves traffic flow by allowing vehicles to travel closely together in a coordinated manner, facilitated by advanced communication technologies and automated driving systems. Studies, such as those conducted by (Hota et al., 2023), have shown that platooning can mitigate congestion, reduce travel time, and avoid collisions through adaptive traffic flow management systems. These systems enable platoons to efficiently navigate through traffic, perform merge and join maneuvers seamlessly, and maintain steady movement even in obstructed scenarios. As a result, platooning not only enhances the efficiency of road

networks but also contributes to smoother and more reliable traffic conditions, ultimately leading to improved overall traffic flow and reduced travel delays (Hota et al., 2023).

- **Improving Energy Efficiency**: Platooning can reduce fuel consumption by 5% to 15% depending on the configuration of the platoon, primarily due to reduced aerodynamic drag (Imad et al., 2021). This benefit is particularly pronounced for heavy-duty trucks, which experience substantial drag at high speeds. When vehicles travel closely together, the lead vehicle cuts through the air, creating a slipstream effect that reduces the air resistance faced by following vehicles. This reduction in drag means that engines do not have to work as hard, resulting in lower fuel consumption. For commercial fleets, these fuel savings can translate into significant cost reductions, especially for industries relying on long-haul transportation, where fuel expenses constitute a major portion of operating costs. Improved fuel efficiency also means that vehicles can travel longer distances on a single tank of fuel, beneficial for long-distance routes and reduces the frequency of refueling stops.
- **Reduced Emissions**: The fuel savings from platooning directly contribute to reduced greenhouse gas emissions, promoting environmental sustainability. Implementing platooning can lead to a 2.8% reduction in total fuel consumption for trucks, which translates into a similar reduction in CO_2 emissions (X. Ma et al., 2021). By consuming less fuel, platooning vehicles emit fewer pollutants, such as carbon dioxide (CO_2) and nitrogen oxides (NOx), major contributors to air pollution and climate change. Reduced emissions improve air quality, particularly in urban areas where traffic-related pollution is a significant concern, leading to improved public health outcomes and a cleaner environment. Many regions have stringent emissions regulations, and platooning can help fleets comply with these standards, avoiding potential fines and enhancing corporate social responsibility profiles. The environmental benefits of platooning extend beyond individual savings to broader societal impacts.

While platooning offers many benefits, its implementation faces several challenges, including:

- Infrastructure demands
- Robust algorithm design
- Feasibility in practical implementation
- Interoperability between vehicles
- Compatibility of communication and sensor technologies from different manufacturers
- Testing and verification of safety, security, and efficiency of platooning systems

4.1.3 Challenges of Platooning

Addressing platooning challenges requires a multidisciplinary approach to ensure reliable and safe operation, widespread acceptance, and effective integration with existing transportation systems and future infrastructure planning.

4.1.3.1 Infrastructure

Implementing platooning systems presents significant challenges from both digital and physical infrastructure perspectives. Digital infrastructure issues primarily revolve around the need for reliable, low-latency V2V and V2X communication systems, where wireless communications' reliability and safety in critical scenarios must be thoroughly tested and validated (Filho et al., 2020). Additionally, ensuring robust data security and seamless software integration across different vehicle systems remains crucial. From a physical infrastructure standpoint, existing roads often require significant upgrades to accommodate platooning vehicle (Metallinos Log et al., 2023; She & Ouyang, 2022). Furthermore, a multi-dimensional survey of cooperative vehicular platooning emphasizes the need for enhanced control strategies, cybersecurity, and comprehensive validation methods to ensure the safe and efficient operation of platoons on existing roads (Vasconcelos Filho et al., 2024).

4.1.3.2 Algorithms Development for Platooning

Platooning algorithms face numerous challenges due to the complexity and dynamics of vehicle coordination and communication. One significant issue is the need for robust communication systems. The reliability of these systems is crucial; any delay or failure can lead to collisions or breakdowns in the platoon formation (Balador et al., 2022). Ensuring secure and reliable communication channels (Gonçalves et al., 2018) is vital to prevent potential cyber-attacks and ensure safe platoon operations(Basiri et al., 2019).

Another major challenge lies in developing effective control algorithms. These algorithms must manage the movement of autonomous vehicles, accounting for diverse scenarios such as sudden stops, variable speeds, and different driving conditions (Sana et al., 2023). The challenge is in designing algorithms that are efficient and adaptable to real-time changes and uncertainties on the road, as emphasized by (Deng et al., 2022). Effective algorithms must handle the coordination of multiple vehicles in real-time (Z. Wang et al., 2023), considering factors like vehicle speed, route optimization, and traffic conditions(Plessen et al., 2016) .

The real-world implementation of these algorithms presents additional difficulties. There are practical issues such as the need for synchronization among multiple vehicles and handling external factors like road conditions and traffic signals (Hou et al., 2023). Scheduling and planning techniques are crucial for effective platoon formation and management(Du et al., 2022). A flexible framework is needed to accommodate these variables while ensuring smooth and safe platoon operations. Current algorithms require significant improvements to manage the complexities of large-scale deployments, including heterogeneous vehicle types and varying traffic densities.

Vehicle platooning offers environmental benefits such as reduced fuel consumption and emissions. However, there are research gaps, particularly in algorithm optimization and integration with existing traffic management systems (Rebelo et al., 2024). Future research should focus on developing more sophisticated algorithms that can dynamically adjust to traffic patterns and minimize negative environmental impact.

Overall, addressing these challenges in platooning algorithms requires a multidisciplinary approach, integrating advancements in communication technologies, control systems, and environmental sciences. The continuous evolution of these algorithms is crucial to fully realize the potential of vehicle platooning in enhancing road safety and efficiency.

4.1.3.3 Implementation of Platooning

Implementing vehicle platooning on a large scale comes with several major challenges, mainly in coordination, infrastructure, costs, and public acceptance. These issues need to be addressed to ensure the system can work effectively and safely, while also being widely accepted.

One of the biggest challenges is coordinating many vehicles, each with different capabilities and constraints. The difficulties in scheduling and planning needed for effective platoon formation and management (Hou et al., 2023). The study in (Metallinos Log et al., 2023) stresses the need for advanced algorithms to manage the creation, maintenance, and dissolution of platoons, especially in mixed traffic conditions. Current algorithms need significant improvement to handle the complexities of large-scale deployments, such as different vehicle types and varying traffic densities.

The initial costs of upgrading infrastructure and vehicles for platooning are also high. This includes installing advanced sensors, communication systems, and automated driving technologies. Achieving the environmental benefits of platooning, like reduced energy consumption and emissions, requires highly efficient algorithms and significant investments in technology(Rebelo et al., 2024). Additionally, adapting existing infrastructure to support platooning involves substantial costs and coordination (Balador et al., 2022). This requires strong investment and planning to ensure the infrastructure can support the new technologies.

Public acceptance is another critical barrier to the widespread adoption of platooning (Aramrattana et al., 2021). Gaining trust and acceptance from the public and stakeholders is crucial, which involves demonstrating the safety and benefits of platooning systems (Castritius et al., 2020). Secure and reliable communication channels are key in preventing cyber-attacks and ensuring safe operation(Balador et al., 2022) which is essential for gaining public trust (Filho et al., 2020). Moreover, algorithms that can dynamically adjust to traffic patterns and environmental conditions are essential(Rebelo et al., 2024), helping to show the practical benefits of platooning to the public.

Ensuring the system can scale without losing safety and efficiency is another significant challenge. Large-scale testing and validation are essential to address this. The importance of large-scale testing to understand the practical implications and benefits of platooning is underlined by the European Truck Platooning Challenge in 2016 (Aarts & Feddes, 2016). Such initiatives provide valuable insights into operational challenges and help refine technologies and strategies for better implementation.

Overall, developing platooning algorithms and implementing them on a large scale involves many challenges that require a multidisciplinary approach, integrating advancements in communication technologies, control systems, and environmental sciences. Continuous research, development, and testing are crucial to overcome these hurdles and fully realize the potential of vehicle platooning in improving road safety and efficiency.

4.1.3.4 Interoperability

Interoperability between vehicles from different manufacturers poses a significant challenge for the large-scale implementation of platooning. Standardizing communication protocols and interfaces is essential to ensure seamless interactions between vehicles in a platoon. The report by the European Commission's Platooning Ensemble in 2021 highlights the importance of a unified platoon management protocol that relies on wireless V2V communication to maintain coordination and safety (Dehlia Willemsen et al., 2020). Similarly, the role of standardization in achieving communication interoperability across various manufacturers' systems is important to ensure that vehicles can effectively communicate and coordinate their movements.

Moreover, compatibility with older vehicles without extensive modifications is crucial for the broad adoption of platooning technologies. The communication between vehicles and RSUs needs a coordinated design and development to integrate both new and existing vehicle technologies. Ensuring that these systems can operate together efficiently requires effective coordination between various stakeholders, including vehicle manufacturers, infrastructure providers, and regulatory bodies. This collaborative approach is necessary to develop and maintain interoperable platooning systems that can function reliably across diverse vehicle types and infrastructures.

4.1.3.5 Test and Verification of Platooning

Comprehensive testing under a wide range of conditions is crucial to ensure the safety and reliability of vehicle platooning systems. This includes utilizing software-in-the-loop (SIL), hardware-in-the-loop (HIL), vehicle-in-the-loop (VIL), and real-world tests. Each of these testing methodologies plays a vital role in the verification process, addressing different aspects of system performance and interoperability.

SIL testing allows developers and traffic engineers to evaluate platooning algorithms within a simulated environment. This method ensures that the software functions correctly before integrating it with hardware components. The simulation methods and tools for collaborative testing described by (Cioroaica et al., 2019) highlight the importance of SIL in early-stage testing, enabling the detection and correction of software issues without the risk associated with physical testing.

HIL testing bridges the gap between pure simulation and real-world testing by integrating actual hardware components into the simulation environment. This method allows for real-time interaction between the software and hardware, providing a more accurate assessment of how the system will perform under real-world conditions. National Instruments emphasizes the critical role of HIL testing in validating the hardware's performance within simulated operational conditions (National Instruments, 2024).

VIL testing further narrows the gap by combining elements of both simulation and real-world testing. VIL testing places the actual vehicle within a controlled testing environment where both simulated and real-world conditions can be replicated. VIL testing fills the gap between SIL/HIL simulations and full-scale road tests, ensuring that the vehicle's response to platooning commands can be accurately assessed in a controlled yet realistic setting[9].

Finally, **real-world testing** is indispensable for validating the entire platooning system in real-life conditions. This phase is essential for verifying that the simulations and controlled environment tests reflect the actual performance and safety of the platooning system on public roads. Real-world testing involves rigorous procedures to ensure compliance with regulatory standards and to identify potential failure modes. The U.S. Department of Transportation highlights the significance of detailed test setups and driving scenarios in evaluating platooning systems under realistic operational conditions (Tiernan et al., 2017).

The integration of SIL, HIL, VIL, and real-world testing methods ensures a comprehensive verification process, addressing various challenges such as system interoperability, hardware-software integration, and real-world applicability. These testing methodologies collectively contribute to the development of reliable and safe platooning systems, ready for deployment on public roads.

4.1.4 Consideration in Developing Guidelines for Field Experiments on Freeway Vehicle Platooning

Field experiments on freeway vehicle platooning are critical for understanding and improving this innovative transportation system. However, conducting such experiments requires careful planning and adherence to well-defined guidelines to ensure safety, reliability, and compliance with regulatory standards. Developing comprehensive guidelines ensures that experiments are conducted effectively while addressing concerns related to safety, data integrity, and ethical considerations.

[9] What is vehicle-in-the-loop testing? (https://www.aptiv.com/en/insights/article/what-is-vehicle-in-the-loop-testing / Accessed: 10/07/2024)

Importance of developing guidelines for field experiments on freeway vehicle platooning

- **Safety Considerations**: Guidelines ensure the implementation of safety protocols, including safe following distances, emergency procedures, and communication protocols among platooning vehicles, reducing accident risks during high-speed experiments.
- **Consistency and Reproducibility**: Standardized procedures in guidelines enable reproducibility across different teams and locations, ensuring that experiments yield comparable and reliable data for advancing platooning research.
- **Regulatory Compliance**: Guidelines ensure that all legal requirements, such as permits, insurance, and traffic laws, are met. They also facilitate coordination with authorities for authorized public roadway use.
- **Data Quality and Integrity**: Clear guidelines aid in selecting sensors, data logging systems, and formats, ensuring high-quality data collection while addressing issues of data security and privacy.
- **Cost and Resource Management**: Guidelines provide frameworks for optimizing resources by outlining efficient planning for test sites, vehicle configurations, and team coordination, minimizing costs.
- **Ethical and Environmental Considerations**: Guidelines ensure ethical practices in minimizing environmental impacts, such as noise and emissions while protecting human participants and ensuring minimal disruption to traffic.

Creating effective guidelines for field experiments on freeway vehicle platooning needs a structured approach to conducting experiments, ensuring that all aspects from safety to data management are thoroughly addressed. Here are the key steps involved in developing such guidelines.

Steps to develop guidelines for field experiments on freeway vehicle platooning

- **Literature Review and Benchmarking**: Examine existing research and guidelines related to freeway vehicle platooning and autonomous vehicle testing to identify best practices and common challenges.
- **Stakeholder Involvement**: Engage engineers, researchers, regulatory bodies, and safety experts to ensure the guidelines meet the needs and concerns of all involved parties.
- **Define Objectives and Scope**: Specify the goals of the guidelines and the types of platooning scenarios to be tested, as well as the conditions under which the guidelines apply.

- **Safety Protocols Development**: Create detailed safety protocols, including vehicle inspections, emergency response plans, and communication procedures tailored to the risks of freeway platooning.
- **Experimental Design**: Provide guidance on selecting test sites, vehicle configurations, and data collection methods, and define metrics for evaluating performance such as fuel efficiency and safety.
- **Regulatory and Legal Compliance**: Include comprehensive sections on the necessary permits, insurance, and coordination with authorities, and provide compliance checklists and templates.
- **Data Management**: Establish procedures for data collection, storage, and analysis, focusing on data accuracy, integrity, security, and privacy.
- **Ethical Considerations**: Develop ethical guidelines to address impacts on participants, road users, and the environment, and protocols to minimize traffic disruption and environmental impact.
- **Pilot Testing and Iteration**: Conduct pilot experiments to test the guidelines' effectiveness, gather feedback, and refine the guidelines based on real-world application.
- **Documentation and Training**: Offer thorough documentation and develop training programs for experimental teams to ensure understanding and effective implementation of the guidelines.
- **Continuous Improvement**: Set up a process for regular review and updates of the guidelines to incorporate new research, technological advancements, and ongoing experiment feedback.

Following these steps will lead to robust, comprehensive guidelines that support safe, efficient, and effective freeway vehicle platooning experiments.

4.2 Platooning Formation

Platooning formation methods refer to the strategies and techniques used to organize and maintain a group of CAVs traveling together.

4.2.1 Types of Platoon Formations

Platooning formations can be categorized based on how vehicles join, travel, and leave the platoon. Here we discuss the main types of platooning formations.

4.2.1.1 Single-File Platooning

Vehicles follow one another in a straight line with minimal lateral displacement in single-file platooning (Fakhfakh et al., 2020). This is the simplest and most common formation.

- **Formation**: Vehicles travel one behind the other, maintaining a consistent distance.
- **Advantages**: Simplifies coordination and communication, ideal for highways and straight roads.
- **Challenges**: Limited flexibility in changing lanes or handling complex traffic conditions.

4.2.1.2 Multi-File Platooning

Vehicles travel in multi-parallel lines (Al-Kaisy & Durbin, 2011; Lin et al., 2022). This formation can increase road capacity and facilitate easier lane changes.

- **Formation**: Vehicles are arranged in multiple adjacent lanes, with each lane maintaining consistent spacing.
- **Advantages**: Allows for more efficient use of road space and smoother lane merging.
- **Challenges**: Requires more sophisticated communication and coordination between vehicles in different lanes.

4.2.1.3 Dynamic Platooning

Dynamic platooning allows vehicles to join or leave the platoon at any point. This formation is highly flexible and adapts to real-time traffic conditions (Altamimi et al., 2023; Hardes & Sommer, 2019). This method involves the ability to split an existing platoon into smaller groups or merge smaller platoons into a larger one based on traffic conditions, road infrastructure, or destination requirements (Dasgupta et al., 2018; S. Wang et al., 2024).

- **Formation**: Vehicles dynamically adjust their positions, joining or leaving the platoon as needed. Vehicles can split from a large platoon into smaller groups or merge into a larger platoon seamlessly.
- **Advantages**: Provides flexibility and adaptability to changing traffic conditions and varying vehicle speeds and allows for better management of road space and traffic flow.
- **Challenges**: Requires advanced communication and decision-making algorithms to ensure safety and efficiency.

4.2.1.4 Pre-defined / Pre-scheduled Platooning

Vehicles are scheduled to form a platoon at a specific time and location, often determined by a central control system (Sokolov et al., 2017).

- **Formation**: Vehicles meet at a predetermined location and time to form the platoon.

- **Advantages**: Predictable and well-organized, suitable for commercial fleets or public transportation.
- **Challenges**: Less flexible for dynamic traffic conditions, require strict adherence to schedules.

4.2.1.5 Ad-Hoc Platooning

Ad-hoc platooning allows vehicles to form a platoon spontaneously while on the route. Vehicles use real-time communication to identify potential platoon partners and join the platoon dynamically (Maiti et al., 2023; Thomas & Vidal, 2019).

- **Formation**: Vehicles form platoons on the fly, based on real-time traffic and communication data. Ad-hoc platooning could be either manual or automated. In manual ad-hoc formation, drivers manually opt to form a platoon using in-vehicle systems. Drivers receive notifications about nearby platooning opportunities. They accept and follow instructions to join the platoon. Vehicles sync up using V2V communication once the driver agrees to join. In automated ad-hoc formation, vehicles automatically detect and join a platoon using sensors and V2V communication. The vehicle identifies a nearby platoon through V2V signals. It automatically adjusts its speed and position to merge into the platoon. Cooperative Adaptive Cruise Control (CACC) and other control algorithms manage the joining process to ensure safety and efficiency.
- **Advantages**: Flexible and adaptable to changing traffic conditions, maximize the benefits of platooning.
- **Challenges**: Requires sophisticated communication and decision-making algorithms for safe and efficient formation. In addition, manual ad-hoc formation has been exposed to high risk due to driver errors.

4.2.1.6 Hybrid Platooning

Hybrid platooning combines elements of pre-defined and ad-hoc platooning. Vehicles may be scheduled to form platoons at certain points but can also dynamically form or adjust platoons in route based on real-time conditions.

- **Formation**: Vehicles follow a pre-defined schedule but can adjust or form new platoons dynamically.
- **Advantages**: Balances predictability and flexibility and adapts to real-time traffic while maintaining some level of schedule.
- **Challenges**: Requires sophisticated algorithms for decision-making and coordination, involves complex communication and control systems.

4.2.1.7 Cloud-Based Coordination Platooning Formation

A cloud-based system oversees platoon formation using real-time data from multiple vehicles (Carletti et al., 2023).

- **Formation**: Vehicles upload their routes and status to a central server. The server analyzes the data to identify optimal platoon formation opportunities. Instructions are sent to vehicles to coordinate joining and formation.
- **Advantages**: Suitable for large-scale fleet management and inter-city transport.
- **Challenges**: It needs higher digital infrastructure and advanced conflict management algorithms for leader selection and needs to address cyber security issues.

4.2.1.8 Infrastructure-Assisted Platooning

Roadside infrastructure (like smart traffic signals or dedicated platooning lanes) aids platoon formation. Communication devices like V2I communication provide support for platooning formation (Shet & Yao, 2021; L. Wang et al., 2023).

- **Formation**: RSUs communicate with vehicles to coordinate platoon formation. Traffic signals and signage provide instructions to drivers or automated systems. Dedicated lanes or zones facilitate easier merging and synchronization.
- **Advantages**: Useful in smart city environments and highways designed for automated driving.
- **Challenges**: It needs a lot of RSU at certain intervals along the roads where platooning will be implemented. This also requires developing secure protocols and a strong V2I communication signal.

4.2.1.9 Market-Based Approaches

Platoon formation is treated like a market where vehicles bid to join or form platoons (Sebe et al., 2021). The follower vehicles save fuel, while the leader does not, so the lead vehicle should be compensated through payment from the follower vehicles. This ensures that both the leader and the follower benefit.

- **Formation**: Vehicle platooning is formed through negotiations using a market mechanism, with algorithms matching vehicles based on factors like destination, timing, the most suitable leader from available bidders, and potential fuel savings. Successful bids lead to platoon formation.
- **Advantages**: A vehicle that wants to participate in platooning selects a leader from the available bidders and begins communication with that chosen leader. This creates mutual benefits. The follower saves fuel, while the leader is compensated with an amount exceeding the additional fuel costs incurred by leading instead of following.

- **Disadvantages**: It demands advanced digital infrastructures including internet, V2V, and V2I.

4.2.2 Key Features of Platoon Formations

Platooning formation involves various concepts that coordinate to achieve safe and efficient vehicle operation. These key features include proximity driving and cooperative control (Gaagai et al., 2023), inter-vehicle communication (Santini et al., 2019), and safety improvements (Smith et al., 2019; Thormann et al., 2022b).

4.2.2.1 Proximity Driving

Proximity driving is a hallmark of platooning, where vehicles maintain a very short distance from one another, significantly closer than what would be considered safe for human drivers. This close formation is enabled by advanced communication and control systems that ensure precise synchronization between vehicles. Proximity driving needs distance management, safety features, and technology integration.

- **Distance Management**: In platooning the safe gap is evaluated using either minimum safe distance or second-based inter-vehicle gap. The time gap (second-based gap) can be a variable time (Hasanzadezonuzy et al., 2018) or constant time gap (Chehardoli & Homaeinezhad, 2017).

  In human-driven vehicles, a safe following distance is typically recommended seconds-based following guidelines as it is stated in the Diver's handbooks of 50 states of the USA including Washington DC (King et al., 2022). The most common recommendation is three seconds, advised by 20 states (e.g., California) (King et al., 2022). Fourteen states suggest two seconds (e.g., New York), eight states recommend four seconds (e.g., Wisconsin), and another eight states propose a range from two to six seconds (e.g., Indiana, Arizona) (King et al., 2022).

  In a platoon, the minimum safe distance for vehicle platooning varies with speed (Peng et al., 2019) and several other factors, including vehicle type, road conditions, emergency braking capability (Schafer & Chen, 2020), and communication delays (Hu et al., 2021). A typical example is heavy-duty vehicles, maintaining a relative distance of 1.2 meters at maximum legal highway speeds is feasible with an appropriate automatic control system (A. Alam et al., 2014).

- **Safety Mechanisms**: Proximity is made safe using precise and reliable communication systems that allow vehicles to react instantly to the movements of the lead vehicle and each other (Van Nunen et al., 2016).

- **Technology Integration**: Sensors, cameras, and radar systems continuously monitor the distance between vehicles and make real-time adjustments to maintain optimal inter-vehicle distance (Choudhury et al., 2016).

4.2.2.2 Cooperative Control

Cooperative control involves the coordinated effort of all vehicles in the platoon to synchronize their movements, including acceleration, braking, and lane changes. The lead vehicle sets the pace and direction, while the following vehicles adjust their behavior to stay in formation. The following key concepts are considered in cooperative platooning control.

- **Lead Vehicle Role**: The lead vehicle, often equipped with the most advanced navigation and control systems, dictates the speed and path of the platoon (Michaud et al., 2006).
- **Synchronization**: The following vehicles use real-time data from the lead vehicle to adjust their speed and position, ensuring smooth and coordinated movements (Varada, 2017).
- **Adaptive Cruise Control (ACC)**: ACC maintains a set speed and automatically adjusts to keep a safe distance from the vehicle ahead. This system is essential for maintaining proper spacing within the platoon (Varada, 2017).
- **Cooperative Adaptive Cruise Control (CACC)**: CACC builds on ACC by incorporating V2V communication to allow vehicles to respond to the lead vehicle and each other almost instantaneously. This technology enhances synchronization by allowing vehicles to coordinate their actions more closely and efficiently (Singh et al., 2018).
- **Lane Changes**: Cooperative control allows for synchronized lane changes, where all vehicles move unison, reducing the risk of collisions (Maiti et al., 2020).
- **Lane Diverging and Merging**: Vehicles in a platoon can safely diverge or merge lanes while maintaining formation. This involves coordinated communication and control, ensuring that each vehicle adjusts its speed and position seamlessly to allow for smooth transitions (Maiti et al., 2020).
- **Emergency Braking Systems**: Automated emergency braking can detect obstacles and apply the brakes faster than a human driver, preventing collisions (Sidorenko et al., 2022).

4.2.2.3 Inter-Vehicle Communication

Inter-vehicle communication, primarily through V2V communication, is critical for sharing data about speed, position, acceleration, and braking status. This communication ensures that all vehicles in the platoon can react almost instantaneously to the movements of the lead vehicle and each other. Platooning relays on V2V or V2I communications to provide data exchange between platooning participants with low latency.

- **V2V Technology**: Vehicles are equipped with communication modules that use DSRC or C-V2X technologies (Jia & Ngoduy, 2016).

- **V2I Communication**: In addition to V2V, platooning vehicles communicate with roadside infrastructure such as traffic signals, road signs, and traffic management systems. This V2I communication provides additional data about road conditions, traffic congestion, and other environmental factors, enhancing the platoon's ability to make informed decisions (Nardini et al., 2018).
- **Data Exchange**: Continuous exchange of data enables real-time adjustments and maintains the integrity of the platoon (Wu et al., 2018).
- **Latency Reduction**: Low latency in communication ensures that there is minimal delay in the transmission of critical information, enhancing safety and coordination (Varada, 2017).

4.2.2.4 Safety Improvements

The coordinated movement of platooning vehicles reduces the likelihood of accidents caused by human error. Automated systems can react faster than human drivers, especially in emergencies. Safety in platooning depends on reaction time, error handling, and emergency handling.

- **Reaction Time**: Automated systems can process information and respond to changes in milliseconds, significantly faster than human reaction times (Pauca et al., 2020).
- **Error Reduction**: By removing human error from the equation, platooning minimizes risks such as distracted driving, fatigue, and misjudgment (Axelsson, 2017).
- **Emergency Handling**: In case of sudden obstacles or hazards, the entire platoon can react simultaneously, preventing chain collisions and enhancing overall road safety (Sidorenko et al., 2022).

4.2.3 Platoon Leader Selection Criteria

Selecting a leader for platooning involves a multifaceted approach (see Figure 4-2) that considers a combination of vehicle capabilities, route optimization, fuel efficiency, driver experience, and sometimes infrastructure inputs. The appropriate method depends on the specific use case, such as logistics, urban environments, or mixed-traffic scenarios. The goal is to ensure the leader can effectively manage the platoon, providing safety, efficiency, and overall performance benefits.

- **Vehicle Capabilities:** Advanced autonomous driving technology, robust communication systems, and enhanced sensor arrays are essential for a leader vehicle. These features enable the leader to navigate complex environments, make real-time decisions, and communicate effectively with following vehicles (Ouyang et al., 2021; Su & Ahn, 2016).
- **Route Optimization:** Effective route optimization ensures the platoon follows the most efficient path, minimizing travel time and avoiding congested or hazardous areas. Advanced navigation systems that adjust routes based on real-time traffic data, road

conditions, and infrastructure inputs are crucial (Farzanullah & Le-Ngoc, 2023). Selecting a leader based on their capability to optimize the route is one of the core leader selection criteria.

- **Fuel Efficiency:** The lead vehicle should be optimized for fuel consumption as it sets the pace and aerodynamic conditions for the following vehicles. An efficient leader reduces overall fuel consumption by maintaining steady speeds and minimizing unnecessary acceleration and deceleration (Ledbetter et al., 2019).
- **Driver Experience:** Experienced drivers in the leader vehicle provide additional oversight, manage unexpected situations, and ensure smooth operation. Their expertise enhances the safety and reliability of the platoon, particularly in mixed-traffic scenarios (Singh et al., 2018).
- **Infrastructure Inputs:** The lead vehicle must be capable of receiving and processing infrastructure inputs like traffic signals, road signs, and V2I communication to optimize its driving strategy. These inputs allow the leader to anticipate traffic changes and adjust accordingly, enhancing efficiency and safety (Hexmoor & Ahmed, 2019).
- **Specific Use Cases:** The method of selecting a platoon leader varies by use case. In logistics and long-haul trucking, the focus is on fuel efficiency and route optimization. In urban environments, maneuverability and real-time adaptability are prioritized. In mixed-traffic scenarios, maintaining safety and coordinating with non-platooning traffic is essential (Sun & Yin, 2021; Ying et al., 2022).

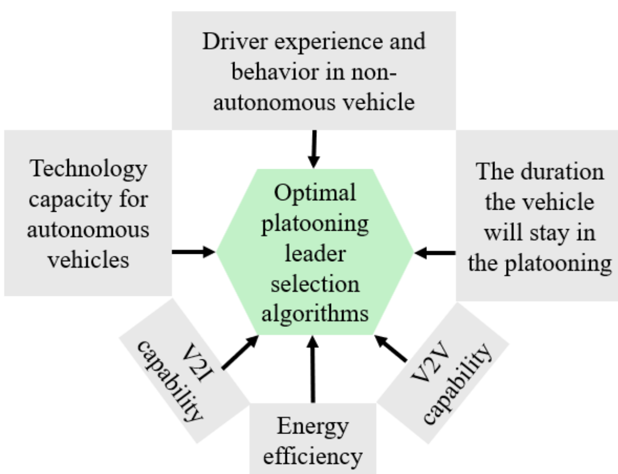


Figure 4-2: Desirable qualities in a platoon leader.

4.2.4 Joining and Leaving the Platoon

Joining and leaving a platoon are critical processes in vehicle platooning systems. These maneuvers rely on advanced communication protocols and control systems to ensure smooth integration and exit, maintaining safety and efficiency.

4.2.4.1 Joining the Platoon

A vehicle planning to join a platoon must detect the platoon, communicate its intention to join, synchronize its speed and position, and finally integrate into the platoon. Detection is achieved through V2V communication, which enables the vehicle to receive signals and recognize the formation, speed, and spacing of platoon vehicles. After notifying the platoon of its intention, the vehicle adjusts its speed and position to match the platoon, ensuring smooth integration without causing disruptions. Automated driving systems facilitate this process by maintaining precise control of speed and spacing.

Research shows that dynamic reconfiguration of communication protocols, such as time-division multiple access (TDMA), is essential for maintaining synchronization and ensuring seamless joining and merging of vehicles into a platoon (Aslam et al., 2020). Secure and efficient key management is also crucial for communication and control during the joining process, as highlighted by the ternary join-exit-tree (TJET) scheme which addresses these aspects for vehicle platooning (C. Xu et al., 2017). Moreover, protocol analysis for joining maneuvers indicates the importance of robust communication strategies to handle interferences from non-automated vehicles and ensure safe integration (Segata et al., 2014). Additionally, performance analysis of joining protocols indicates the importance of optimizing communication strategies to handle the dynamic nature of platoon formation and ensure reliable integration (Khaksari & Fischione, 2012).

4.2.4.2 Leaving the Platoon

A vehicle planning to leave a platoon must communicate its intention to exit, desynchronize its speed and position from the platoon, and then safely exit. V2V communication allows the vehicle to signal its intention, enabling other platoon members to adjust their positions in preparation for the departure. The vehicle then creates a safe gap between itself and the other vehicles by adjusting its speed and position. Finally, the vehicle exits the platoon, ensuring minimal disruption to the remaining vehicles, and resumes independent travel. This process is also facilitated by automated driving systems that ensure precise control during desynchronization and exit.

Implementing robust protocols for leaving the platoon, such as those proposed (Farag et al., 2019), ensures stable platoon management and safety during these maneuvers. Moreover, advanced control strategies like Model Predictive Control (MPC) further enhance the safety and efficiency of exiting maneuvers by optimizing the vehicles' actions in coordination with the platoon leader (Graffione et al., 2020).

4.3 Platooning Testing and Verification

Testing in platooning involves evaluating the behavior and performance of the platoon system under various conditions to ensure it operates safely and as intended while verification in platooning involves checking that the system complies with regulations, standards, and specifications established during the design phase.

4.3.1 Test and Verification Methodologies

To ensure the safety, reliability, and efficiency of platooning systems, a comprehensive approach to testing and verification is necessary. This approach can be classified into x-in-the-loop tests and real-world tests, each with its subcategories.

4.3.1.1 X-in-the-Loop Testing

These tests involve various levels of simulation to validate different components and their interactions in a controlled environment. They help in identifying and resolving issues early in the development cycle. Figure 4-3 demonstrates the testing processes of X-in-the-loop which include SIL, HIL, and VIL.

4.3.1.2 Software-in-the-Loop (SIL)

SIL testing is crucial for validating the algorithms and control strategies of the platooning system in a simulated environment. This involves running the software components on a computer simulation to ensure they function correctly. Methods include testing control algorithms for vehicle spacing, speed synchronization, and coordinated braking. Scenario testing simulates various traffic conditions, such as heavy traffic, lane closures, sudden stops, and different weather conditions like rain, snow, and fog. Fault injection is used to introduce software bugs and simulate sensor failures, allowing developers to test the system's robustness and error recovery mechanisms. Performance metrics such as latency and accuracy are measured to ensure the system responds promptly and maintains precise operations (Cioroaica et al., 2019).

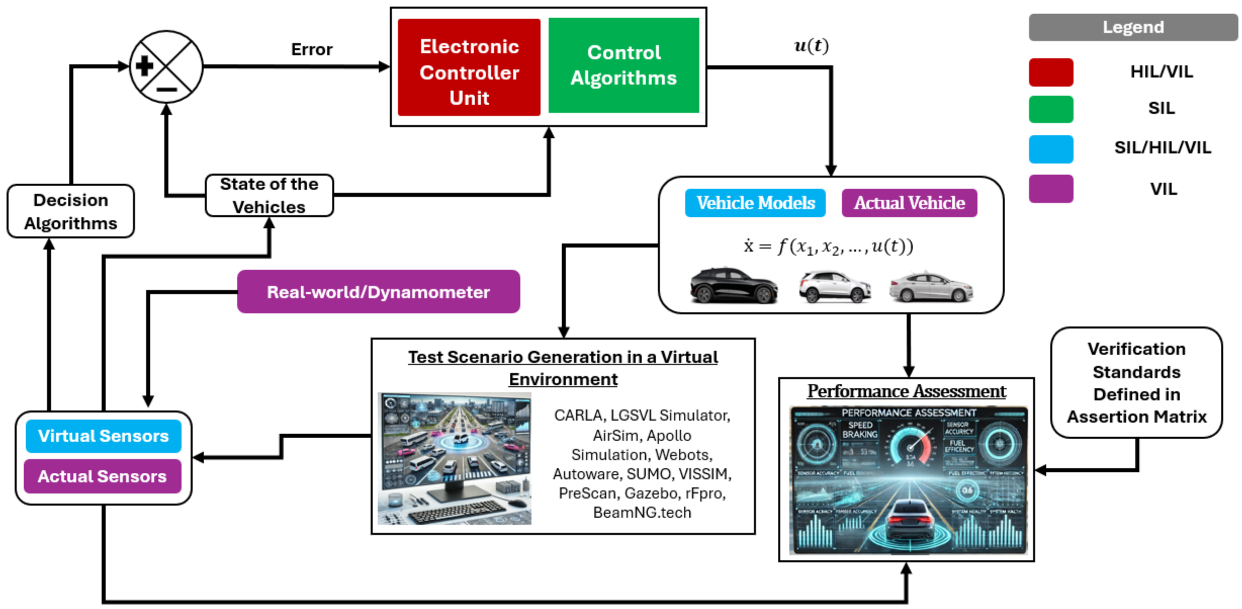


Figure 4-3: SIL/HIL/VIL systems architecture.

4.3.1.3 Hardware-in-the-Loop (HIL)

HIL testing involves integrating real hardware components with a simulation environment to validate their interaction with the software. This includes connecting actual sensors, such as lidar and radar, to test their accuracy and data fusion capabilities. Actuator testing ensures that braking and steering systems respond correctly to control commands. Communication testing is critical for verifying reliable V2V and V2I data exchange. Real-time performance is evaluated by measuring processing times and system stability under continuous operation and varying conditions. This ensures that the hardware components and the software control system work seamlessly together (National Instruments, 2024).

4.3.1.4 Vehicle-in-the-Loop (VIL)

VIL testing uses real vehicles connected to a simulation environment, providing a more realistic testing scenario. Full system integration tests the complete platoon control system, including sensors, actuators, and communication modules, in dynamic driving scenarios. Driver interaction is assessed by evaluating how drivers interact with the system, including manual overrides and take-over requests. Safety validation is conducted by simulating emergencies, such as sudden obstacles or vehicle malfunctions, to ensure safety protocols are effective. This testing phase bridges the gap between simulation and real-world deployment, ensuring the system behaves as expected in realistic conditions[10].

[10] What is vehicle-in-the-loop testing? (https://www.aptiv.com/en/insights/article/what-is-vehicle-in-the-loop-testing / Accessed: 10/07/2024)

4.3.1.5 Real-World Testing

Real-world tests are conducted to evaluate the performance, reliability, and safety of systems in actual operating conditions. These tests move beyond controlled environments to assess how the system behaves under real-life scenarios, ensuring it can handle the variability and unpredictability of everyday use. This includes testing various environmental conditions, traffic situations, and over extended periods to ensure the system meets regulatory standards and performs consistently in the real world. Real-world testing will be categorized into two types: road traffic testing and closed-area testing.

4.3.1.6 Road-Traffic Testing

Road-traffic testing evaluates the platooning system on public roads in real traffic conditions, ensuring it performs reliably outside controlled environments. Urban and highway testing assesses system performance in diverse traffic environments, from congested city streets to high-speed highways. Environmental testing examines the system's reliability and safety under various evaluated system durability and long-term performance, ensuring it can handle the variability and unpredictability of real-world driving. Regulatory compliance testing ensures the system meets all relevant legal and safety standards for public road usage, validating that the system adheres to safety protocols and guidelines for real-world deployment.

4.3.1.7 Closed Area Tests

Closed-area tests are conducted in controlled, secure environments like test tracks or proving grounds. These tests involve predefined scenarios to assess specific behaviors, such as high-speed travel and close formation driving. Edge cases and unusual conditions are tested to ensure the system can handle rare but critical situations. Stress testing involves pushing the system to its operational limits under extreme conditions, such as maximum load, high speed, and adverse weather, to identify potential failure points. Performance benchmarking measures metrics like fuel efficiency, energy consumption, and response times, providing a comprehensive evaluation of the system's capabilities in a controlled setting. One good example of a closed area testing facility is the SunTrax testing facility.

SunTrax, a cutting-edge facility created by Florida's Turnpike Enterprise, a division of the Florida Department of Transportation, is committed to researching, developing, and testing new transportation technologies within secure and controlled settings. The facility includes an arrival and conference (AC) building, workshops, geometry track, loop track, oval track, urban, pick-up/drop-off, suburban, noise, vibration, and harshness, technology pad, wet test track, observation tower, and support. For more information about the facility, readers can refer to the SunTrax website, ‘https://suntraxfl.com/sectors/geometry-track/’, which is provided in (SunTrax Facility, 2024).

4.4 Testing and Verification Framework

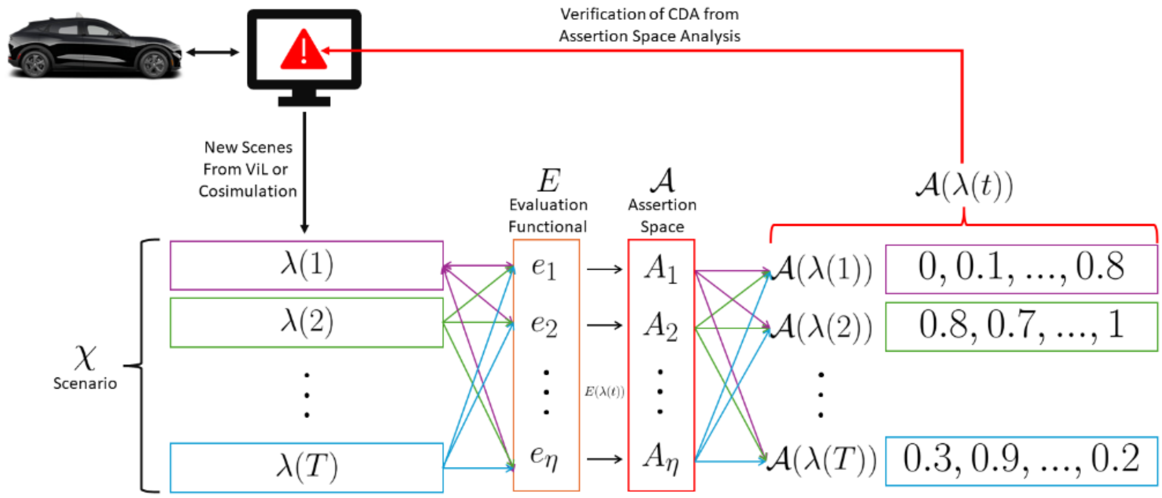


Figure 4-4: Architecture of implemented VIL-embedded testing and verification framework.

The rapid advancement in CDA technologies necessitates robust and systematic testing and verification frameworks to ensure safety, reliability, and performance. Traditional real-world vehicle testing methods fall short in capturing the complexities of a vast sea of possible edge case scenarios, thereby limiting the effectiveness of vehicle systems designed to operate in dynamic and unpredictable environments. Additionally, as research rapidly expands, a systematic and easily portable real-time framework grows in benefit, allowing researchers to find a comparable standard and language of communication for safety and efficacy of CDA systems.

To address this, a comprehensive testing and verification framework that integrates theoretical models, simulation environments, and performance metrics tailored for CDA systems is proposed and implemented (Figure 4-4).

4.4.1 Overview

Our testing and verification framework is an adaptation of the autonomous vehicle testing framework presented in (Alnaser et al., 2019, 2021). Notably, the framework was modified to support a more computationally scalable testing and verification pipeline. The framework revolves around three aspects: the scenario, evaluation functional, and assertion space.

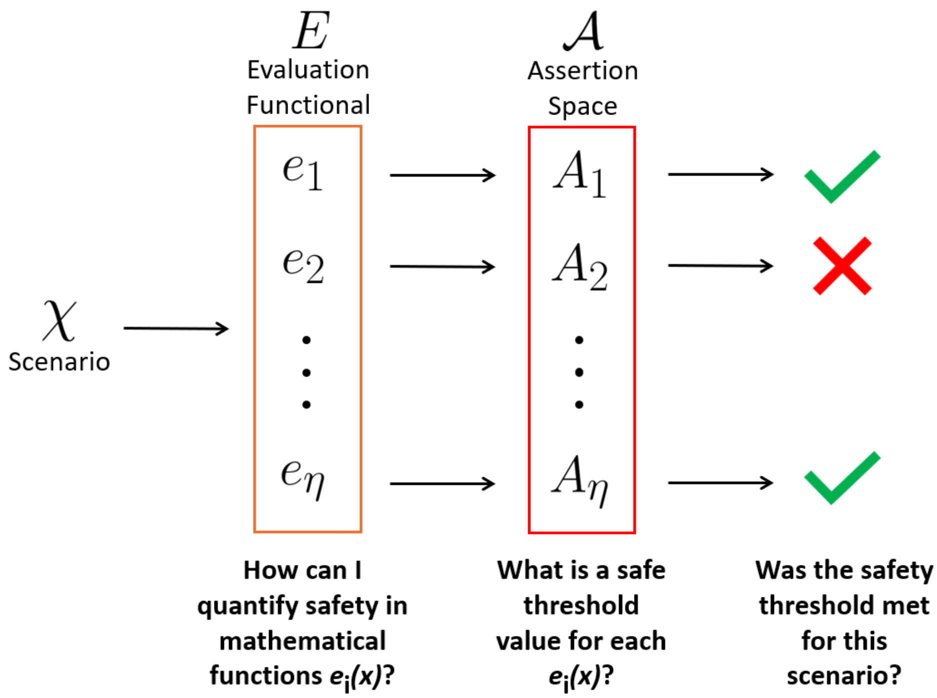


Figure 4-5: Logic flow between the scenario, evaluation functional, and assertion space.

Scenario: The scenario is a high-dimensional mathematical object that stores the real-world data of a test. Within the scenarios, there are discrete snapshots in time called scenes of the scenario.

Evaluation functional: A set of functions that describe safety and performance metrics. These can be as simple as following distance and as complicated as entire machine learning algorithms dedicated to analyzing the safety of a system.

Assertion space: For each evaluation function, there is an assertion function that determines if the test was considered a pass or fail as shown in Figure 4-5. The assertion space is the set of all assertion functions and is specifically designed for the operational design domain (ODD) of the test. Here, ODD refers to the specific conditions and environments under which an advanced vehicle feature is designed to operate safely. This includes factors like road types, weather conditions, traffic levels, speed ranges, geographic areas, and other relevant operational parameters.

4.4.1.1 Separating Testing and Verification

Separating the evaluation functional and assertion space into two distinct mathematical entities allows for more precise mathematical and computational handling of testing and verification aspects.

Testing: This involves specific, typically unit-based, analysis. The evaluation function provides a framework for detailed, complex, physics-based, and data-driven analysis. When evaluating systems for improvement, measurable numerical values are crucial, beyond just pass-fail outcomes. This is the primary role of the evaluation function.

Verification: This involves broader, often normalized analysis. The assertion space provides a user-friendly framework that allows for normalized and statistical analysis. Additionally, it facilitates comparisons across different contexts or experimental designs. The assertion space not only supports normalized analysis but also maintains a binary pass-fail system while providing at-a-glance metrics that indicate the performance quality of the tested system.

4.4.1.2 Real-time Extensions

The use of scenes within a scenario facilitates real-time analysis. Figure 4-4 demonstrates how live VIL and co-simulation testing can introduce new scenes into the testing framework in real-time. This transition from post-analysis to real-time analysis ensures that the framework remains robust and consistently applicable across various forms of testing, provided that time-series data can be collected.

Feedback from the assertion space, or even evaluation functional, can be used to facilitate robust SIL and co-simulation environments. This framework is designed to be easily integrated with other systems, such as scenario generation, ensuring seamless interaction and comprehensive analysis across different testing platforms.

4.4.2 Definitions of a Testing Scenario

The following formulas are modifications of the autonomous vehicle testing framework presented in (Alnaser et al., 2019, 2021) to improve computational implementations and previously mentioned improvements to the testing and verification pipeline.

4.4.2.1 Objects in a Scene

An object in a scene can represent anything from agents like cars or pedestrians to static objects like traffic signage.

$$o_i(t) = (r_i(t), v_i(t), a_i(t), \sigma_i), \tag{4.1}$$

where r, v, and a represent the object's position, velocity and acceleration, or collectively the vehicle’s pose. σ represents the type of object, such as a vehicle or stop sign, notably not mutable over time.

The collection of all objects in a scene can be defined as

$$O(t) = \{o_1(t), o_2(t), \dots, o_n(t)\}, \tag{4.2}$$

where n is the number of objects.

4.4.2.2 Road Networks

A road network object, R, represents the topology and traffic patterns of a given scene. Practically, this can be represented using various open-source file standards, such as OpenStreetMap (OSM) or OpenDRIVE.

OSM relies on data contributed by volunteers, known as “mappers,” who use manual survey, GPS devices, aerial imagery, and other free sources to gather geographic information. The collected data is then entered into a database, which is publicly available. The key elements of OSM are:

<node>: Represents a single point in space, defined by latitude and longitude (e.g., street corner or a park bench).

<way>: Represents a sequence of nodes, which form polyline or polygon (e.g., a road or a building outline).

<nd>: References a node ID within a way to define a path.

<tag>: Provides additional information about nodes, ways, or relations (e.g., the type of road, speed limits).

<relation>: Represents a relationship between nodes, ways, or other relations, defining complex structures. (e.g., a bridge or a bus route).

The .osm file structure allows for detailed storage of road topology and traffic patterns. By organizing nodes and ways, the structure can accurately represent the physical layout of roads. Here is an example of an .osm file:

```
<osm version=”0.6” generator=”OSM”>
  <node id=”1” lat=”27.9506” lon=”-82.4572” />
  <node id=”2” lat=”27.9507” lon=”-82.4573” />
  <way id=”3”>
    <nd ref=”1” />
    <nd ref=”2” />
    <tag k=”highway” v=”residential” />
  </way>
</osm>
```

While .osm files use the XML format, they can be translated into XAML for better visualization of the OSM data as it allows for a more interactive and customizable manners. XAML format uses

<Ellipse>: Represents a node.

<Polyline>: Represent a way, of connecting multiple nodes.

Below is an example of how an OSM node might be represented in XAML:

```
<Canvas xmlns= http://schemas.microsoft.com/winfx/2006/xaml/presentation>
```

```
    <Ellipse Canvas.Left="100" Canvas.Top="150" Width="10" Height="10" Fill="Blue" />
    <Polyline Points="100,150 200,250" Stroke="Black" StrokeThickness="2" />
</Canvas>
```

4.4.2.3 Scenes

A scene λ is a snapshot in time of the space in which the test is being conducted, including the road network R and collection of objects O that fully define the scene at that time as

$$\lambda(t) = \big(R(t), O(t)\big). \tag{4.3}$$

4.4.2.4 Scenarios

A scenario χ can be thought of a neighborhood of discrete scenes. Typically, this will represent a singular complete test under a certain ODD. A scenario is formally defined as

$$\chi = \{\lambda(t_0), \dots, \lambda(t_f)\}, \tag{4.4}$$

with initial time t_0 and final time t_f.

4.4.3 Evaluation of a Testing Scenario

4.4.3.1 Evaluation Functions

An evaluation function e is a mathematical function that calculates some performance or safety metric for a specific scene as

$$e = f_e\big(\lambda(t), P(t)\big), \tag{4.5}$$

where f_e is a known linear or nonlinear function, $P(t)$ are optional extra parameters provided for computational flexibility. These parameters could for example be a reference maximum speed limit or threshold for safe performance.

As an example, we can define an evaluation function to observe the headway time. Let us define this function $e_{headway}$ as

$$e_{headway}\big(\lambda(t)\big) = \big(x_i(t) - x_{i+1}(t)\big)/v_i(t). \tag{4.6}$$

The scene variables $x_i(t)$ and $v_i(t)$ represent the longitudinal position and velocity of i-th car and are obtained from the scene at that time $\lambda(t)$. The calculation $x_i(t) - x_{i+1}(t)$ results in the distance between the two vehicles. The final output is the number of seconds it would take the i-th car to collide with the car in front of it, should the forward card instantly come to a stop.

More complicated functions can be swapped in to calculate metrics like safety envelopes or full vehicle dynamics models.

4.4.3.2 Evaluation Functional

The evaluation functional E is defined as a set of evaluation functions as

$$E = \{e_1, e_2, \dots, e_\eta\}, \tag{4.7}$$

where there are η evaluation functions e in E. Different testing scenarios are likely to require different sets of evaluation metrics; the evaluation functional provides a compact way to share and express the entire suite of evaluation metrics.

4.4.3.3 Assertion Functions

Each evaluation function e_i will have an associated assertion function A_i to compute if the safe threshold was met. The assertion function is defined similarly as follows,

$$A = f_A\big(\lambda(t), P(t)\big), \tag{4.8}$$

where f_A is a known linear or nonlinear function.

As a continuation of our previous example, we can define the assertion space such that there is a threshold headway time h and the maximum deviation that is allowed is Δ_{max}. The assertion function on $e_{headway}$ would be defined as

$$A_{headway}(\lambda(t), h, \Delta_{\max}) = \frac{|e_{headway} - h|}{\Delta_{max}}. \tag{4.9}$$

A passing output would range from 0 to 1, with 0 being perfection and 1 being at the edge of the maximum allowed deviation. Any value greater than 1 does not constitute a passing scene. The larger the value of A, the less safe the test was in that metric, here being headway time. A common method to propose definitions of A_i over e_i are to use naturalistic driver studies: collected human-driven data evaluated under E (Maiti et al., 2020).

4.4.4 Assertion Space

An assertion space $\mathcal{A}$ is the collection of all assertion functions. It may at times be convenient to refer to the entire set of assertion functions at once using $\mathcal{A}$.

$$\mathcal{A} = \{A_1, A_2, \dots, A_\eta\}. \tag{4.10}$$

4.4.5 Test and Validation Guidelines

While the proposed testing and verification framework provides a strong and well-defined basis of language for computation, further considerations can be made during implementation.

4.4.5.1 Validating Performance Metrics

Typically, many performance metrics, whether for safety or traffic efficiency, are target-based. Meaning that there is a desired score to achieve, and the driver has an instantaneous score. To calculate the error between the desired and actual score, root mean square error (RMSE) is used. Compared to other metrics like average error, RMSE is desirable for its harsh penalty of outliers and its retention of units. RMSE over a dataset will react more strongly to outliers, which is a desirable quality for safety metrics where large deviations in the safety metrics are not tolerated. Additionally, RMSE keeping the units of the dataset makes it simpler to understand and correlate to the original metric.

RMSE over an N sized dataset is defined as follows

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \hat{x}_i)^2}{N}}, \tag{4.11}$$

where x_i is the actual metric achieved by the driver and $\hat{x}_i$ is the desired value of the metric at a time i.

4.4.5.2 RMSE over the Assertion Space

While for pass-fail scenarios, simply identifying failing values over the assertion space may be adequate, performance validation requires more detailed attention. To calculate RMSE over the assertion space, the actual assertion value $A_i\big(\lambda(t), P_i(t)\big)$ is compared against the expected assertion value of 0. This substitution into (4.10) yields

$$RMSE_A = \sqrt{\frac{\sum_{t=1}^{T}\left(A_i\big(\lambda(t), P_i(t)\big) - 0\right)^2}{N}} = \sqrt{\frac{\sum_{t=1}^{T} A_i\big(\lambda(t), P_i(t)\big)^2}{N}}. \tag{4.12}$$

In addition to the simple pass-fail, $RMSE_A$ offers a more comprehensive view of performance. This metric allows for detailed assessments of models across various scenarios, providing insights into which scenarios perform better and by what margin.

When scenarios are systematically organized, $RMSE_A$ can facilitate comparative testing of different CDA models for vehicle control, highlighting their relative strengths and weaknesses.

For example, one could imagine an assertion function over a scenario of low-speed suburban traffic (~35mph) and high-speed highway traffic (~65mph), A_{low} and A_{high} respectively. Using the same CDA algorithm, comparing $RMSE_{A_{low}}$ and $RMSE_{A_{high}}$ can show how the CDA algorithm performance may change in different low and high-speed ODDs.

4.4.5.3 Validating Traffic Adherence

Violations of traffic regulations are a strongly analogous metric to the safety of a driver, as traffic regulations are designed and imposed to increase safety (Maiti et al., 2020).

Instantaneous violations are singular instances of a traffic violation, such as failing to yield or running a red light. Calculating the total number of violations and mean number of violations per mile will provide normalized insights into the stability of a driver's ability to prevent instantaneous violations.

Continuous violation**s** are traffic violations that occur over time, such as speeding or improper lane departures and deviations. While one could simply count the number of violations occurring, it would be more insightful to quantify the severity of the violation as well as the duration that the violation(s) occurred. For example, saying that a driver violated the speed limit once does not provide enough violation. They could have been driving over the speed limit for 20 minutes, 2 seconds, or 2 hours. Having extra information about the duration of the violation is important.

However, we can do better than just time. A driver going 100mph over the speed limit for 5 seconds is significantly more dangerous than a driver going 10mph over the speed limit for the same 5 seconds. Calculating the distance covered during the traffic violation would be a suggested metric to analyze the duration of severity. Here the 100mph driver will cover 10 times the distance the 10mph car will cover.

Using distance and time to measure duration of continuous violation is a novel approach and can be used alongside proposed methods like RMSE. The benefits to additionally computing the distance and time violations allow engineers to put into perspective the stability of the CDA under test. Average error and deviation do not intuitively express how often the CDA under test may be under performing. However, a simple statement such as "speeding occurred throughout 5 miles of the 10 miles test drive," is quickly understood and puts into perspective the rate of occurrences of speeding. This combined with "speeding had a RMSE of 5mph over the limit," provides a holistic analysis of CDA performance.

To demonstrate an example of this, speed limit adherence is demonstrated on sample data. We will impose an artificial maximum speed limit of 25 m/s (~55 mph) and a minimum speed limit of 15 m/s (~35 mph) Figure 4-5: Logic flow between the scenario, evaluation functional, and assertion space. shows highlights violations of the maximum speed limit in red and violations of the lower speed limit in blue.

For this specific driver in Figure 4-5, the maximum speed limit was violated for a total of 1500m (~0.9 miles), and the lower speed limit was violated for a total of 320m (~0.2 miles).

Notably, in Figure 4-5, visually overtime there appear to be more violations of the lower speed limit with respect to time but analyzing distance shows that more distance was covered while violating the upper speed limit. The choice to use time or distance for tracking continuous violation duration often involves using both holistically and is dependent on the context of the assessments being made.

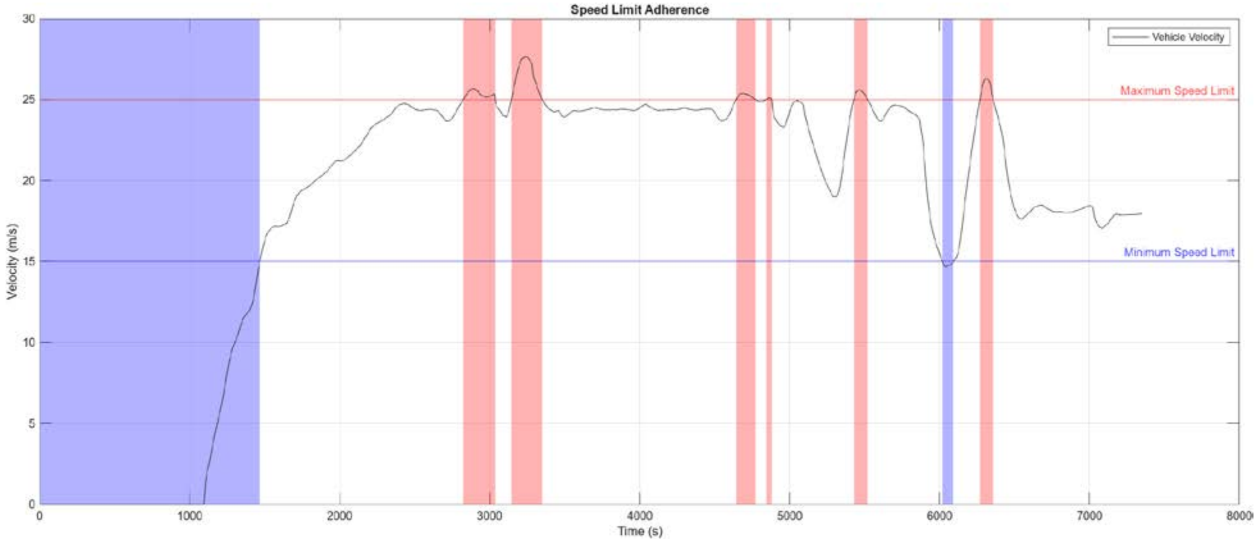


Figure 4-6: Continuous speed limit violations with maximum speed limit violations in red and minimum limit violations in blue.

4.4.6 Freeway Platooning Field Experiments

4.4.6.1 Test Vehicles

All test equipment was provided by the RANCS Research Lab. The equipment included the Cohda Mk6 RSU and Cohda Mk6 OBU with its accessories. The Cohda Mk6 RSU and OBU can support DSRC, C-V2X, cellular networks, Wi-Fi, and Bluetooth connectivity. The three lab research vehicles are a Ford Fusion Hybrid (see Figure 4-7), a Ford Mustang Mach-E (see Figure 4-8), and a Cadillac XT5 (see Figure 4-9). An overview of the CDA technologies in the platoon is summarized in Table 4-1.

Table 4-1: Lab Vehicles' technological CDA configurations

Sensor	Ford Fusion	Mustang Mach-E	Purpose
Camera	Mako-G		Vision and Sensing
Radio	Cohda Mk6 OBU (Figure 4-10)		DSRC and C-VX Communication
Global Navigation Satellite System (GNSS)/IMU	ADMA Genesys Pro	Novatel PwrPak 7	Localization
Radar	APTIV ESR 24V		Sensing
Lidar	Velodyne Ultrapuck	Ouster OS-32	Vision and Sensing
Drive by Wire	Dataspeed Drive-by-Wire Kit		Vehicle control and miscellaneous sensors

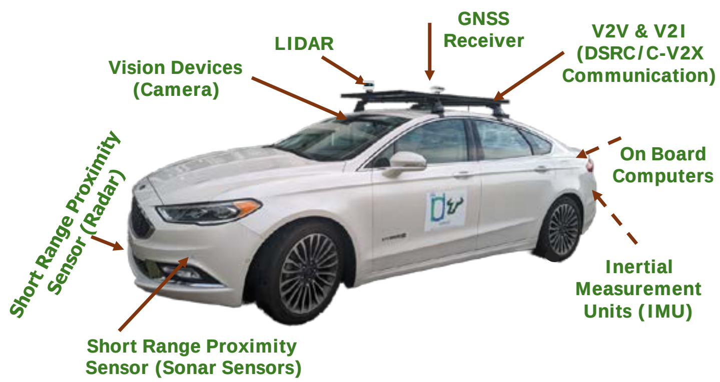


Figure 4-7: Ford Fusion Hybrid

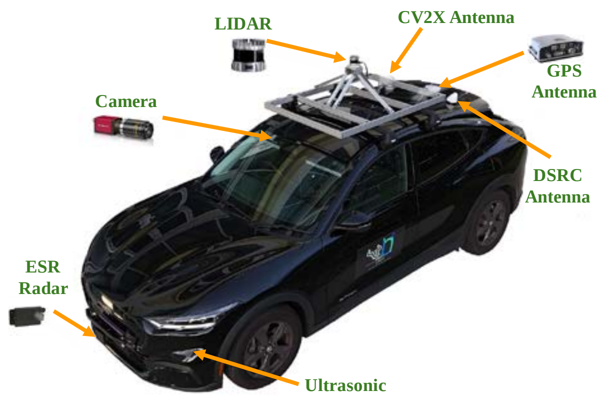


Figure 4-8: Ford Mustang Mach-E

Figure 4-9: Cadillac XT5

Figure 4-10: Cohda Mk6 RSU (left) and Cohda Mk6 OBU (right).

4.4.6.2 Methodology

The following experiments were chosen due to their wide breadth of covering CAV interactions on the freeway.

- OEM ACC
- Platooning
- V2I – RSU Slowdown
- Freeway Merging and Diverging

The field experiments were mainly conducted on the oval track sector, utilizing the east straight of the oval track for the V2I – RSU Slowdown and Freeway Merging and Diverging experiments. The straight sections feature a gantry to mount the RSU and on and off ramps for freeway merging and diverging. Sector usage is outlined in Figure 4-11. A more detailed testing schedule can be found in Appendix B.

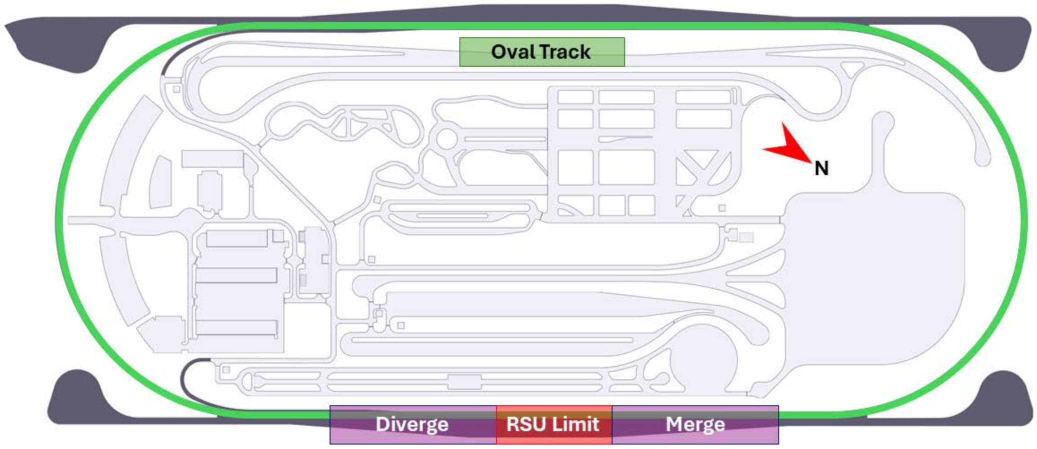


Figure 4-11: Utilized sectors for field experiments at SunTrax.

A set of freeway vehicle platooning tests in mixed traffic involves evaluating the performance, safety, and coordination of automated platoons operating alongside conventional vehicles. These tests assess how well platoons can integrate with regular traffic and respond to dynamic traffic conditions while ensuring minimal disruption and maintaining safety standards for all road users. The field experiment at SunTrax includes a human-driven Cadillac XT5, representing a public vehicle, within the platoon to simulate a mixed traffic scenario.

4.4.6.3 OEM Adaptive Cruise Control (ACC)

Figure 4-12: ACC platoon formation.

In an initial evaluation of commercially available systems, OEM ACC systems were tested in platoon formation shown in Figure 4-12. The three test vehicles activated their ACC modes and were driven around an oval track.

4.4.6.4 Platooning

A CACC system was subsequently tested. The two trailing test vehicles were equipped with C-V2X communication technology, enabling the exchange of velocity information. This exchange allows for faster response times compared to traditional reactive sensing methods within a freeway cruise control context. The benefits of the CACC system over a conventional ACC system become more pronounced as the number of vehicles in the platoon increases.

The lead vehicle in the platoon employed the ACC system to interact with a separate public vehicle introduced to simulate mixed traffic conditions. This public vehicle induced small changes in speeds to stress-test the CACC system. The platoon, including the public vehicle, completed three laps around the oval track, providing a robust environment to evaluate the performance and reliability of the CACC system under dynamic driving conditions. The velocities and acceleration of the platoon throughout the test can be seen in Figure 4-13.

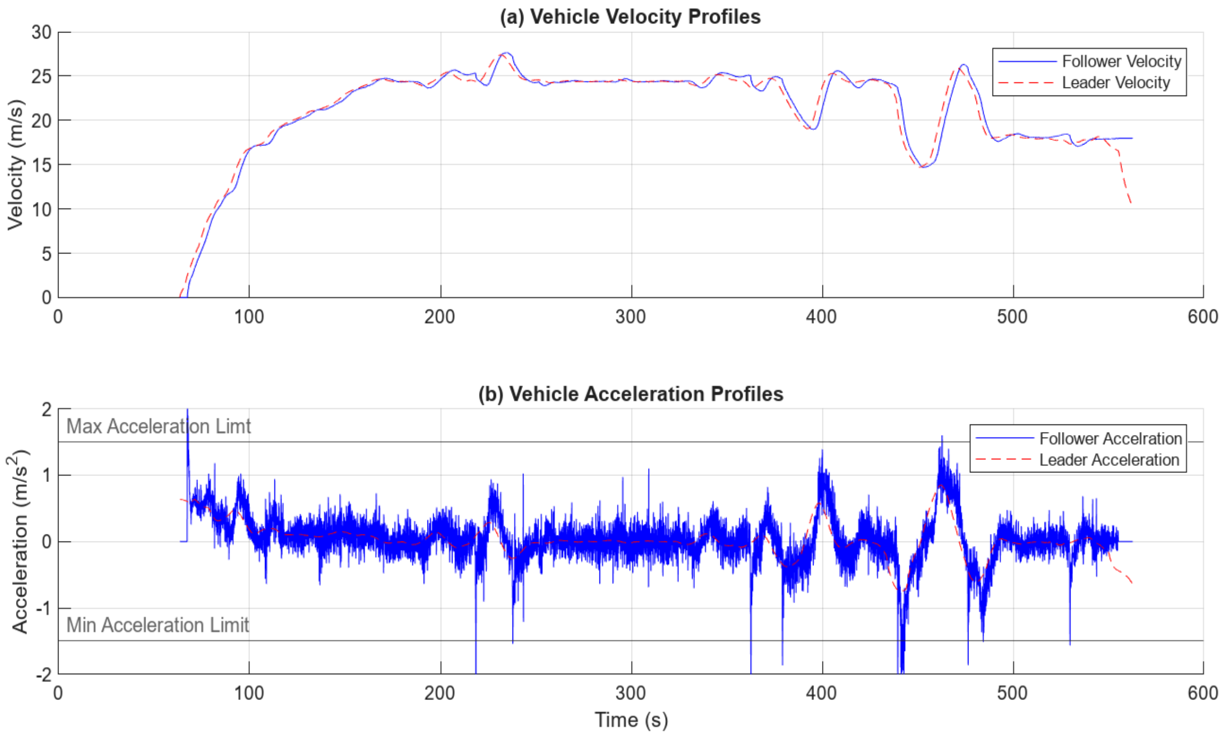


Figure 4-13: Vehicle dynamics profiles of the platooning test.

4.4.6.5 V2I – RSU Slowdown

Figure 4-14: RSU mounted on the side of the gantry structure.

To demonstrate V2I interactions, a slowdown test was conducted using a Cohda Mk6 RSU. During the test, the platoon of vehicles drove past the RSU (see Figure 4-14). Figure 4-15 demonstrates how upon entering the communication range of the RSU, the ego vehicle's CACC algorithm correctly ignored the leader vehicle in front of it and initiated a control slowdown to 35 mph. This demonstrated the efficacy of V2I interaction.

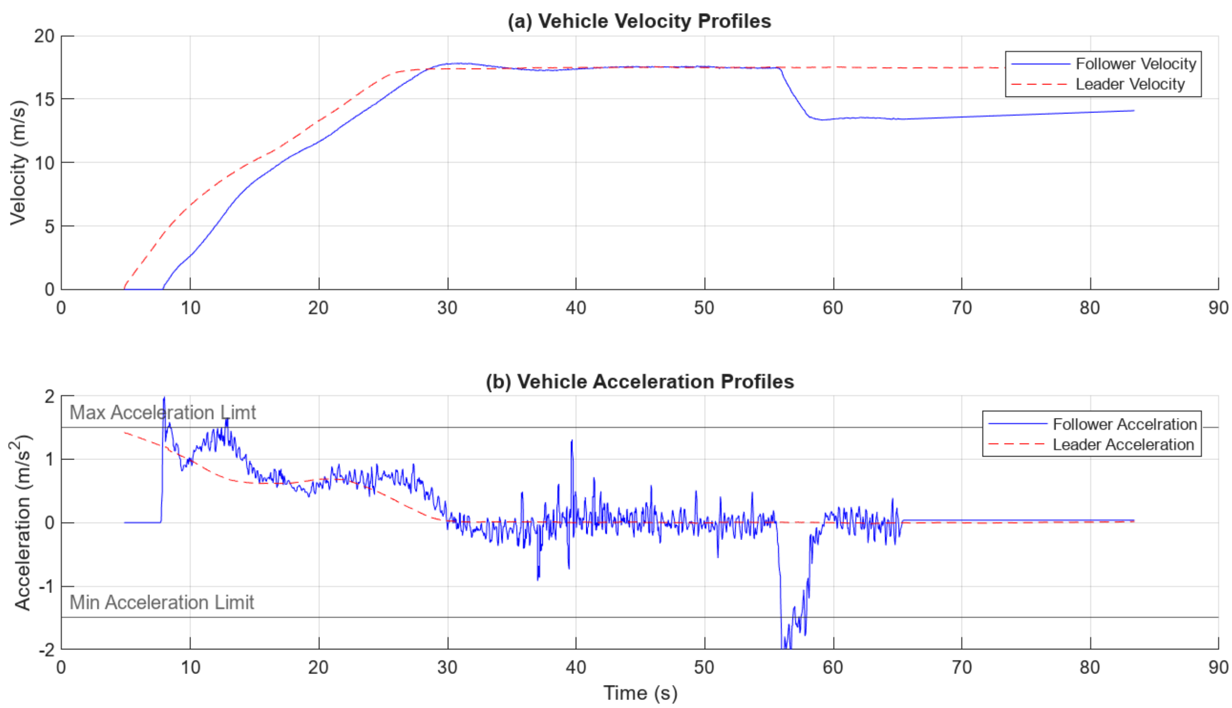


Figure 4-15: Vehicle dynamics profiles of RSU test.

The initial deceleration seen at approximately 55 seconds in Figure 4-15 occurs due to the test vehicle entering the RSU slowdown zone outlined in Figure 4-16. The result can be seen once all vehicles leave the slowdown zone. In Figure 4-17, the following distance between the public and test vehicle is greatly expanded while the platoon maintained their original following distance as they slowed down together.

Figure 4-16: RSU slowdown zone marked onto east straight of test location.

Figure 4-17: Resulting increase in following distance between V2I engaged platoon and public vehicle.

4.4.6.6 Freeway Merging and Diverging

Figure 4-18: Ego vehicle merging back into a platoon at freeway gore point.

A common maneuver on the freeway involves diverging and merging off and onto the freeway, typically one of the most dangerous aspects for drivers. In this demonstration, we showcase the ability of a cooperative system to perform a freeway merge. The ego vehicle employs a CACC algorithm to follow a lead vehicle, with a public vehicle trailing behind it. The ego vehicle successfully merges off the freeway onto an offramp for a short duration and then merges back into its original position at a subsequent gore point (see Figure 4-18). The necessary ego acceleration can be seen in Figure 4-19 as the slight lateral travel into the ramp steals some longitudinal velocity for lateral velocity.

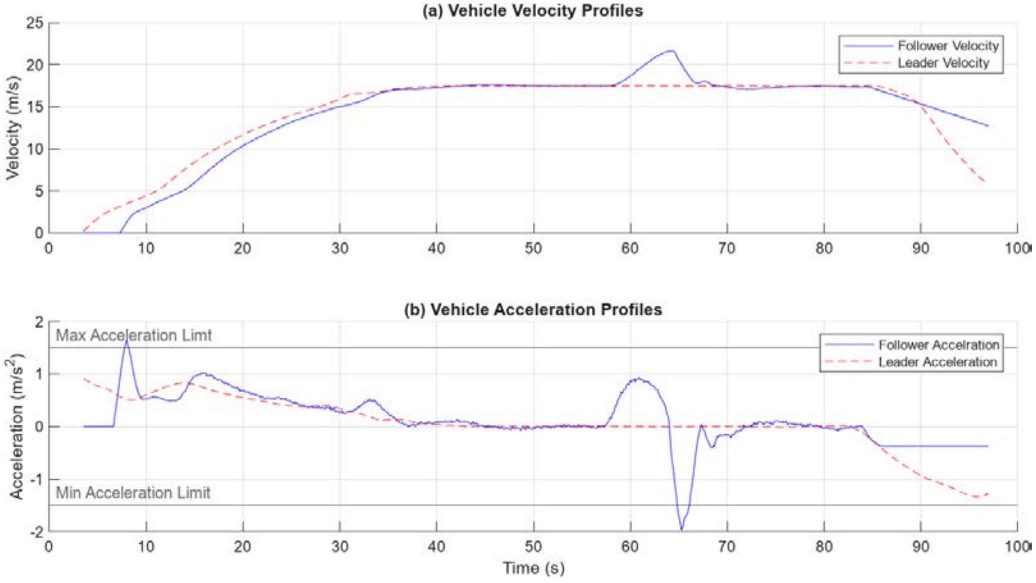


Figure 4-19: Vehicle dynamics profiles of freeway tests.

When a vehicle moves straight ahead, all of its velocity is in the x-axis direction (moving forward), with no velocity in the y-axis direction (sideways). This is shown with the right black arrow in Figure 4-20.

When the vehicle turns without accelerating, the direction of the velocity changes, but the total speed stays the same. In the figure on the right (Figure 4-20), you can see that as the car turns, some of its forward speed (represented by the red arrow) gets "stolen" to give the car sideways speed, shown by the blue arrow. This means the car's forward speed (red arrow) becomes smaller.

Since the car's forward speed has decreased during the turn, it moves slower than the other cars around it, which could cause the cars behind it to slow down. To keep up with traffic, the turning car needs to accelerate in the direction of the green arrow so its new forward speed (vx') becomes as close as possible to its original speed before the turn.

This change in speed during the turn, and the necessary acceleration to maintain speed, can be seen in Figure 4-19 (b), where the vehicle accelerates to keep its speed around 60 seconds.

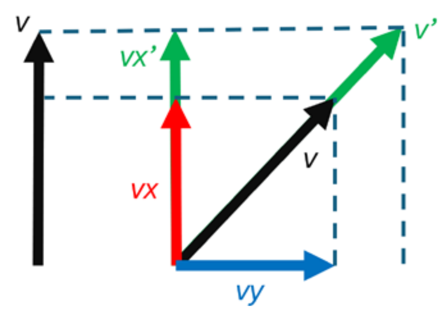


Figure 4-20: Velocity vectors of straight and turning vehicles.

4.5 Results and Discussion

4.5.1 Freeway Platooning

OEM systems are performing to their ODD in their current form, demonstrating sufficient functionality for single-file cruise control. However, their ODD is very limited to the full necessary features an L4 CDA system would expect on a freeway. Even with the advent of L3 autonomous solutions, challenges may arise in multi-file cooperation, as these systems operate as sole autonomous agents without the capability for coordinated interaction with other vehicles.

CDA systems have the potential to significantly enhance various aspects of driving. These systems can reduce the following distances and lane sizes, while also providing obvious advantages such as never getting tired and potentially improving night-time visibility. These benefits contribute to safer and more efficient driving experiences.

4.5.1.1 Results of Framework

The headway time evaluation function and assertion space are defined in the section 4.4.2 have been computed for the platooning field experiment as shown in Figure 4-21. Data collection occurs before the test has begun and continues to run even after the test is completed. This tends to include driving the vehicle to position it in the proper platooning order and driving to safely remove the vehicle from the testing track after test completion. Data collected before 100 seconds and after 500 seconds in Figure 4-21 is not a part of the test conducted and should not be considered. Extra data is only provided as the velocity profiles help more easily identify the nature and context of the test.

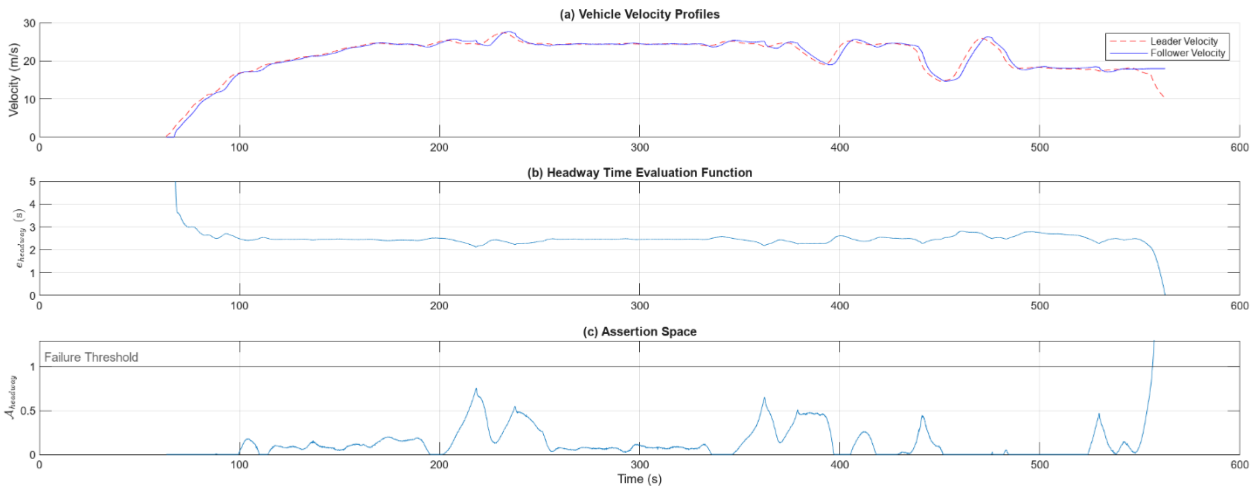


Figure 4-21: Framework assessment over platooning field experiment.

The assertion space was defined with an arbitrary target headway time of 2.5 seconds and a maximum deviation of 0.5 seconds. Figure 4-21(c) clearly demonstrates that the test was passed. The following facts of the test can be easily determined from the assertion space.

- The test is considered a pass throughout the testing session (100s-500s). This is because the assertion space $A_{headway}$ never exceeded the value of 1.
- At its peak, the test came up to 70% of the allowed 2.5 second headway speed. This is because the assertion space $A_{headway}$ reached a value of 0.7, or 70%.
- On average, the test was 19.7% of the 2.5 second headway speed allowed. This is because the root mean square error $RMSE_{A_{headway}}$ was calculated at 0.197, or 19.7%.

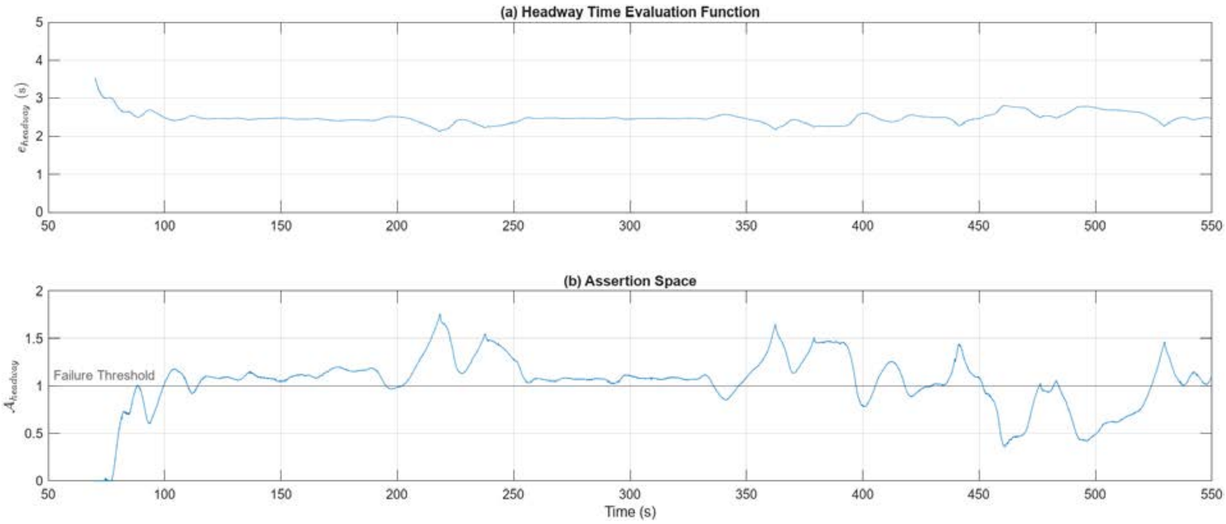


Figure 4-22: Same as Figure 4-21 with a stricter target headway of 3 seconds.

To demonstrate what a less compliant system may look like during assertion analysis, an arbitrarily lower target headway time was chosen. Shown in Figure 4-22, many more failures can be seen as the assertion climbs and hovers of the critical failure threshold of 1. An RMSE of 1.08 was calculated for this new threshold.

4.5.1.2 Application of Framework

The 0-to-1 normalization of the assertion space allows multiple parameters to be compared at the same level for passing and failing the test. A value greater than 1 will fail the test as they pass the threshold for safety requirements. Figure 4-22 (b) demonstrates the advantage of normalization of the testing safety parameters.

4.5.1.3 Limitations

Challenges with hardware integration and data collection were encountered during the project, however all challenges were successfully overcome without affecting the quality of the proposed testing framework. One notable challenge was the last-minute issues in hardware and software integration, which resulted in some of the sensors being unavailable during testing phases. Specifically, this led to position data exhibiting drift errors, as we were unable to utilize certain sensors that would have otherwise provided more accurate data.

However, these issues were overcome utilizing the redundant sensor suite and additional computations. Position information can be inferred from velocity data, albeit with less accuracy compared to GPS and RADAR data.

The framework's capabilities and functionality were still successfully demonstrated despite the challenges. The data collected and processed using the framework provided expected results and analysis. Most importantly, the systematic utility of the framework was demonstrated, with multiple use-case examples of validating vehicle safety and expanding the framework for larger suites of analysis through its robust mathematical foundations.

The initial pilot testing successfully demonstrated that an initial platform for CDA technologies has been laid and has set the stage for more detailed investigations into specific field experiments, such as merging. Moving forward, we are now well-positioned to investigate aspects such as more autonomous implementation and technical logistics in greater detail. This could include studies such as specific maneuvers like freeway merging and diverging or incorporating co-simulation for testing at larger scales of real traffic.

4.5.2 Role of Infrastructure in Freeway Platooning

4.5.2.1 Freeway Speed Management

V2I technology can significantly enhance freeway speed management by supporting work and construction zones, facilitating emergency response, and integrating with ITS for overall traffic management. In work and construction zones, V2I can provide real-time updates to vehicles about lane closures and speed reductions, ensuring safer and more efficient navigation through these areas. During emergency responses, V2I can prioritize emergency vehicles by dynamically adjusting traffic signals and clearing lanes, reducing response times. Additionally, ITS can utilize V2I data to monitor traffic flow and implement adaptive speed limits, optimizing traffic conditions and reducing congestion.

4.5.2.2 Improving Merging Logistics

Using RSUs to provide vehicles merging onto the highway with information about traffic speed and density holds great promise for improving traffic flow and safety. RSUs can communicate with platoons and basic CACC systems, facilitating smoother merges for entire platoons. By centralizing the sharing of all traffic velocities and positions, RSUs can enable merging vehicles to execute better and safer maneuvers. This approach is particularly beneficial in situations where the sensing systems on sole autonomous agents may be hindered by visual barriers, such as those encountered on on-ramps and off-ramps. Furthermore, establishing a common RSU communication standard would provide OEMs with a unified framework to integrate into their systems, enhancing compatibility and performance across different vehicle manufacturers.

4.5.2.3 The Key Aspects in the Evaluation of Existing Infrastructure

Evaluating the existing infrastructure for freeway vehicle platooning involves assessing the current capabilities, limitations, and readiness of roadways and supporting technologies to accommodate and optimize platooning systems. Below is a detailed evaluation of the key aspects:

1. Roadway Design and Layout

- **Lane Width and Road Markings**: Many freeways already feature standard lane widths and clear road markings, which are essential for lane-keeping and vehicle alignment within a platoon (Kasai & Onoguchi, 2013). However, some older roads may lack the precision in markings needed for accurate vehicle tracking, especially in challenging weather conditions (Sultana & Ahmed, 2021).

- **Lane Number and Capacity**: Multi-lane highways are generally suitable for platooning, allowing for the formation of vehicle groups without significantly disrupting regular traffic flow. However, in areas with fewer lanes, platooning may cause congestion or interfere with other road users.

2. Traffic Management Systems

- **Traffic Signal Coordination**: Most existing traffic signals are not yet fully integrated with V2I communication systems, which can hinder the ability of platoons to navigate intersections efficiently. Advanced traffic management systems that prioritize platoons could significantly improve traffic flow and safety.

- **Ramp Metering and Access Control**: Existing ramp metering systems are often designed to manage individual vehicle flow rather than coordinated platoons, which could lead to delays or disruptions in platooning efficiency during freeway access and egress.

3. Communication Infrastructure

- **V2V and V2I Communication Readiness**: While some highways have begun integrating V2I technology, widespread deployment is still in progress. Full platooning potential relies on robust V2V and V2I communication systems to ensure real-time data exchange, coordination, and safety.

  The existing cellular network infrastructure supports basic communication needs for platooning but DSRC or 5G networks are required for low-latency, high-reliability connections between vehicles and infrastructure. Many freeways lack the necessary DSRC coverage or 5G availability for optimal platooning operations.

4. Safety Infrastructure

- **Roadside Barriers and Clear Zones**: Most freeways are equipped with barriers and clear zones that can enhance safety during platooning. However, in areas with narrow clear zones or outdated barriers, the risk of collision increases, especially in high-density platoons.

- **Emergency Access and Response**: Current emergency response systems may not be fully adapted to handle incidents involving platoons, where multiple vehicles might be involved. Infrastructure needs to support quick access for emergency vehicles and clear procedures for platoon breakdowns.

5. Data Collection and Monitoring Systems

- **Roadside Sensors and Cameras**: Existing infrastructure often includes traffic cameras and sensors, but these are typically designed for traditional traffic monitoring rather than the specific needs of platooning, such as tracking vehicle spacing and communication integrity. Upgrading these systems to monitor and manage platoons effectively is necessary.
- **Data Logging and Analysis**: Most current infrastructure lacks integrated data logging systems needed to capture detailed information on platoon behavior, vehicle dynamics, and environmental conditions in real-time. Enhanced data collection infrastructure is essential for gathering historical data, which can be leveraged to analyze and improve platooning performance as well as guide infrastructure development. However, this improvement comes with the opportunity cost of increased storage demands, which in turn represents higher economic costs

6. Power Supply and Maintenance

- **Electric Vehicle (EV) Charging Stations**: As many platooning systems are likely to involve electric vehicles, the availability of charging stations along freeways is a critical consideration. Currently, charging infrastructure is unevenly distributed, which could limit the range and effectiveness of platooning for EVs.
- **Infrastructure Maintenance**: Regular maintenance of roadways, signals, and communication systems is crucial for the smooth operation of platoons. Many regions face challenges in maintaining this infrastructure at the level required for reliable platooning, leading to potential safety and operational risks.

7. Regulatory and Legal Framework

- **Platooning Policies**: While some regions have started developing regulations to govern platooning, these are often not fully aligned with the existing infrastructure capabilities. There is a need for a cohesive regulatory framework that supports the deployment and management of platooning systems on freeways.
- **Public Acceptance and Awareness**: Public understanding and acceptance of platooning are still limited, which can impact the successful integration of platooning into existing traffic systems. Educational campaigns and clear signage are needed to inform drivers about platooning zones and protocols.

8. Environmental Considerations

- The existing infrastructure for platooning must be evaluated based on its environmental benefits, particularly how well it supports fuel efficiency and emissions reduction through smooth, efficient vehicle movement. It should also minimize impacts such as noise pollution, habitat disruption, and energy consumption. This involves assessing road quality, lane markings, and traffic management systems to ensure they facilitate safe, uninterrupted platoon movement, which helps reduce fuel consumption and emissions.

- Additionally, the evaluation should examine the use of renewable energy sources for powering infrastructure systems and the availability of charging stations for electric vehicles. It’s also essential to consider the potential ecological impact of any infrastructure upgrades, ensuring minimal habitat disruption and sustainable land use. Overall, the focus is on aligning infrastructure with the environmental benefits of platooning, such as improved fuel efficiency and lower emissions.

5 Co-Simulation Use to Support Testing

5.1 Introduction

CDA is defined as the automated vehicle system that enables cooperation among vehicles and/or the infrastructure by utilizing machine-to-machine communication technology to enhance road users' safety and efficiency (SAE International, 2021). With the introduction of CAV technology, it is expected that the CDA will be an important feature of future transportation systems, resulting in significant improvements in mobility, safety, and sustainability at the traffic level and individual vehicle level.

Since the penetration of CDA vehicles into the traffic stream is not anticipated to happen in the near future, real-world test tracks and simulations are expected to play a vital role in CDA research, testing, and evaluation. Co-simulation has been proposed as an important approach for testing and evaluating automated vehicle technologies and applications for scenarios that cannot be adequately and efficiently tested at a test facility or the real world, such as testing under different traffic compositions, congestion levels, environment conditions, and system management strategies. Co-simulation is the simulation of a system using a combination of tools and models. When simulating CDA, these tools and models can include microscopic traffic simulation, vehicle dynamics simulation, automated vehicle sensor and control simulation, and communication simulation combined with other advanced technology and vehicle control platforms. Simulation can be integrated with software-in-the-loop and hardware-in-the-loop platforms to test various components of connected, automated, and cooperative driving.

This section 5 investigates the use of co-simulation to test CDA applications using a use case of a freeway work zone in the presence of CDA to demonstrate the co-simulation use. The document provides a review of the literature for the use of software-in-the-loop co-simulation that incorporates multiple simulation tools such as traffic simulation tools, an automated vehicle simulation tool, and a communication simulation tool combined with CDA control platforms. The review of literature also includes a review of hardware-in-the-loop simulation that interfaces real-world CDA hardware with the simulation environments. The document then provides a test plan of the use case of CDA vehicles approaching the work zone. The test plan includes the use case description, tested units, operational design domain, the selected performance metrics, test scenarios, and test procedures. Finally, the document presents the results from the application of the developed test plan for the use case using a selected co-simulation modeling platform to demonstrate the use of such platforms. The demonstration provides a comparison of traffic-level and vehicle-level performance measures of a freeway work zone with one-lane blockage in the presence of individual CDA vehicles and CDA vehicles in platoons under different scenarios and parameters.

5.2 Review of Literature

As stated earlier, co-simulation has been proposed as an important approach for testing and evaluating automated vehicle technologies and applications. This section presents first a review of currently available software-in-the-loop co-simulation. Then, it reviews the hardware-in-the-loop applications for CDA simulation.

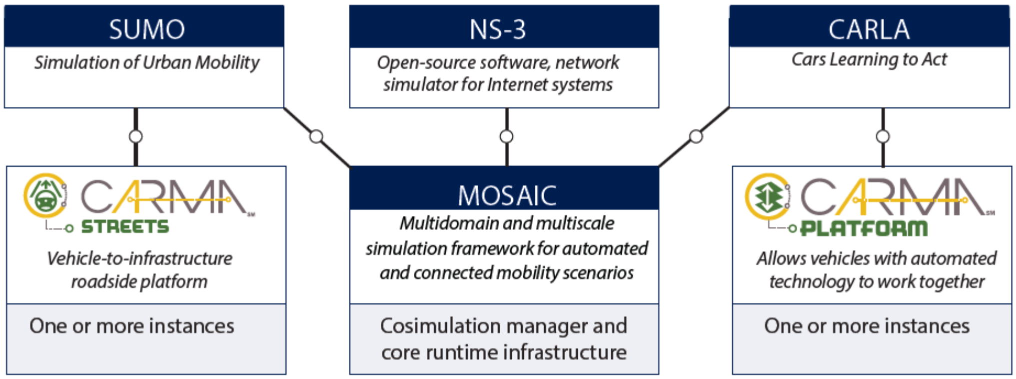
5.2.1 Software-in-the-Loop

Integrations of different simulation tools have been used in the testing and verification of CAVs. Microscopic traffic simulation tools, like VISSIM, AIMSUN, TransModeler, and Sumo, have been used for many years to assess traffic performance under different conditions and improvement alternatives. These traffic simulation tools have been utilized by themselves to evaluate the impact of CAVs on traffic operations. However, these tools have certain limitations, including their inability to emulate vehicle sensors, detailed simulation of V2X communication technologies, and vehicle dynamics. Some co-simulation applications have integrated traffic simulation tools with tools that can simulate vehicle sensors, vehicle-to-vehicle communication tools, and vehicle dynamics.

This section reviews two co-simulation platforms that have been used in CDA research and testing. These are the CARMA co-simulation, which has been developed by the Federal Highway Administration (FHWA), and the OpenCDA, which is an open-source CDA simulation developed by the University of California in Los Angeles. Both of these platforms were considered for use in this study, as explained later in this document.

5.2.1.1 CARMA Co-Simulation

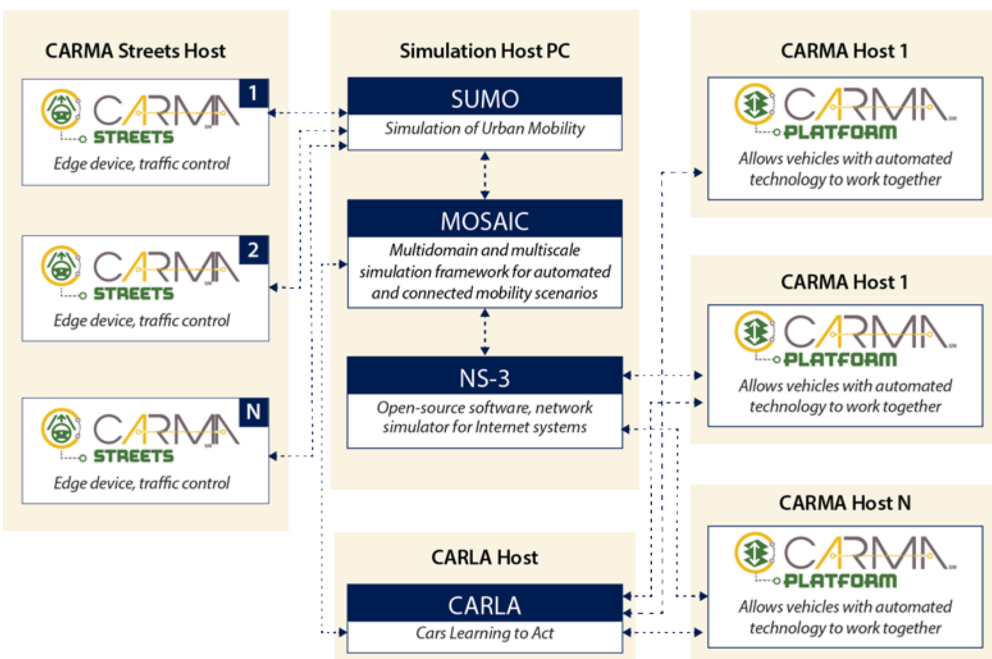
The FHWA has introduced the CARMA program as an open-source CDA environment to promote the research and testing of CDA features. The CARMA research team has developed a co-simulation environment named CARMA Everything-in-the-loop (XIL), which consists of six core components. These components are the CARMA Platform, CARMA Streets, Modular Selection And Identification for Control (MOSAIC), Simulation of Urban Mobility (SUMO), CAR Learning to Act (CARLA), and Network Simulator 3 (NS-3) (Rush et al., 2021; USDOT CARMA, 2022), as shown in Figure 5-1.



[Source: FHWA, (USDOT CARMA, 2022)*]*

Figure 5-1 CARMA XIL framework and architecture.

In the CARMA co-simulation, SUMO works as the traffic microsimulation software; CARLA as a vehicle dynamics and sensor simulator; and NS-3 as a communication simulation tool. In addition to the above three simulation environments, the co-simulation uses the multi-scale and multi-domain simulation framework, MOSAIC, as the core runtime infrastructure and simulation manager. CARMA Platform and CARMA Streets provide vehicle-to-vehicle and vehicle-to-infrastructure collaboration platforms. Figure 5-1 illustrates the architecture that describes the interfaces among the six core components of the CARMA XIL framework (USDOT CARMA, 2023).



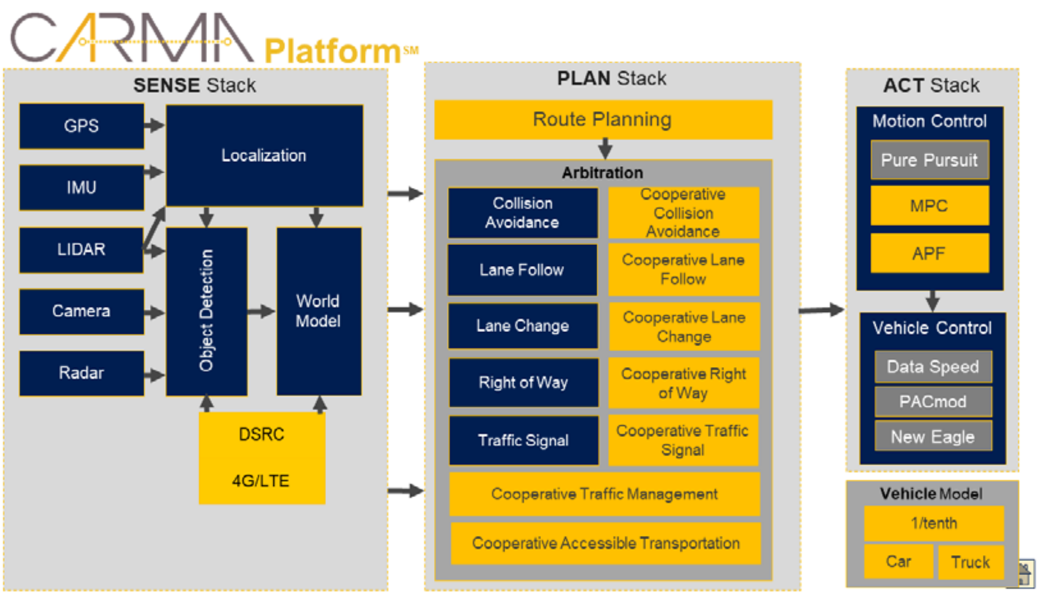
[Source: FHWA, (USDOT CARMA, 2022)*]*

Figure 5-2 CARMA XIL co-simulation framework and architecture.

5.2.1.1.1 CARMA Platform

CARMA Platform is a vehicle-based environment for automated cooperative vehicles to share information and intents and cooperate with other vehicles and infrastructure. The CARMA Platform includes a planning plugin API, controller plugin API, and hardware driver API. The planning plugin API allows the installation of plugins for strategic and tactical planning of vehicle behaviors and trajectories to exercise specific algorithms and cooperative interactions (Rush et al., 2021). The controller plugin API provides for the implementation of low-level motion-planning algorithms. The hardware driver API allows users to install the platform on appropriately equipped vehicles.

The CARMA platform can also compose, transmit, and receive V2X communication messages according to the SAE J2735 standards to enable vehicles to cooperate with the infrastructure and other vehicles. Figure 5-3 illustrates the key components and architecture of the CARMA Platform's framework. The CARMA Platform supports features such as yielding, lane changing and merging, cruising, platooning, and speed harmonization.



[Source: FHWA, (CARMA, 2020; USDOT CARMA, 2023)*]*

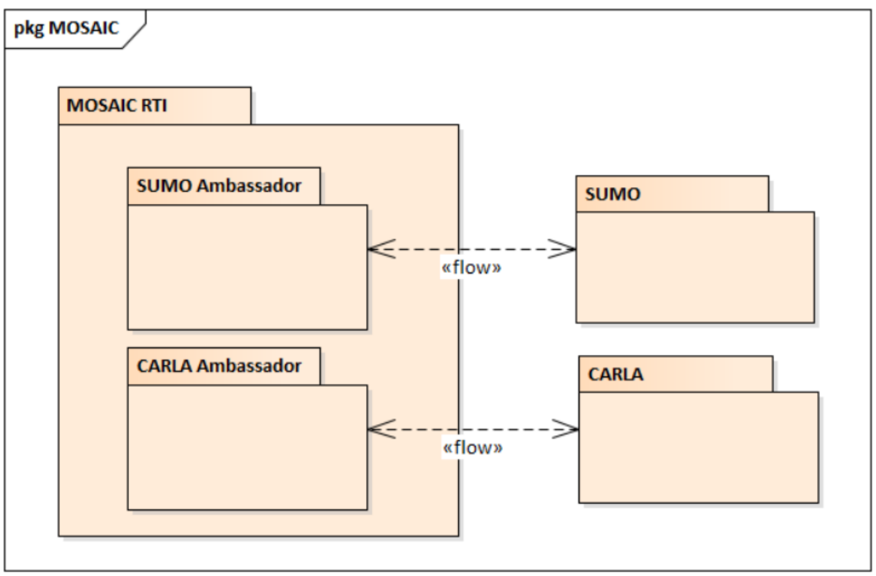
Figure 5-3 Key components, framework, and architecture of carma platform.

5.2.1.1.2 CARMA Streets

CARMA Streets is an infrastructure-based tool that facilitates the cooperation of CDA vehicles with other vehicles and infrastructure components through information sharing and communication messages (Rush et al., 2021). This application supports testing several transportation management use cases to enhance CDA technology to improve transportation operations and safety. Currently, CARMA Streets supports five specific services: intersection model service, message service, scheduling service, signal optimization service, and traffic signal controller service.

5.2.1.1.3 MOSAIC

MOSAIC is a multi-domain and multi-scale simulation framework widely used for connected and automated mobility scenarios. In CARMA, this tool serves as the co-simulation manager and is used as the core runtime infrastructure of the co-simulation process for simulation coordination and data exchange (Rush et al., 2021). As the co-simulation manager, it combines individual simulators (like SUMO and CARLA) with the whole co-simulation environment. Figure 5-4 depicts the MOSAIC framework for integrating the SUMO and CARLA into the CARMA XIL co-simulation platform. The CARMA research team initially decided to integrate the CARLA into the SUMO API, which connects to MOSAIC, where CARLA will utilize SUMO's traffic control interface (TraCI) to exchange data. However, that integration caused issues in data collection and visualization. Therefore, MOSAIC integrates the SUMO and CARLA individually to allow direct data communication.

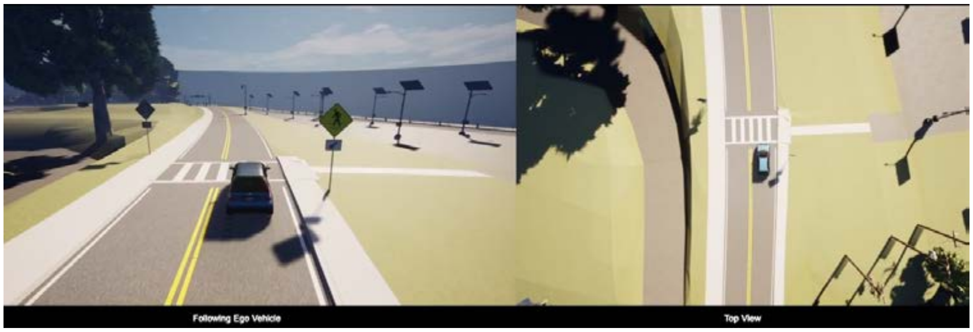


[Source: FHWA, (Rush et al., 2021)*]*

Figure 5-4 MOSAIC integration with CARLA and SUMO for the CARMA XIL.

5.2.1.1.4 CARLA

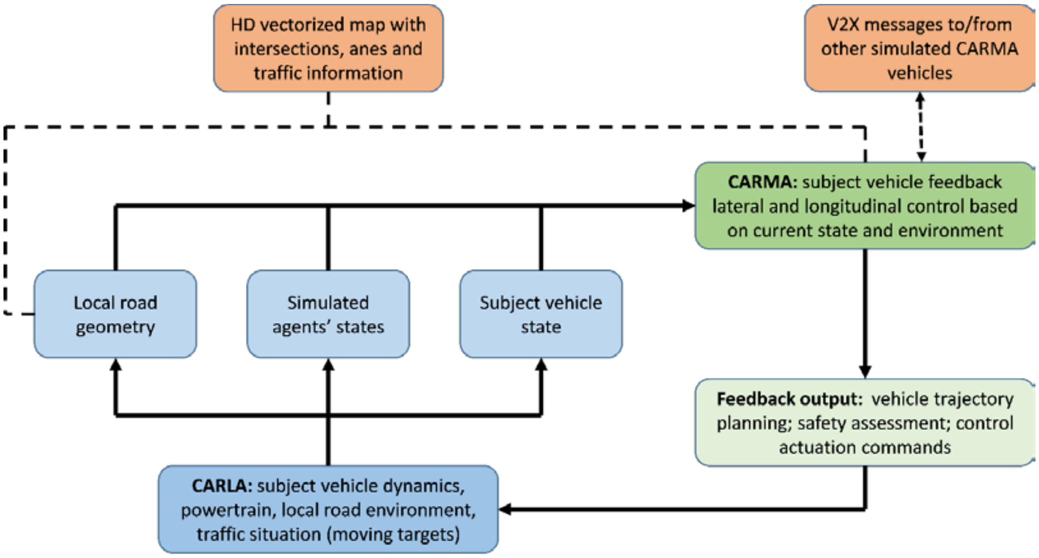
CARLA is an open-source simulation platform for testing and validating autonomous driving systems (Dosovitskiy et al., 2017) for various driving scenarios, highway settings, traffic patterns, and weather conditions. Developers can alter the behaviors of vehicles, pedestrians, and roadway components in a simulation scenario using a set of APIs. CARLA supports a range of on-board sensors; including camera, lidar, and radar, allowing the simulation of the input data that an automated vehicle would receive in the real world. This simulator has been used widely for developing and evaluating the perception, planning, and control algorithms of automated vehicles. In the CARMA XIL co-simulation, CARLA simulates virtual vehicles, roadway geometry, and other objects, and each CARMA simulation step develops a control command for the subject or ego vehicle. Figure 5-5 shows an example screenshot of the CARLA simulator while running CARMA XIL (USDOT CARMA, 2022).



[Source: FHWA, (USDOT CARMA, 2022)*]*

Figure 5-5 Example screenshot of the CARLA simulator while running CARMA XIL.

Figure 5-6 illustrates the interactions of the subsystems of CARMA and CARLA in CARMA XIL. Both of these parties share a data store that contains standard high-definition (HD) maps with all the data required for navigation and guidance policy. The subject vehicle states are obtained from CARLA, and the relative location and orientation of all other objects are transmitted to the CARMA instance in each time frame. Based on this information, the CARMA platform generates feedback control commands for the subject vehicles based on the current state and environment. These commands are then communicated back to CARLA.



[Source: FHWA, (USDOT CARMA, 2023)*]*

Figure 5-6 The architecture of integrating CARLA with CARMA XIL.

5.2.1.1.5 SUMO

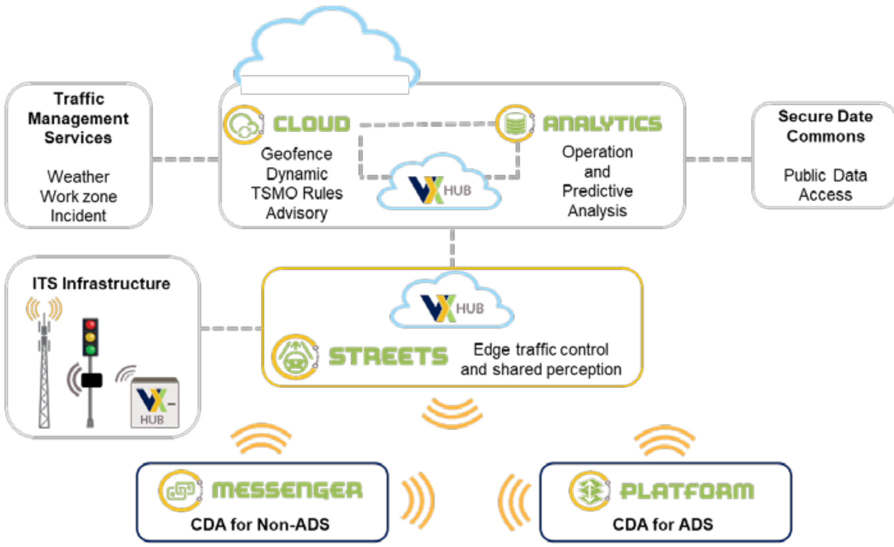
SUMO is an open-source transportation network simulator used in the CARMA XIL co-simulation as the microscopic traffic simulation component. During the co-simulation, the vehicles are first modeled in the SUMO and then they are simulated in CARLA with the help of the MOSAIC framework (Rush et al., 2021). In the CARMA XIL environment, SUMO is responsible for managing the traffic behavior and state-tracking of most vehicles at a lower level of resolution than CARLA. Additionally, it manages the states and operations of infrastructure elements such as traffic signal controllers.

5.2.1.1.6 NS-3

NS-3 is an open-source discrete-event-based network simulation tool widely used for the internet system (NSNAM, 2023). Researchers and academia mainly use this tool to model and simulate network systems and protocols. In CARMA XIL, NS-3 is used as a part of the communication system to emulate the data and message exchanges for the V2V and V2I communications with the help of the MOSAIC framework (Rush et al., 2021). Integrating NS-3 into CARMA XIL involves two key components: the data interchange module and the C-V2X module. The data interchange module enables the transmission of data packets within the simulated network, whereas the C-V2X module provides the option to simulate and configure C-V2X technology. The integration of NS-3 enhances the functionality of the CARMA XIL system, enabling it to more realistically simulate the transmission and reception of data accurately.

5.2.1.1.7 CARMA Cloud

CARMA Cloud is an open-source, cloud-based service that enables communication and cooperation among cloud services, vehicles, infrastructure, and road users (USDOT CARMA, 2023). It features a web interface that displays road elements such as speed limit information, closed or open lanes, and traffic lights. It also allows the application of infrastructure-based CDA strategies through rules for road users to manage traffic flow. CARMA Cloud simultaneously performs bidirectional communication, data exchange, and management of multiple remote vehicles and identifies and communicates cooperative driving parameters (like platooning parameters). It can define geofences, rules of practice, and conditions for automated vehicles. Figure 5-7 shows the functionalities of CARMA Cloud.



[Source: FHWA, (USDOT CARMA, 2023)*]*

Figure 5-7 Capabilities and functionalities of CARMA cloud architecture.

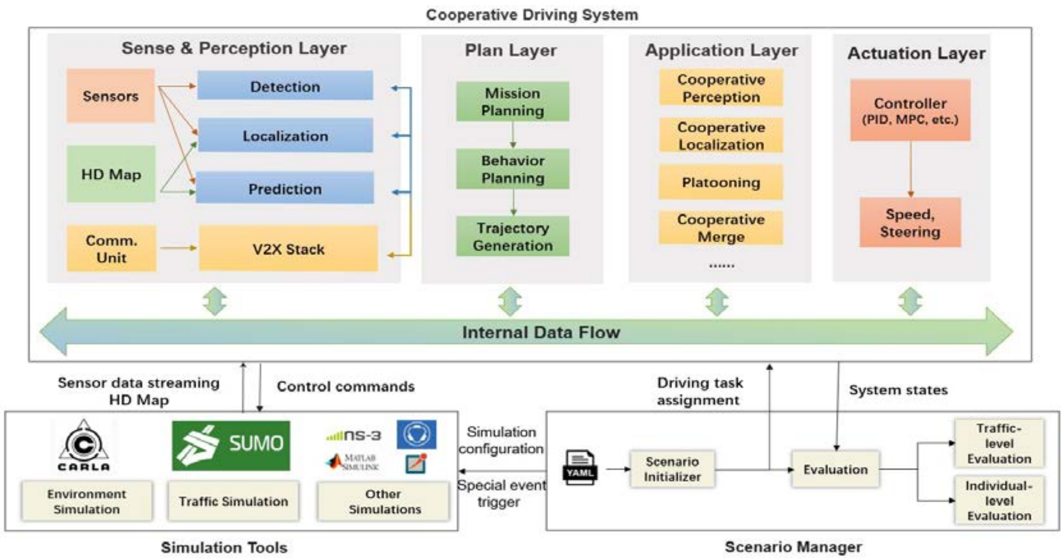
5.2.1.1.8 CARMA Messenger

CARMA Messenger is a vehicle-based application that facilitates communication between non-automated vehicles and other road entities and the CDA network (USDOT CARMA, 2023). It allows communication between vehicles with SAE Level 0-2 autonomy and CDA Class A and B using OBU to transmit alert messages and share data with other road users for safe and efficient driving. By providing a means for non-automated vehicles to participate in CDA, CARMA Messenger helps advance CDA technology's development and improve overall road safety.

5.2.1.2 OpenCDA

The Mobility Lab at the University of California, Los Angeles, has developed the OpenCDA as an open-source co-simulation platform for developing and testing CDA (R. Xu et al., 2021b). OpenCDA consists of three key components: a co-simulation platform, a full-stack prototype cooperative driving system, and a scenario manager. This platform allows testing different CDA algorithms at the traffic and individual automated vehicle levels. The full-stack CDA software includes the common automated and cooperative driving modules, including sensing, computation, and actuation capabilities, in addition to SAE J3216-defined cooperative features, including vehicular communication and information exchange. OpenCDA, developed in Python, provides a variety of popular cooperative driving applications, such as platooning, cooperative perception, cooperative merge, and speed harmonization. It also includes a database of predefined testing cases for benchmarking and easy APIs for customization.

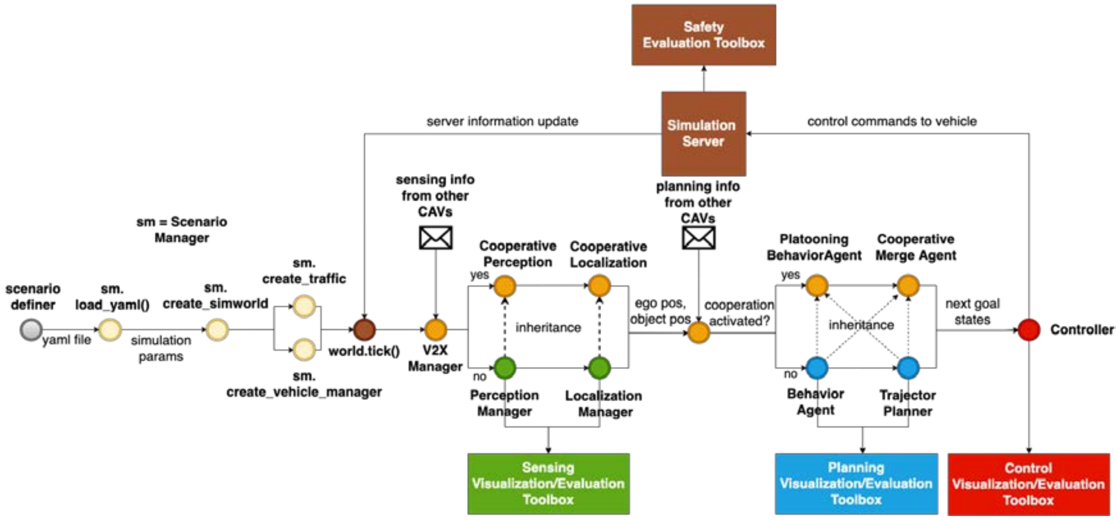
Figure 5-8 illustrates the components and architectural design of the OpenCDA co-simulation platform that consists of three key elements: cooperative driving system, simulation tools, and scenario manager. The cooperative driving system in OpenCDA contains a Sense and Perception Layer responsible for generating, processing, and utilizing data from onboard sensors such as lidar and camera devices. This layer also contains a Plan Layer, which generates plans and trajectories for the vehicles. The Application Layer allows driving tasks such as cooperative merging and platooning based on cooperative perception and localization. Finally, the Actuation Layer is where low-level vehicle dynamic controls occur, involving the underlying vehicle controller's throttle, brake, and steering outputs.



[Source: Mobility Lab, UCLA, (R. Xu et al., 2021b)*]*

Figure 5-8 Components and framework of OpenCDA co-simulation platform.

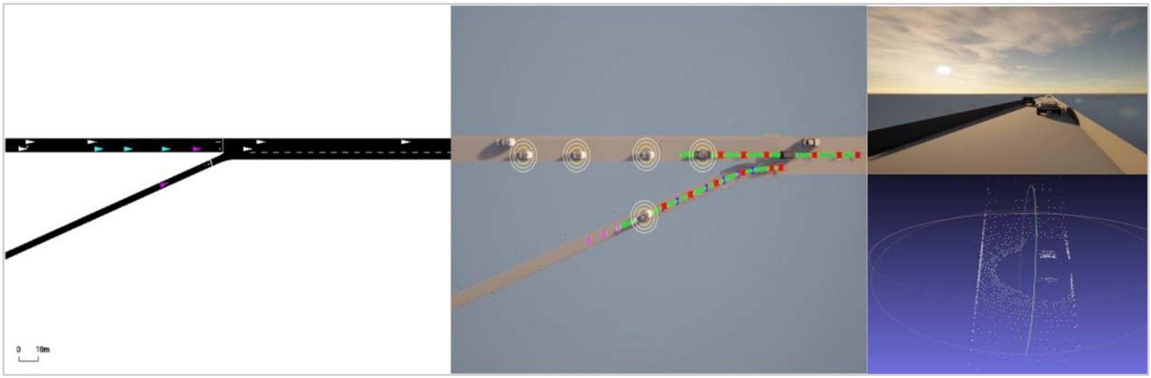
The OpenCDA utilizes SUMO as a traffic simulator and CARLA as the vehicle dynamic and sensors simulator. Furthermore, the framework allows for integrating additional simulators, such as communication simulators (e.g., NS-3) and vehicle dynamics simulators (e.g., CARSim). The scenario manager component of the OpenCDA involves scenario configuration, scenario initializer, system-specific event initializer, and evaluation functions. The simulation logic flow of OpenCDA during runtime is shown in Figure 5-9. The users are required to create a configuration file in the YAML Ain't Markup Language (YAML) file format based on the OpenCDA template to configure the CARLA server settings, traffic flow specifications, and CAV parameters. YAML is a data serialization format that humans can easily read and understand (YAML, 2023). The Scenario Manager loads the configuration file, retrieves necessary parameters, and delivers them to the CARLA server to generate traffic flow and create a Vehicle Manager for each CAV. The sensors mounted on each CAV collect information about the surrounding environment and share it through the V2XManager. The processed sensing information is delivered to modules for planning and decision-making, and the final control commands are generated by the Control Manager and applied on a CV by the CARLA server.



[Source: Mobility Lab, UCLA, (R. Xu et al., 2021b)*]*

Figure 5-9 Logic flow and functionalities among the components of OpenCDA co-simulation.

An example of running platooning scenarios in OpenCDA under a co-simulation configuration is demonstrated in Figure 5-10 (R. Xu et al., 2021b). The image on the left shows a simulation snippet in SUMO, while the middle image represents the corresponding view in CARLA, with green lines indicating the planned trajectory path and red dots representing points. The image on the right displays the RGB image and 3D lidar points captured by the sensors installed in the CAV. The example used a customized benchmark map of a basic freeway merge segment, including a two-lane freeway and a single-lane on-ramp.



[Source: Mobility Lab, UCLA, (R. Xu et al., 2021b)*]*

Figure 5-10 Screenshots of running platooning scenario in OpenCDA.

5.2.2 Hardware-in-the-Loop Simulation

Software-in-the-loop, including the co-simulation environments discussed in the previous section, provide powerful platforms for testing and evaluating CAVs. However, any simulation effort contains some level of abstraction in order to model real phenomena, impacting the fidelity and reliability of the simulation results (Shah et al. 2019). HIL simulation has been used to develop and evaluate complex real-time systems to increase confidence in simulation results. HIL simulation is an approach that combines physical entities, like onboard equipment on CAVs and infrastructure equipment with traffic simulation software. It has been used in transportation engineering in examining technologies and applications, including those related to traffic control, vehicle dynamics, automated vehicle sensing and control, V2X communication technologies, and so on.

The basic HIL simulation system in transportation applications traditionally used in transportation engineering consists of three fundamental components: traffic simulation software, physical signal controller, and controller interface device (CID) (J. Ma et al., 2018). In this HIL platform, the traffic simulation software introduces virtual vehicles and detectors and sends the necessary data to the physical signal controller, where the controllers react to those virtual detectors' calls as if they were from physical detectors. Middleware or the CID is usually used to establish the communication between the physical signal controllers and the simulation platform through the sending and receiving the Simple Network Management Protocol (SNMP) requests, which follow the National Transportation Communications for ITS Protocol (NTCIP) standards (J. Ma et al., 2018). The CID connects the signal controllers and simulation software by translating the control pin logic levels to the microscopic simulation model (Stevanovic et al., 2009). Through the CID, the controller processes virtual detector signals, generates signal statuses, and returns the signal states to the simulation software.

Zulkefli et al. (2017) proposed a HIL system testbed to assess CV applications' performance utilizing a laboratory powertrain research platform. The platform includes the VISSIM traffic simulator, a physical engine, an engine loading device, and a virtual powertrain model. In this system, vehicle dynamics of a target vehicle simulated in VISSIM simulation and road conditions are transmitted to the powertrain platform, where the power demand is calculated. The engine is operated using an optimization method to minimize fuel consumption, while the dynamometer is modified to the desired engine load based on the target vehicle data. The test results indicated rapid data transfer every 200 ms and accurate tracking of optimized engine operating points and desired vehicle speed. The study concluded that the platform could provide precise fuel consumption and emissions measurements, which are difficult to achieve using traffic simulation tools by themselves.

Szendrei et al. (2018) designed a HIL simulation platform for testing CV applications, utilizing the SUMO open-source simulation software and physically connected vehicle equipment. OBUs are assigned to specific vehicles in the traffic simulation model, collecting the vehicle's simulated sensor data and providing warnings using the Human-Machine Interface (HMI) devices. The RSUs communicate with V2X devices, providing infrastructure information. The study concluded that the HIL V2X simulation framework can support the development and testing of V2X applications in realistic traffic conditions provided in a laboratory environment.

Mafakheri et al. (2021) utilized a HIL simulation to test the performance of V2X communications with cellular (LTE or 5G) technology and Institute of Electrical and Electronics Engineers (IEEE)

802.11p (corresponding to ITS-G5 in Europe) technology, focusing on the information exchange between physical vehicles and surrounding simulated virtual objects. The objective was to reproduce this exchange efficiently, with computations performed fast enough to facilitate real-time application testing. Specifically, the study addressed non-ideal positioning and channel propagation simulation, accounting for current impairments. Optimization solutions were detailed to achieve an order of magnitude increase in the speed of the simulation by balancing minor accuracy losses with substantial reductions in computational time, achieving speed increases of more than an order of magnitude in the experiments.

Ma et al. (2018) developed a HIL proof-of-concept platform to test a prototype of CV-based CACC and signalized intersection approach and departure (SIAD), respectively. This system included a physical CAV, a field track, CV equipment, and a microscopic simulation tool. The microsimulation software forms virtual background traffic that is synchronized with the physical CAV and traffic controller through the transmission of basic safety messages (BSMs) and vehicle sensor data. The findings of the study demonstrated a better assessment of the CACC string performance and SIAD using HIL.

Sunkari et al. (2018) developed HIL simulation that combines physical CV devices and traffic signal operations with simulated traffic to test CV applications and technologies. This platform utilizes a microscopic simulation tool to generate detector calls for actuated traffic signal controllers, receive data from the controller, and send it to the CV. The findings from the study indicated that the HIL simulation platform was effective in testing various CV-based applications.

Lee et al. (2020) presented a HIL simulation for developing, testing, and evaluating cooperative eco-driving systems using connected hybrid electric vehicles. The simulation environment includes an AV simulator, driving simulator, and communication simulator, combined with an onboard electronic control unit (ECU) for control testing and connected vehicle equipment for testing V2X communication. The system allowed investigation of the performance of the cooperative eco-driving speed guidance application by evaluating the total fuel consumption between driving with eco-speed and driving without it. The study findings indicated the effectiveness of the developed HIL environment in evaluating the improved fuel efficiency of the application.

Gelbal et al. (2020) and Cantas et al. (2019) introduced a HIL simulator for developing and testing CAVs applications, with the main purpose of developing and testing automated driving algorithms. The HIL simulator consists of a vehicle dynamic and sensor simulator, a physical ECU on-board a real-world vehicle, and two RSU-OBU units for V2X communication. The authors demonstrated the use of the HIL simulator in developing and testing lane keeping, CACC, and signalized intersection operations.

Wang et al. (2023) developed a co-simulation framework for pedestrian and CV hardware-in-the-loop systems. The study utilized real-world connected vehicle equipment in conjunction with CARLA automated vehicle simulation and SUMO traffic simulation tools. The framework enabled rigorous testing of a V2P warning system, demonstrating significant safety enhancements for pedestrians with the application of the system.

Shah et al. (2019) proposed a HIL simulation framework to evaluate CV applications with an emphasis on assessing the performance of real-time communications. In this framework, emulated vehicle trajectories were collected from the traffic simulation and fed to modules that emulate the behaviors of the medium access control, which is part of the data link layer to control data transmission, and the physical layer, responsible for the physical connections among devices. The modules create BSM of the emulated vehicles. A real or physical host vehicle receives these BSMs using its OBU receiver. The research found that the proposed solution was not only able to produce results as accurately as a software-based solution using the NS-3 communication simulation, but it is also faster by around two orders of magnitude, allowing it to maintain real-time performance without a noticeable loss in accuracy.

5.3 Test Plan

5.3.1 Software-in-the-Loop Co-simulation

5.3.1.1 Overview

This chapter explains a test plan for SIL co-simulation to demonstrate the use of co-simulation for assessing driver level and vehicle level performance in the presence of CDA. The test plan includes the description of the use case utilized in the demonstration, tested units, operations design domain, test objectives and performance metrics, test scenarios, and test procedures. The test plan is based on the "Standard for Software and System Test Documentation" of the IEEE, specifically the 2008 revised version of the original IEEE Std 829-1998 version.

5.3.1.2 Use Case Description

The use case of this study involved CDA-equipped vehicles approaching a freeway work zone area with a lane blockage situation. It includes demonstrating merging mechanisms of single CDA vehicles from the blocked lane into CDA platoons in the adjacent lane, operating utilizing CACC technology, and evaluating the impacts on traffic flow and CDA vehicle movements in the vicinity of work zones. The use case includes the following:

1. An infrastructure application that provides instructions to the platoon approaching the work zone regarding platoon lane selection and lane change restriction,

2. An infrastructure application that provides instructions to the single CDA vehicle approaching the work zone regarding the point where it starts communicating its desire to change lanes out of the lane blocked by the work zone to merge into a platoon,

3. An infrastructure application that provides instructions to the platoon and single CDA regarding the desired speed at the work zone.

5.3.1.3 Tested Units

The tested units include CDA vehicles in platoons, single CDA vehicles, non-CDA vehicles, and infrastructure support components. All vehicles are virtual vehicles spawned by simulators in the co-simulation environment. Below is a description of these tested units.

- Subject Vehicles (SVs): These are individual CDA vehicles and CDA vehicles in platoons. The individual CDA vehicles travel on the right lane of a three-lane freeway segment that has a lane blockage downstream due to a work zone. CDA vehicles driving in a platoon are instructed to drive on the adjacent lanes (the middle lane of the three-lane freeway) to facilitate merging. The individual CDA vehicles attempt to merge into the adjacent lane ahead of the lane blockage, whenever possible, by joining a platoon approaching the work zone on the adjacent lane. Vehicles within the platoon follow each other according to the cooperative driving system algorithm in the co-simulation. These SVs are generated and controlled by the automated vehicle simulator component (CARLA) and SUMO in the co-simulation environment. It is assumed that these vehicles had an automation level of 3 or higher according to SAE J3016 standards and a cooperative driving class of C or higher according to SAE J3216 standards.
- Object Vehicles (OVs): These are human-driven vehicles (HVs) traveling on the same lane and adjacent lanes of the SV approaching the work zone. These OVs are spawned and managed by the traffic simulator of the co-simulation platform (SUMO in this project) and synchronized with the automated vehicle simulator (CARLA in this project). The OVs follow built-in car-following and lane-changing models available in the traffic simulator.
- Infrastructure Support Component: The infrastructure support is the management component of the co-simulation environment, responsible for the provision of guidance regarding the merging of single CDA vehicles from the blocked lane to the adjacent open lane, as outlined in the Use Case Description section. In case there is no platoon on the adjacent lane in the vicinity of the single CDA, the single CDA will utilize the lane-changing model used in utilizing the co-simulation platform with no cooperation.

5.3.1.4 Operational Design Domain (ODD)

The ODD identifies the operating environment assumed for the test, including the highway facility classification, traffic conditions (different congestion levels), lane and shoulder blockages, if any, pavement conditions, and environmental conditions (e.g., lighting conditions, sun location, and rain/clear conditions). The test was conducted for a three-lane freeway segment, which is straight and flat with clear lane markers. The base scenario is in daylight with a clear sky, dry conditions, and no impact from the sun. Other tested scenarios include heavy rain and wet pavement in daylight.

5.3.1.5 Test Objectives and Performance Metrics

The test will use a set of performance metrics according to the objectives of the test as follows:

- Objective 1: Investigate the ability of co-simulation to simulate automated vehicle sensors and their utilization in CDA vehicle trajectory settings.
    - Performance Metric 1-1 - Time to Slow Down: This metric reflects the detection range of the following vehicles under different weather and lighting conditions based on the time traveled before the following CDA vehicle adjusts its speed to the leading vehicle.
    - Performance Metric 1-2 – Safe Time to Collison: This metric reflects the ability of the following vehicle to maintain a safe inter-vehicle time gap that is higher than the critical time to collision in the presence of a slow down by the leading vehicle.
    - Performance Metric 1-3 – Maintaining Platoon Stability: Ability of the platoon to maintain its stability with the slowing down of the lead vehicle with different sensor types.
    - Performance Metric 1-4 – Spot Speed: The instantaneous speed of the follower vehicle while following the leader vehicle under different weather situations and sensor types.
- Objective 2: Demonstrate the use of co-simulation to evaluate the merging mechanism of single CDA vehicles into platoons in the adjacent lane, including the required lane change of the single CDA and the speed change of the cooperated vehicles to provide and utilize gaps for merging.
    - Performance Metric 2-1 – Oscillations during Merging: This metric quantifies the variation in speeds and accelerations of vehicles in the traffic stream. A high number of oscillations can reduce platoon and traffic stability and increase the potential for rear-end collisions.
- Objective 3: Determine the Impact on General Traffic
    - Performance Metric 3-1 Change in Average Traffic Speed: This metric reflects the average slowdown of traffic approaching the work zone as reflected by speed measurements at different points upstream of the work zone.

5.3.1.6 Test Scenarios

The test scenarios conducted in this study cover different ODD (sunny, rain, fog, and night light conditions), different market penetration rates of CDA vehicles, different distances at which vehicles on adjacent lanes are advised to start communicating with each other to change lanes, and different distances ahead of the work zone that the merging CDA vehicles are advised to start sending messages for merging. Table 5-1 enumerates the test scenarios. The base scenario is the situation with only human-driven non-CDA vehicles approaching the work zone. The Merge Advisory Distance denotes the location upstream of the lane blockage, where the first merging advisory is received to initiate merging from the closed lane. The V2V communication distance defines the distance at which communication between a single CDA and a platoon is initiated in order for the single CDA to merge into the platoon. For example, a distance of 115 ft denotes the distance from the merging vehicle to the follower or the leader of the platoon, whichever is closer, at which the merging vehicle on the blocked lane starts sending messages to join the platoon. A 100% wet pavement with 100% precipitation and 50% cloud coverage is rainy weather conditions with different rain intensities (100% is the highest intensity in CARLA). Details of the weather variation are explained in the 5.3.1.11 Co-simulation Modeling section. The CDA % indicates the market penetration rate of the CDA vehicles with respect to the total demand approaching the work zone.

Table 5-1 Conducted test scenarios in this study

Test Scenarios	**Scenario Details**	**Upstream Merging Advisory Distance, mile**	**V2V Distance, ft**	**Weather**	**CDA, %**
1	0mi 0ft Sunny 0% 3000vph	0	0	Sunny	0%
2	3mi 115ft Sunny 5% 3000vph	3	115	Sunny	5%
3	3mi 115ft Sunny 10% 3000vph	3	115	Sunny	10%
4	3mi 115ft Rainy (w+s) 5% 3000vph	3	115	Rainy (w+s)	5%
5	3mi 115ft Rainy (w+s) 10% 3000vph	3	115	Rainy (w+s)	10%
6	3mi 115ft Rainy (wo) 5% 3000vph	3	115	Rainy (wo)	5%
7	3mi 115ft Rainy (wo) 10% 3000vph	3	115	Rainy (wo)	10%
8	3mi 500ft Sunny 5% 3000vph	3	500	Sunny	5%
9	3mi 500ft Sunny 10% 3000vph	3	500	Sunny	10%
10	3mi 500ft Rainy (w+s) 5% 3000vph	3	500	Rainy (w+s)	5%
11	3mi 500ft Rainy (w+s) 10% 3000vph	3	500	Rainy (w+s)	10%
12	3mi 500ft Rainy (wo) 5% 3000vph	3	500	Rainy (wo)	5%
13	3mi 500ft Rainy (wo) 10% 3000vph	3	500	Rainy (wo)	10%
14	1mi 115ft Sunny 5% 3000vph	1	115	Sunny	5%
15	1mi 115ft Sunny 10% 3000vph	1	115	Sunny	10%
16	1mi 115ft Sunny 5% 3000vph	1	115	Sunny	5%
17	1mi 115ft Sunny 10% 3000vph	1	115	Sunny	10%

Note: V2V: Vehicle-to-Vehicle; CDA=Cooperative driving automation; HV=human driven vehicle; vph=vehicle per hour; wo = modified weather parameters only; w+s = modified weather + sensor parameters; Weather = Details of these categories are explained in explained in 5.3.1.11 Co-simulation Modeling section.

The simulation time for all scenarios was intended to be 4,500 seconds with a warm period of 900 seconds (15 minutes). However, a few scenarios were simulated for 2400-3200 seconds with 900 seconds warm-up due to limited computer resources since CARLA requires significant computer resources to run the model could not run for more than this period on the computer that we used. It should be mentioned here that co-simulation requires significantly more resources than traffic simulation and requires a few hours to run compared to a few minutes when running traffic simulation.

5.3.1.7 Test Procedures

For all testing scenarios, except the base scenario, the CDA platoons were spawned in the middle of the 3-lane freeway, and the single CDA vehicles were placed in the right-most lane. The HVs were generated randomly on all lanes. The right-most lane was closed at a point to represent a lane blockage at a work zone. This lane blockage forced the single CDA vehicle to change lanes and merge into the adjacent lane. Although the single CDA was spawned in the right-most lane, it was allowed to change lanes to travel any lane before merging into a platoon. Also, based on the traffic situations, the single CDA vehicle was capable of merging into the platoon using any of the three possible combinations: front, back, and middle of a platoon.

The CDA and HV vehicles were generated into the simulation according to the market penetration rate of the CDA, as per Table 5-1. After vehicles were input into the network, the CDA vehicles were controlled by the vehicle dynamics and sensor simulator (CARLA in this study), and the HVs were moved by the traffic simulator (SUMO in this study). The study collected the vehicle trajectory, traffic speed, and travel time data from the co-simulation, allowing the estimation of various performance measures.

5.3.1.8 Tools and Study Area Selection

Traffic simulation tools like VISSIM, AimSun, and SUMO are widely used in research and practice. In contrast, the utilization of co-simulation in transportation engineering is relatively new and not widespread. Traffic simulation tools have limitations when testing and evaluating emerging vehicle technology that motivates the use of a co-simulation environment in this study. The use of an autonomous vehicle simulator allows the consideration of the impact of the performance of automated vehicle sensors on automated vehicle movements. When these simulators are combined with traffic simulation models and a CDA platform, the resulting co-simulation allows the assessment of the impact of automated vehicle movement on general traffic.

It is essential to select the right tool to meet the objectives of this test initially. This study initiated testing scenarios with the CARMA co-simulation platform. However, this option gave issues such as having CARMA vehicles not spawning, spawn vehicles not moving, and spawn vehicles not following the desired route. After recognizing that these issues may not be easy to fix, the research team selected the OpenCDA as the cooperative vehicle platform and modified the source code of OpenCDA version 0.13.0 for use as the co-simulation tool in this research. The OpenCDA co-simulation suit integrates the SUMO traffic simulator with the CARLA vehicle dynamics and sensor simulator and applies CDA control algorithms. This study utilized SUMO version 1.20 and CARLA version 0.9.12.

A co-simulation platform like OpenCDA controls the vehicle dynamics based on the emulated sensors, including lidar, radar, and Camera data, and allows the modification of the sensors' parameters to reflect real-world sensor performance. In contrast, standalone simulation tools like SUMO do not have these features. Furthermore, co-simulation has the potential to consider the impacts of different weather conditions on vehicle sensor performance, which is not possible in SUMO.

5.3.1.9 Study Area

To meet the objectives, this study utilized a hypothetical freeway segment that involves three upstream lanes with a right lane closure due to a work zone. As shown in Figure 5-11, the freeway three-lane network consists of a three-mile section upstream of the work zone (in green color in the figure), a one-mile work zone with a single-lane closure, and a one-mile section after the work zone (not filled with color). Other geometric and traffic parameters of the hypothetical network are 12 ft lane width, 3,000 vehicles/hr (vph) demand, 65 mph speed limit for the non-work zone segments, 55 mph speed limit for the work zone segment, 0% grade, 0% heavy vehicle, and no horizontal curves. Speed and travel time data were collected at every one-mile network segment (blue-colored bars).

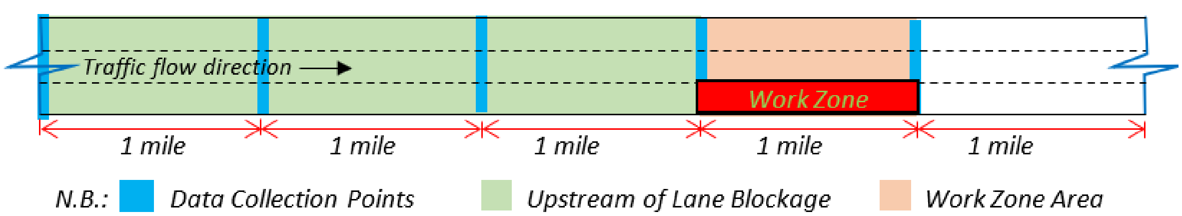


Figure 5-11 Hypothetical work zone study area.

5.3.1.10 Platoon Formation, Lane Changing and Merging Mechanisms

OpenCDA contains built-in applications to test and evaluate CDA vehicle platoons, lane-changing operations, and merging mechanisms (UCLA Mobility Lab, 2021). These built-in applications were utilized and modified for the purpose of this study. According to the merging mechanism into a platoon, the single CDA vehicle continuously searches for merging into a platoon. Once the single CDA vehicle comes to a platoon at a distance of or lower than the specified V2V communication distance, the CDA vehicle sends merging requests to the platoon. Based on criteria, including the available maximum number of platoon members, inter-vehicle gap, and speed difference, the platoon accepts or rejects the merging request of the single CDA vehicle. The destination points of the CDA vehicle and the availability of gap distance on the adjacent lane regulate most of the lane-changing behavior. The single CDA vehicle can merge in three different ways into a platoon: ***front join***- where a single CDA vehicle usually needs to slow down to merge into the platoon from the front and become the new leader of the platoon; ***back join***- where a single CDA vehicle typically speeds up to match the platoon speed, merge from the back of the platoon and become the last follower member of the platoon; and ***cut-in join***- where the existing platoon members need to either speed up or down to create a gap to allow the CDA vehicle to merge into the middle of the platoon. To achieve desired platooning and merging behavior, the system adjusts the necessary parameters, like platoon speed, inter-vehicle gaps in a platoon, maximum vehicle number in the platoon, and maximum speed of the single CDA vehicles while merging a platoon and guaranteeing the merging into the platoon. In this study, the platoons were spawned on the middle lane and restricted from changing lanes, whereas the CDA vehicles were generated on the rightmost lane and allowed to travel freely at any lane before merging into the platoon.

By default, the co-simulation system in the CDA vehicles locates the surrounding vehicles' positions directly from the co-simulation server in terms of the x, y, and z coordinates (UCLA Mobility Lab, 2021). However, it has the option to integrate an additional machine learning-based perception module to achieve enhanced object detection, which was used in this study. The perception module processes the lidar records and the captured images from the camera to detect surrounding objects. This gives better vehicle detection, which can be useful during merging or lane-changing mechanisms.

5.3.1.11 Co-simulation Modeling

The CARLA simulator allows variations of weather conditions, including the introduction of rain, fog, and snow. By introducing weather variations, the simulation can capture the challenges and complexities associated with different weather scenarios, providing a more comprehensive and realistic training and testing environment for automated driving systems. CARLA is capable of simulating different weather conditions like rain and fog. Users can modify the weather parameters to reflect a real-world weather scenario. Unfortunately, CARLA does not have the capability to input exact real-world weather parameters like rainfall intensity mm/hour rather, it allows input as a percentage.

Table 5-2 shows the utilized weather and sensor parameters in this study to reflect weather scenarios in the initial sensor study and final use case testing. Bi et al. (2022) concluded that the 100% precipitation intensity of CARLA reflects 50 mm/hr rainfall intensity from the real world and that the 100% fog intensity of CARLA is comparable to 1 g/m^3 foggy water content from the real world. They recommended that the detection range of RADAR be reduced from 295.28 ft (90 m) to 285.10 ft (86.9 m) due to heavy fog (3.57%) and to 254.59 ft due to heavy rain (15.98%). Filgueira et al. (2017) found that the lidar detection range was reduced by less than 1% for metal signs, stone façade, traffic signs, and vertical retro-reflective signs; 2-7.4% for asphalt pavement, and 10.4% for concrete walls. Kutila et al. (2016) observed that severe fog, snow, and rain deteriorated the lidar sensor capabilities by up to 25%. Tang et al. (2020) found that lidar sensors of AV showed a higher probability of failing to detect pedestrians with a detection range of 98.43 ft (30 m) in rainy weather. In this study, the weather variation feature of CARLA was tested to compare the impact of heavy rain on the operation of CDA vehicles at the work zone with and without changing the detection range. The precipitation parameters were modified based on the study of Bi et al. (2022). Brief definitions of the utilized weather scenarios used for the sensor impact study are as follows:

1. Sunny: a sunny day with a sensor range of 328 ft (100 m),
2. Rainy 50% (wo): rainy weather with adjusted weather parameters only to reflect 25 mm/hr real-world rainfall,
3. Rainy 100% (wo): rainy weather with adjusted weather parameters only to reflect 50 mm/hr real-world rainfall. In use case testing, this weather condition was considered as "Rainy (wo),"
4. Rainy (w+s): rainy weather with both adjusted weather parameters and reduced sensor detection range to reflect 50 mm/hr real-world rainfall,
5. Foggy 50% (wo): foggy weather with adjusted weather parameters only to reflect 0.5 g/m^3 real-world foggy water content,
6. Foggy 100% (wo): foggy weather with adjusted weather parameters only to reflect 1 g/m^3 real-world foggy water content,
7. Foggy (w+s): foggy weather with both adjusted weather parameters and reduced sensor detection range 1 g/m^3 real-world foggy water content.

Table 5-2 Utilized weather and sensor parameters for initial sensor impact study

Parameters	**Default values**	**Sunny**	**Rainy 50%(wo)**	**Rainy 100% (wo)**	**Rainy (w+s)**	**Foggy 50% (wo)**	**Foggy 100% (wo)**	**Foggy (w+s)**
Weather Parameters:								
Cloudiness, %	0	0	50	50	50	0	0	0
Precipitation, %	0	0	50	100	100	0	0	0
precipitation deposits, %	0	0	50	100	100	0	0	0
Wetness, %	0	0	50	100	100	0	0	0
Fog, %	0	0	0	0	0	50	100	100
Sensor Parameter:								
RADAR range, ft		328	328	328	275.59	328	328	316.29
Lidar Range, ft		328	328	328	246	328	328	N/A

Here: wo = weather only; w+s = weather + sensor range; N/A: not applicable, did not test; In use case testing, "Rainy 100% (wo)" weather condition was considered as "Rainy (wo)."

After conducting the simulation experiments, the simulated data were collected and processed to evaluate the impact of the work zone on the individual level and traffic flow level measures under different test scenarios, as mentioned in Table 5-1. A systematic approach was implemented to collect and process data from both CARLA and SUMO using similar parameters and configurations to ensure comparability. This approach includes collecting data for the same time frame to enable meaningful comparisons. By synchronizing the data collection process, it becomes possible to align the outputs from different simulation tools and establish a common framework for the analysis.

The speed and travel time data for both HV and CDA vehicles were collected using SUMO, where SUMO virtual point detectors were used to collect speed data at every one-mile segment, and multi-entry-exit type detectors were used to collect travel time for each segment. Also, SUMO was used to record vehicle trajectories for both HV and CDA vehicles. The SUMO output data were exported to the Extensible Markup Language (XML) files, which were processed and parsed into a spreadsheet format for further analysis. The lxml Python module was used in this study to convert the XML file to the spreadsheet (lxml, 2019).

The merging CDA vehicles data were collected from CARLA directly using the main scenario Python script, which records data from when single CDA vehicles send merging requests to the successful merge into the platoon. The data collected includes the merging time, merging distance, speed, and acceleration during the merging of the CDA vehicles. The data were recorded from CARLA directly in the data frame or spreadsheet format, so post-data processing was not required.

5.3.2 Hardware-in-the-Loop Co-simulation

The HIL co-simulation demonstration involves a 5-vehicle CACC platoon. The last vehicle in this platoon was a real vehicle (ego vehicle) and the four vehicles ahead of it are virtual vehicles in the CARLA simulator. During the test, the platoon encounters an obstacle on the road, requiring all vehicles to come to a safe stop. This demonstrates the coordination between the simulated and real-life systems.

5.3.2.1 HIL Configuration

The simulation PC running CARLA was connected to a Cohda Mk6 RSU, which serves as the communication interface as demonstrated in Figure 5-12. The RSU sends target velocity data to the real vehicle using C-V2X. HIL enables testing and validation of CACC platooning at a reduced cost and time while enhancing safety by closely replicating real-world conditions. Additionally, HIL allows the use of external machines to run algorithms in computationally intensive simulation software, eliminating the need for high-performance computing hardware within the actual vehicle. Moreover, when multiple real vehicles are involved, a centralized architecture simplifies the process by avoiding the need to determine which vehicle's computer should handle the simulation.

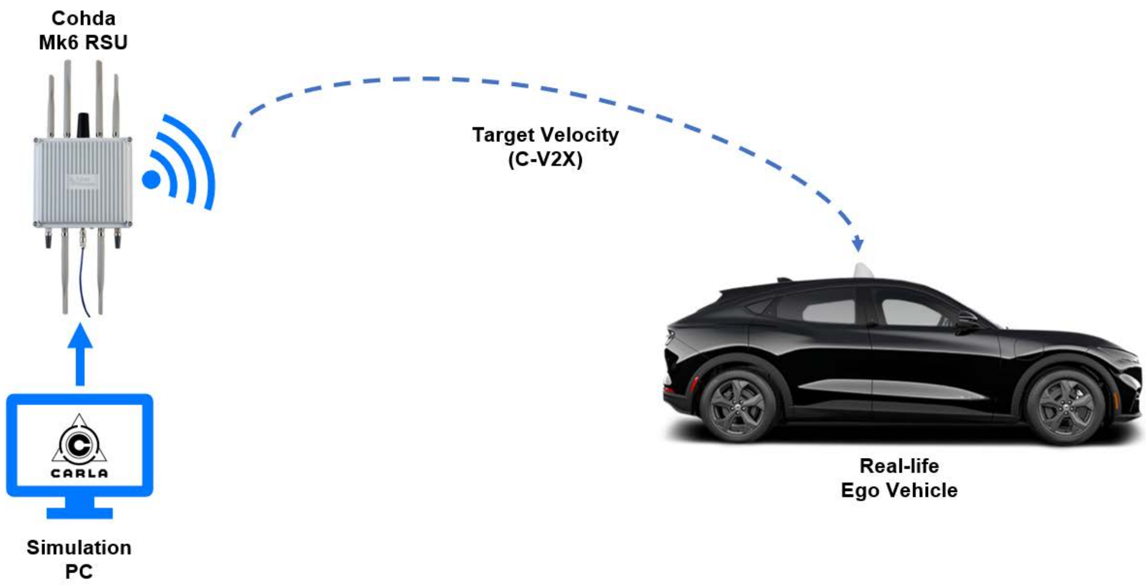


Figure 5-12 High-level HIL co-simulation architecture.

5.3.2.2 Real-life Vehicle Configuration

The real vehicle is equipped with a Cohda Mk6 OBU that receives data from the RSU, as shown in Figure 5-13. The OBU communicates with the real vehicle's PC using serial ethernet. The real vehicle's PC processes the incoming data and sends velocity commands to the Drive-by-Wire Kit, which controls the vehicle's actuation systems.

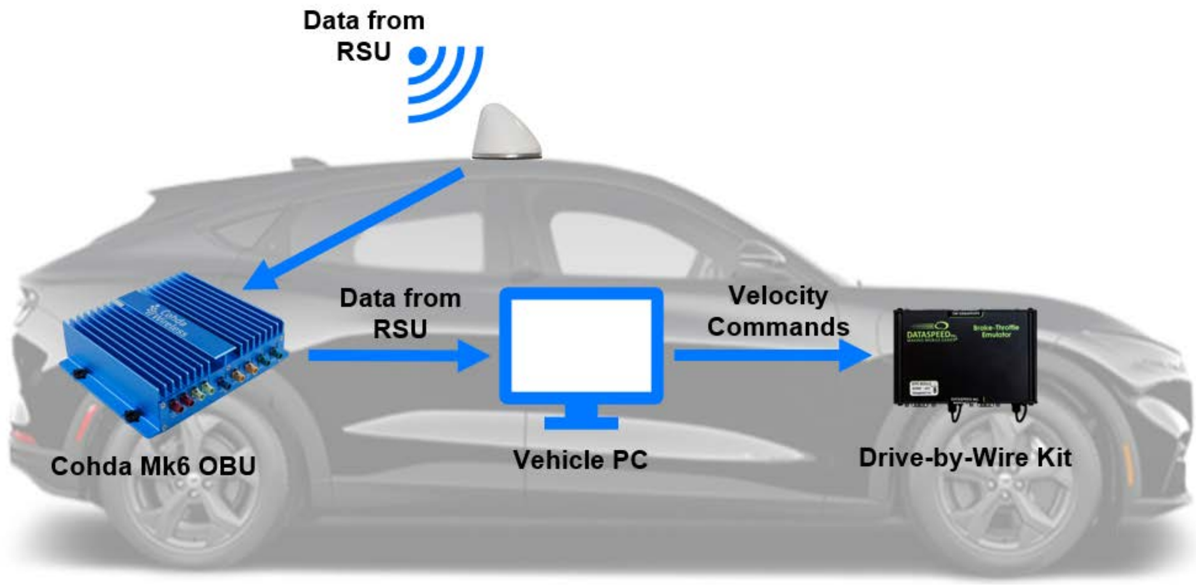


Figure 5-13 Real-life vehicle configuration architecture.

5.4 Results and Discussions

This chapter reports and discusses the results of the analysis performed in this study to demonstrate the use of co-simulation analysis according to the test plan presented in the previous chapter.

In the case of SIL co-simulation, the utilized co-simulation platform is OpenCDA which consists of CARLA and SUMO, in addition to a CDA control platform. First, an initial examination of the feasibility of the use of co-simulation to examine the impacts of the sensors of automated vehicles on vehicle and traffic operations is presented. Then, the results obtained from exercising co-simulation to examine the impacts of CDA operations on individual vehicles and traffic operations at freeway work zones are provided.

In the case of HIL co-simulation, the CARLA simulator and one real vehicle are considered in the simulation. 4 virtual vehicles are involved in the CARLA simulator. The velocity profiles of the real-world vehicle are provided. The real-world vehicle is supposed to track the leader's virtual vehicle's velocity.

5.4.1 Software-in-the-Loop Co-simulation

5.4.1.1 Ability of Co-Simulation to Emulate Vehicle Sensors

This study first examined the ability of co-simulation to simulate automated vehicle sensors under different weather conditions and their utilization in CDA vehicle trajectory settings. This assessment relies on using CARLA's emulation of vehicle sensors.

5.4.1.1.1 Investigation of Sensor Simulation

As explained in the literature review section, CARLA emulates the use of lidar and RADAR sensors to assist vehicles while navigating the roadway and camera sensors for object detection, like perceiving surrounding vehicles and lane marking. This study examined the performance of CDA vehicles equipped with these three sensors with the settings of different time gaps between the following and leading CDA vehicles. By default, the OpenCDA co-simulation platform uses a time gap (the safety time-to-collision [TTC] parameter in OpenCDA) of 4 seconds. This study investigates performance with a time gap setting from 1 1 second to 5 seconds.

Figure 5-14 shows the speed fluctuation of the following vehicle at different time steps to accommodate the slowdown of the leading vehicle if the following vehicle is equipped with lidar only and if the vehicle is equipped with RADAR only.

Figure 5-15 shows the speed fluctuation of the following vehicle at different time steps to accommodate the slowdown of the leading vehicle if the following vehicle is equipped with a combination of lidar and camera sensors.

Table 5-3 shows two summary statistics, which are:

Total Speed Oscillation at the Following State

It is the sum of the absolute deviation between the leader and follower speeds in mph. This statistic sums up the absolute deviations between the leader's and follower's speeds over all simulation seconds, as in the equation:

$$\text{Total Speed Oscillation} = \sum_{i=1}^{N} |V_{leader}(t_i) - V_{follower}(t_i)| \qquad 5\text{-}1$$

Where N denotes the total number of simulation time points, $V_{leader}(t_i)$ denotes the speed of the leader at a time t_i and $V_{follower}(t_i)$ denotes the speed of the follower at a time t_i.

Root Mean Squared Deviation of Follower Speed from Leader Speed

This measure estimates the root mean square of the deviations, giving a measure of how much the follower's speed deviates from the leader's speed on average.

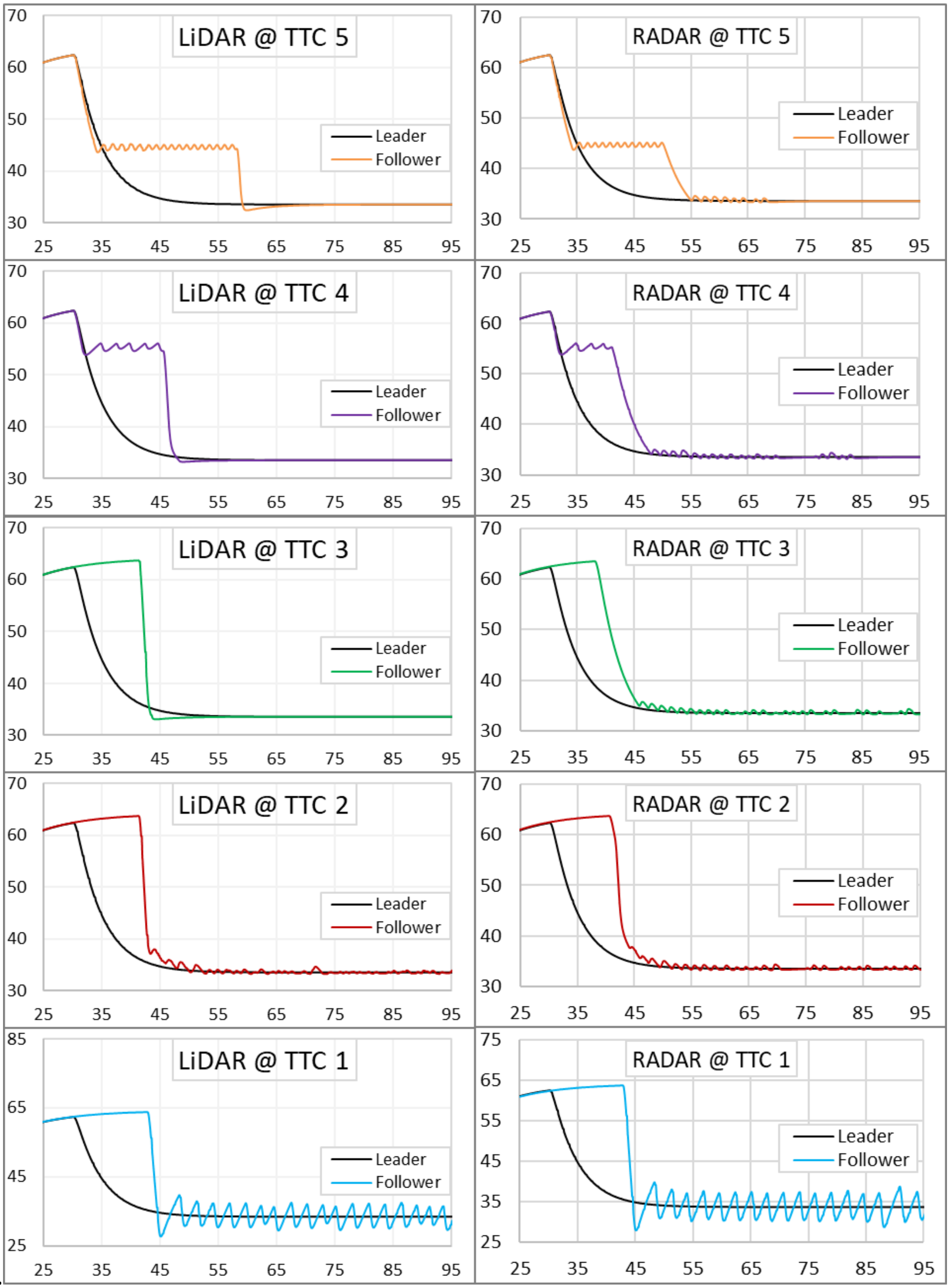
$$\text{RMSD} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(V_{leader}(t_i) - V_{follower}(t_i))^2} \qquad 5\text{-}2$$

Where N denotes the total number of simulation time points, $V_{leader}(t_i)$ denotes the speed of the leader at a time t_i and $V_{follower}(t_i)$ denotes the speed of the follower at a time t_i.

Figure 5-15 indicate that CDA vehicles with CARLA-emulated sensors were able to slow down properly without colliding with the leader CDA and follow the leader vehicle with the specified time gap settings.

In the case of the CDA vehicle with lidar sensor only, the follower vehicle started showing speed oscillation at a time gap of 2 seconds or lower. Higher speed oscillations denote higher instability in the following state. Therefore, this finding verifies that the safety threshold of a time gap of 4 seconds used in the OpenCDA is sufficient for smooth CDA maneuver and following. On the other hand, CDA vehicles with RADAR sensors showed small speed oscillations even at a time gap of 5 seconds. It is interesting to see from Figure 5-14 the significant increase in the oscillations when TTC was decreased from 2 sec to 1 sec with both the lidar and RADAR sensors.

Regarding the total absolute speed oscillation and RMSD measures presented in Table 5-3 the RADAR sensor resulted in higher oscillations than the lidar sensor. The best sensor combination was observed with lidar and camera, which resulted in a smooth car-following state for the follower vehicles even at a 1-sec gap, as indicated in Table 5-3 and Figure 5-15.



For all the above graphs: x-axis = Simulation seconds; y-axis = Speed, mph

Figure 5-14 Speed profile of leader and follower vehicles with lidar and RADAR at different time gap values.

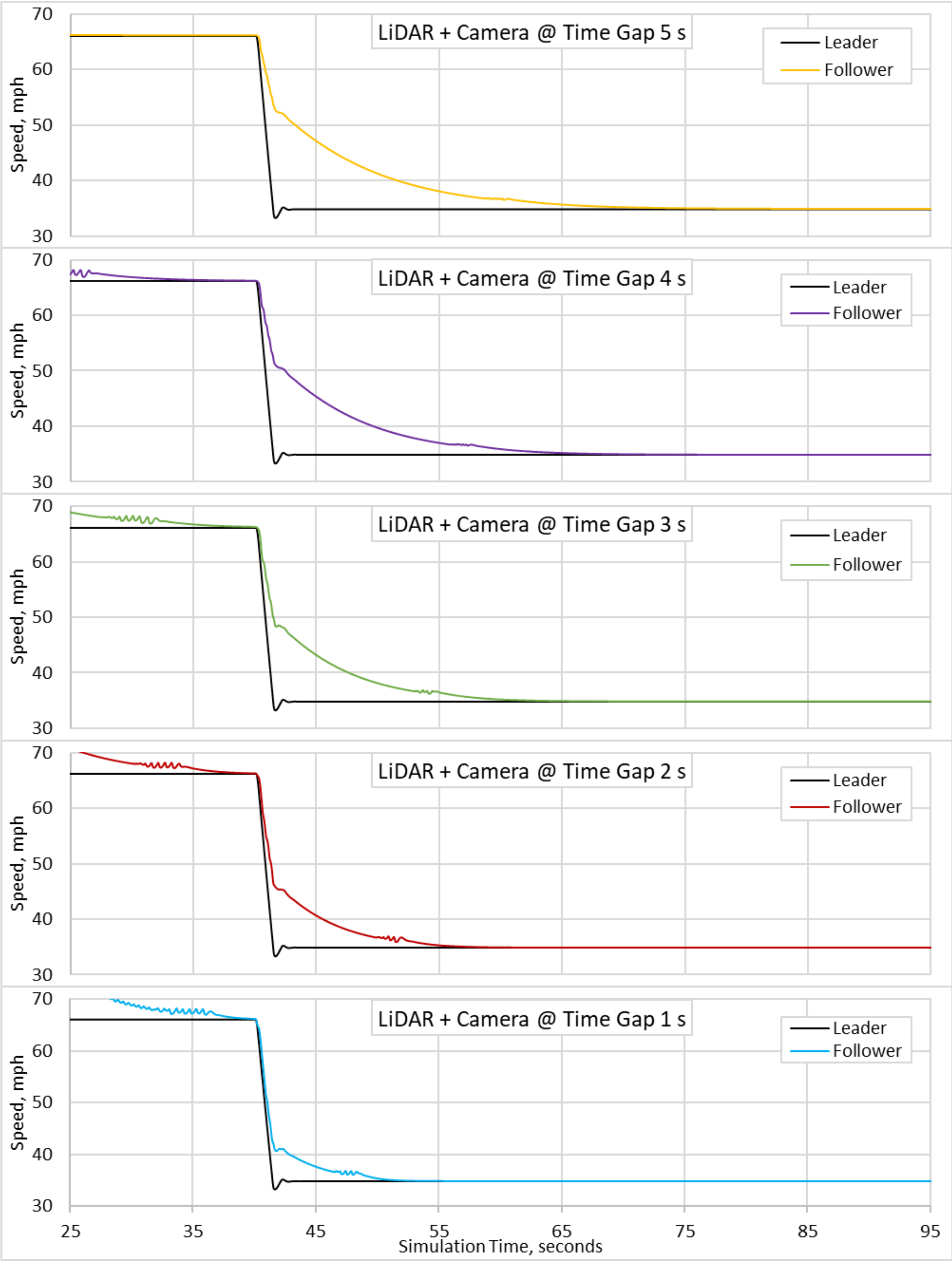


Figure 5-15 Speed profile of leader and follower vehicles with lidar + camera combination at different time gap values.

Table 5-3 Speed deviation of the follower CDA from leader CDA during the following state after adjusting speed to the leader.

Scenario	Total Speed Oscillation at Following State, mph	RMSD	Reaction Time (sec.)
Lidar with Time Gap 5 s	0.00	0.00	27.70
RADAR with Time Gap 5 s	34.96	0.09	20.60
Lidar+Camera with Time Gap 5 s	0.00	0.00	0.20
Lidar with Time Gap 4 s	0.00	0.00	15.80
RADAR with Time Gap 4 s	62.23	0.12	10.70
Lidar+Camera with Time Gap 4 s	0.00	0.00	0.20
Lidar with Time Gap 3 s	0.00	0.00	10.90
RADAR with Time Gap 3 s	289.39	0.27	8.60
Lidar+Camera with Time Gap 3 s	0.00	0.00	0.15
Lidar with Time Gap 2 s	205.48	0.44	10.90
RADAR with Time Gap 2 s	289.10	0.26	10.20
Lidar+Camera with Time Gap 2 s	0.00	0.00	0.15
Lidar with Time Gap 1 s	2166.90	1.42	12.50
RADAR with Time Gap 1 s	2779.35	2.51	12.40
Lidar+Camera with Time Gap 1 s	0.00	0.00	0.15

Table 5-3 provides another important parameter, reaction time, which is the time difference between the time the lead vehicle started reducing speed and the time the follower vehicle started reducing speed to follow the leading vehicle. It was observed that the follower vehicle equipped with only a lidar sensor showed the highest reaction time among other sensor scenarios, such as with RADAR only and lidar with the camera.

5.4.1.1.2 Investigation of Weather Impact on Simulated Sensors

This study compared the impact of weather on sensor performance. The weather impacts were investigated by 1) modifying the weather parameters in CARLA, or 2) modifying the sensor's detection range using the findings of previous studies that investigated the impact of weather on sensors using real-world data.

Figure 5-16 shows the impacts of weather on CARLA sensors, as assessed by the following vehicle speed. The Sunny scenario is used as the base weather condition. Details of the other weather conditions are provided in Table 5-2.

Figure 5-16 shows that changing the weather parameters in CARLA does not show any significant impact on the follower CDA-equipped vehicle trajectory for both sensors with RADAR and lidar. However, adjusting the sensor's detection range to reflect the weather conditions as per previous studies from Table 5-2 shows substantial impacts. With RADAR, when adjusting the sensor parameters in CARLA, the follower vehicle detected the leader vehicle and started following the leader at 32.60 simulation seconds under Sunny conditions. In contrast, the follower started the car-following state at 33.90 seconds and 34.90 seconds for Foggy and Rainy conditions, respectively. This indicates that in rainy weather, the follower started following the leader 2.3 seconds or 151.93 ft later compared to sunny weather. In foggy conditions, the distance was 1.3 seconds or 80.64 ft later than sunny conditions. With lidar, it was observed that the follower detected the leader in Rainy conditions and started following at 1.5 seconds or 122.93 ft later compared to the sunny conditions. In summary, adverse weather conditions delayed the follower vehicle's response to the slowdown of the leading vehicle.

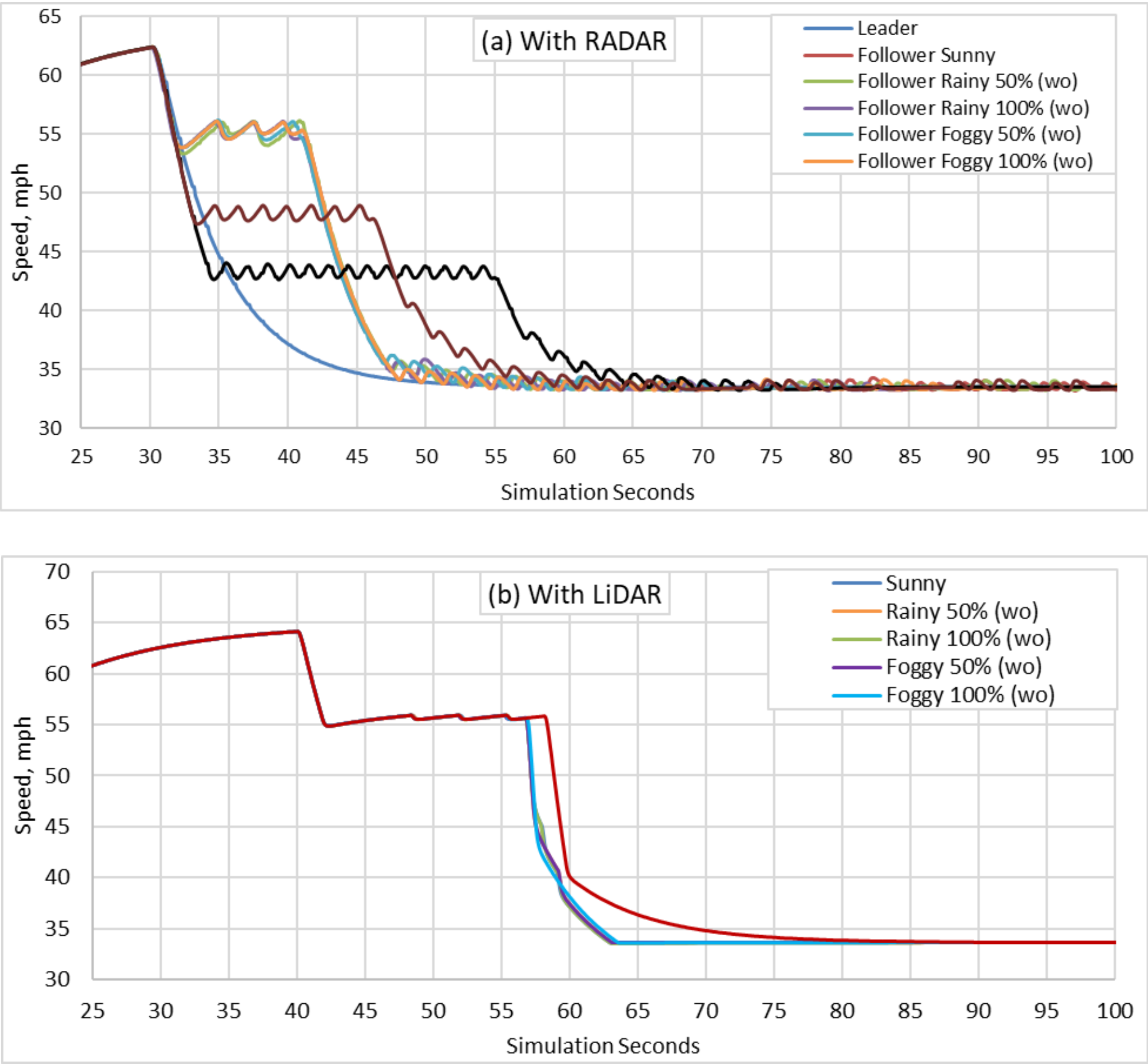


Figure 5-16 Speed profile of follower CDA vehicle at different weather conditions at time gap 4 seconds.

5.4.1.1.3 Merging Maneuver Checking

In this report, the use case considers a lane blockage in the vicinity of a work zone, which required mandatory lane changes for CDA vehicles from blocked lanes to merge into platoons in the adjacent lane. Therefore, it is essential to study the capability of the co-simulation platform to perform proper merging maneuvers from a blocked lane. OpenCDA has three merging approaches: front join, cut-in (from the side) join and back join. All three merging approaches were verified to work correctly in this study without causing collisions between vehicles. From the speed profile, it was found that the merging CDA vehicle either sped up or slowed down to come to a particular location from the platoon and then changed lanes to merge into the platoon. No abrupt behavior was observed. From the distance from the leader, it was noticed that all CDA vehicles maintained sufficient safe distances among them.

5.4.1.2 Impact on General Traffic

This section provides the results of using co-simulation to evaluate the impact of CDA operations on the general traffic, with the merging of single CDA vehicles from the blocked lane to platoons in the adjacent lanes. The analyses focused on the impact of the V2V communication distance (the distance at which the vehicles are instructed to start communicating with the purpose of joining the platoon), weather variations, market penetration of CDA-equipped vehicles, and the start of merging ahead of the work zone.

5.4.1.2.1 Impact of V2V Communication Distance

Figure 5-17 and Table 5-4 present the change of the traffic speed in sunny weather with 5% of CDA vehicles in the traffic compared to the base condition (no CDA vehicle in the traffic) with two V2V communication distances, which are 115 ft and 500 ft. The total demand, including CDA and HVs, is set at 3,000 vph. The x-axis denotes the location of the speed data collection points along the freeway segment, starting from 3 miles upstream of the lane closure point because of the work zone to the end of the work zone. The y-axis represents the percentage change in speed with respect to the base condition.

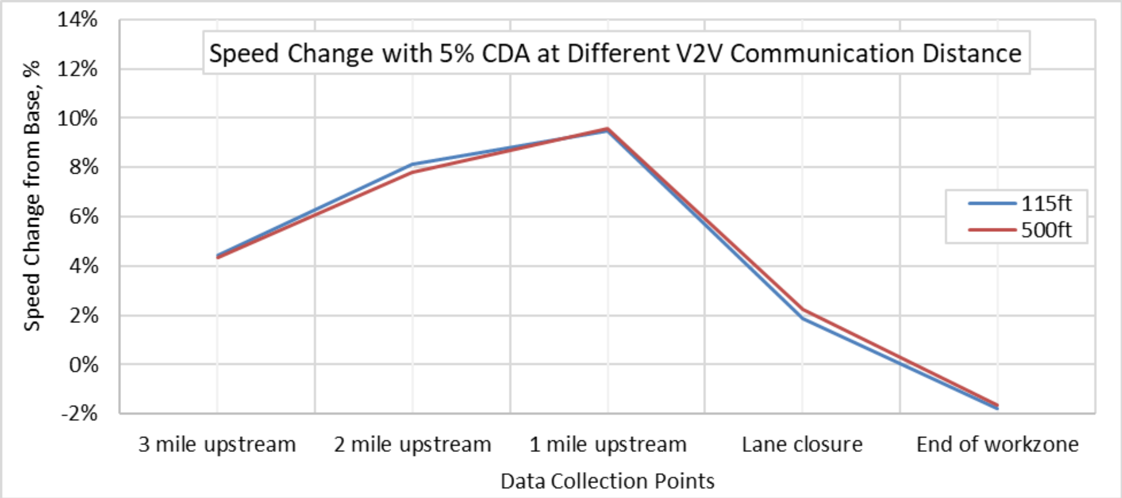


Figure 5-17 Speed change from base condition at different v2v communication distances with 5% CDA of the total traffic.

Table 5-4 Speed at different CDA penetration and v2x communication distance

V2X Communication Distance	CDA %	CDA Demand, vph	Data Collection Point	Speed, mph	Speed Change from Base, %
N/A (base)	0	0	3 mile upstream	61.51	0.0%
115ft	5	150	3 mile upstream	64.22	4.4%
500ft	5	150	3 mile upstream	64.18	4.4%
115ft	10	300	3 mile upstream	64.28	4.5%
500ft	10	300	3 mile upstream	64.22	4.4%
N/A (base)	0	0	2 mile upstream	59.21	0.0%
115ft	5	150	2 mile upstream	64.03	8.1%
500ft	5	150	2 mile upstream	63.84	7.8%
115ft	10	300	2 mile upstream	64.61	9.1%
500ft	10	300	2 mile upstream	64.11	8.3%
N/A (base)	0	0	1 mile upstream	57.80	0.0%
115ft	5	150	1 mile upstream	63.28	9.5%
500ft	5	150	1 mile upstream	63.34	9.6%
115ft	10	300	1 mile upstream	63.98	10.7%
500ft	10	300	1 mile upstream	63.92	10.6%
N/A (base)	0	0	Lane closure	50.65	0.0%
115ft	5	150	Lane closure	51.59	1.8%
500ft	5	150	Lane closure	51.79	2.2%
115ft	10	300	Lane closure	52.61	3.9%
500ft	10	300	Lane closure	52.47	3.6%
N/A (base)	0	0	End of workzone	54.10	0.0%

Table 5-4 continued

115ft	5	150	End of workzone	53.14	-1.8%
500ft	5	150	End of workzone	53.21	-1.6%
115ft	10	300	End of workzone	53.50	-1.1%
500ft	10	300	End of workzone	53.28	-1.5%

The speed increase at different V2V communication distances with 10% CDA penetration is shown in Figure 5-18. This graph shows a similar trend of speed enhancement compared to the lower CDA percentage. It was observed that the traffic speed increased with the incorporation of the CDA vehicles and was the highest (about 9.6% and 10.6% increase with 5% and 10% CDA vehicles, respectively) at one mile upstream of the work zone with 5% CDA vehicles. In addition, it was found that the speed change was close for a V2V communication distance of 500 ft compared to 115 ft.

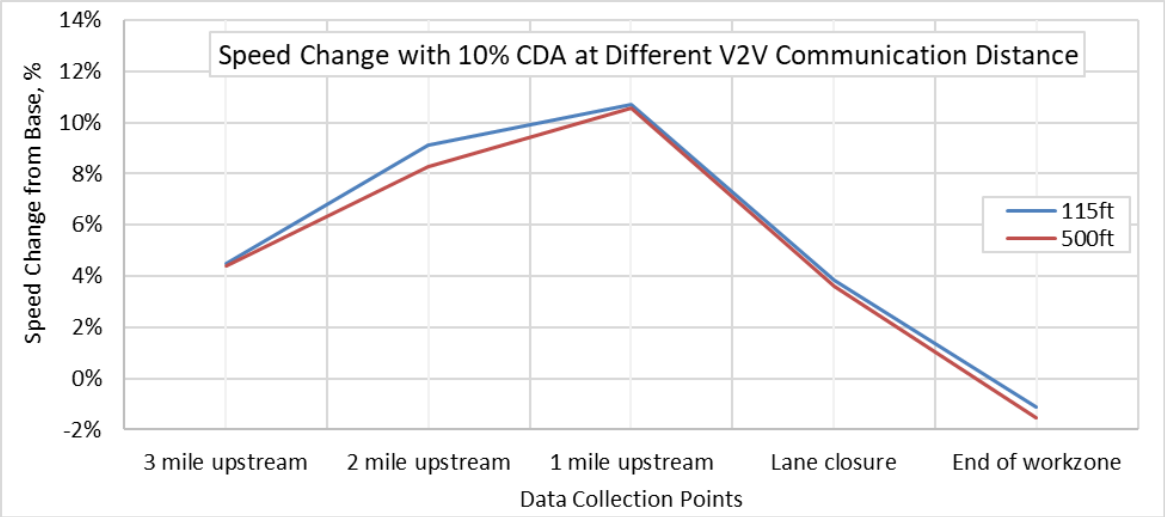


Figure 5-18 Speed change from base condition at different V2V communication distances with 10% CDA of the total traffic.

From the animation simulation, it was observed that sometimes with the higher CDA penetration with the 500 ft communication distance, HVs from the adjacent lane (left lane) compete with the single CDA vehicle on the right lane to occupy the gap opened in the platoon traveling in the middle lane. In these cases, the merging CDA vehicle needs to start the merging process again to finally merge into the platoon.

5.4.1.2.2 Impact of Weather Variation

Table 5-5 and Figure 5-19 illustrate the speed change with the 10% CDA vehicles in the traffic stream compared to the base conditions (without a CDA vehicle) under five different weather conditions. Details of these five investigated weather conditions are described in Table 5-2, and brief definitions of these conditions are:

1. Sunny: a sunny day with default sun angle and lidar range,
2. Rainy (wo): rainy weather with adjusted weather parameters only to reflect 50 mm/hr real-world rainfall,
3. Rainy (w+s): rainy weather with both adjusted weather parameters and reduced lidar detection range to reflect 50 mm/hr real-world rainfall.

The results in Table 5-5 show only a small decrease in speed due to changing weather and lighting conditions.

Table 5-5 Variation of speed at different weather conditions

Weather Conditions	Data Collection Point	Speed, mph	Speed Change from Base, %
N/A (base)	3 mile upstream	61.51	0.00%
Sunny	3 mile upstream	64.28	4.51%
Rainy (wo)	3 mile upstream	64.27	4.50%
Rainy (w+s)	3 mile upstream	64.27	4.49%
N/A (base)	2 mile upstream	59.21	0.00%
Sunny	2 mile upstream	64.61	9.12%
Rainy (wo)	2 mile upstream	64.63	9.15%
Rainy (w+s)	2 mile upstream	64.62	9.13%
N/A (base)	1 mile upstream	57.80	0.00%
Sunny	1 mile upstream	63.98	10.69%
Rainy (wo)	1 mile upstream	63.96	10.66%
Rainy (w+s)	1 mile upstream	63.93	10.60%
N/A (base)	Lane closure	50.65	0.00%
Sunny	Lane closure	52.61	3.86%
Rainy (wo)	Lane closure	52.54	3.72%
Rainy (w+s)	Lane closure	52.56	3.77%
N/A (base)	End of workzone	54.10	0.00%
Sunny	End of workzone	53.50	-1.11%
Rainy (wo)	End of workzone	53.44	-1.21%
Rainy (w+s)	End of workzone	53.46	-1.19%

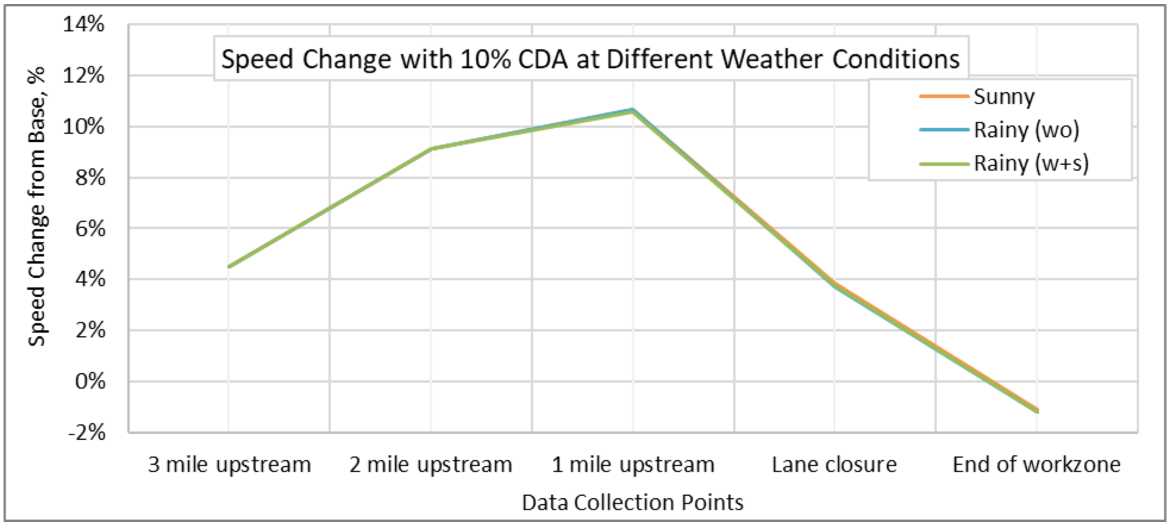


Figure 5-19 Analyzing the impact of weather conditions on CDA-enabled traffic flow.

5.4.1.2.3 Impact of Merging Advisory Distance

This study investigated the impact of two merging advisories– an early merge, implemented 3 miles upstream of the work zone, and a late merge, implemented at 1 mile upstream of the work zone– with 5%, 10%, and 20% market penetration of the CDA equipped vehicles. Figure 5-20 and Table 5-6 present the effects of different merging advisory distances with varying market penetration of CDA vehicles in sunny weather conditions with 115 ft V2V communication distance and 3,000 vph demand.

The results indicate that the overall speed of traffic increased with higher CDA market penetration, reaching a 17.59% improvement. A significant speed increase was observed in the late merge scenario as the CDA penetration rate rose from 10% to 20%. The traffic speed increased from 10.91% to 17.59% when transitioning from early to late merge. This improvement could be attributed to the higher prevalence of CDA vehicles at 20% penetration. It appears that the late merge strategy with the increased market penetration allows CDA vehicles to fully utilize the closed lane up to the merging point, increasing the number of gaps available in the right lane for the merging of the HV vehicles. With the increase in the market penetration of CDA, there will be more opportunity for the single CDA vehicles to cooperate with platoons on adjacent lanes and thus, one mile ahead of the work zone is sufficient for this purpose under the investigated demand level.

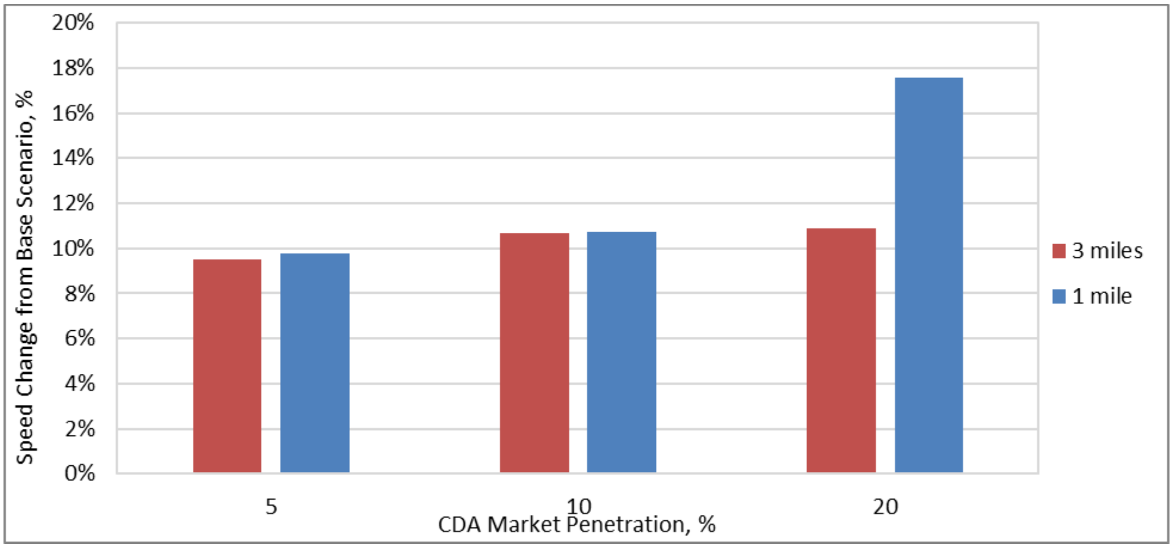


Figure 5-20 Increase of speed at different merging advisory.

Table 5-6 Impact of merging advisory distance and higher penetration on speed.

Merging advisory, mile	CDA %	Speed, mph	Speed Change from Base, %
N/A (base)	0	57.80	0.00%
3	5	63.28	9.49%
1	5	63.46	9.80%
3	10	63.98	10.69%
1	10	63.99	10.70%
3	20	64.11	10.91%
1	20	67.97	17.59%

5.4.1.3 Oscillations during Merging at Work Zone

This section describes the results obtained to evaluate the speed fluctuation and acceleration of the merging vehicle for the last 200 ft distance ahead of the merging point.

5.4.1.3.1 Impact of Market Penetration and Communication Range

Figure 5-21 illustrates the acceleration and speed fluctuations of the merging CDA vehicles in the last 200-ft distance ahead of the merging point under different CDA market penetrations and V2V communication distances at 5% CDA penetration and 3,000 vph demand level. Here, the x-axis denotes the distance to merge, while the y-axis presents acceleration and speed during the merge. Figure 5-21 indicates that the merging vehicle experienced more acceleration and speed fluctuations with shorter V2V communication distances (115 ft). The shorter communication distance resulted in more frequent and abrupt adjustments in the merging vehicle's speed, potentially leading to greater instability. Although the impact on traffic performance with the investigated demand (3,000 vph) is small, as indicated in the previous section, it is expected that a more significant impact on the communication distance on traffic performance could occur at higher demand levels. The longer V2V communication distances (500 ft) generally resulted in smoother speed fluctuations, especially at lower CDA market penetrations. This observation suggested that longer communication distances provided more time for the merging CDA vehicles to adjust their speeds and coordinate with other CDA vehicles of the CDA platoon, leading to a more stable merging process. The RMSD values of speed and acceleration, as per equation 4, provide a quantitative measure of the impact of the V2V communication range. At lower CDA market penetration (5%), increasing the V2V communication range from 115 ft to 500 ft reduced the speed variation in terms of RMSD from 3.25 to 0.43 and acceleration variation in terms of RMSD from 2.72 to 1.31, respectively.

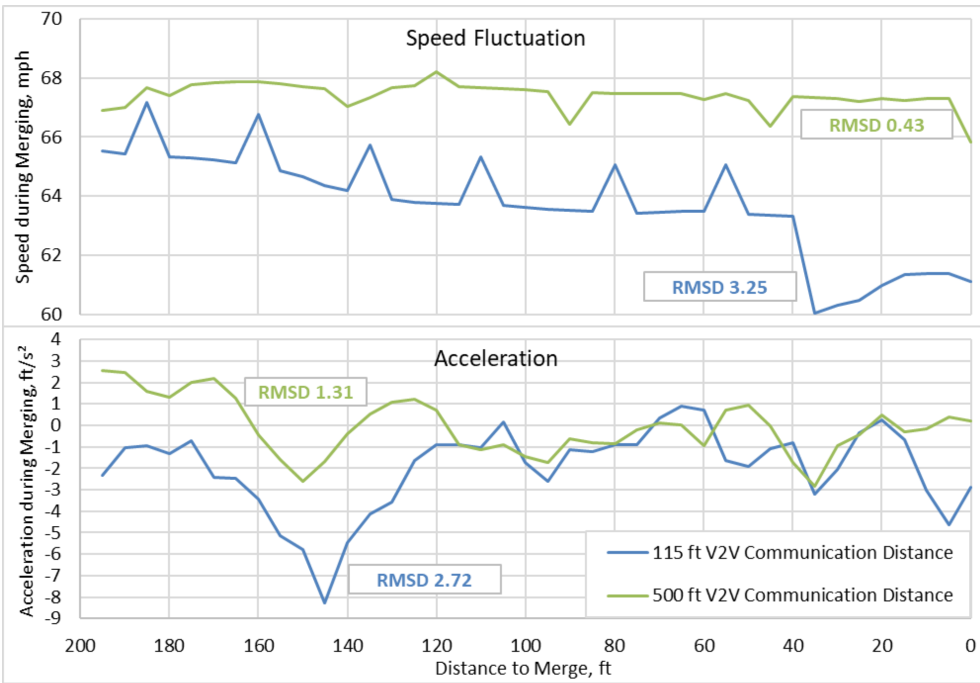


Figure 5-21 Acceleration and speed fluctuation of merging vehicles in the last 200 ft before merging points at different V2V communication distances at 5% CDA penetration.

However, the opposite behavior was observed with the higher CDA market penetration. Figure 5-22 depicts the acceleration and speed variations of merging vehicles during the last 200 feet of the merging point under different V2V communication distances at 10% CDA market penetration.

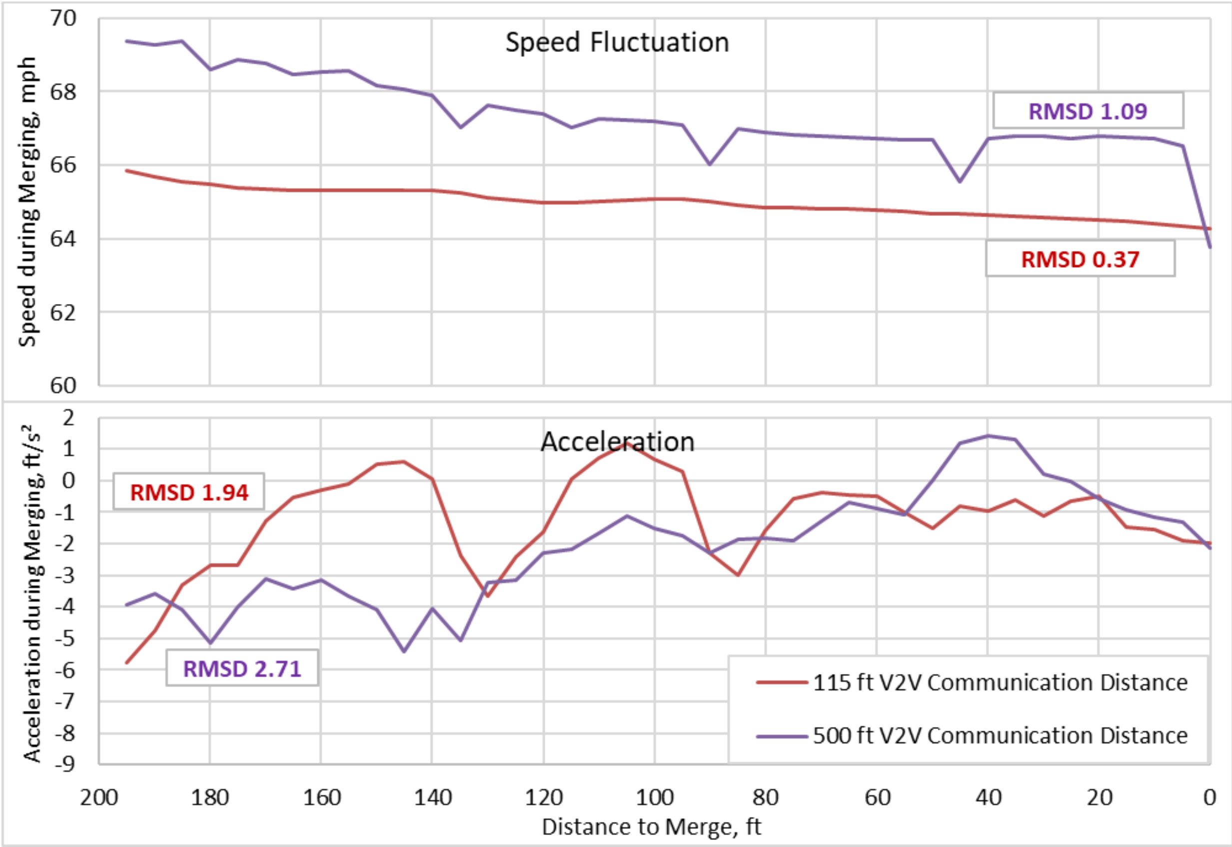


Figure 5-22 Acceleration and speed variation of merging vehicles before the last 200 ft of merging point at different V2V communication distances at 10% CDA market penetration.

From the simulation animation, it was observed that, with a 500 ft V2V communication distance, the merging CDA vehicles would immediately attempt to change lanes to join the CDA platoon lane as soon (as they came within 500 ft of the platoon.) The merging vehicle traveled some distance in the platoon's lane to get closer before joining the platoon. However, this maneuver created an initial 500 ft gap between the merging vehicle and the platoon immediately after the single CDA vehicle changed lanes to merge. In most cases, the HVs from adjacent lanes switched lanes—either from the left or right—into the middle lane, occupying the initially created 500 ft gap. As a result, the merging vehicle encountered an obstruction posed by the HVs before it could join the platoon. Consequently, the merging vehicle needed to change lanes again, either left or right, to overtake the HVs before switching lanes once more to join the platoon. This scenario was particularly common with a 500 ft V2V communication range and became more frequent at a 10% CDA vehicle penetration rate. Therefore, speed oscillations and acceleration fluctuations were comparatively higher under conditions with a 500 ft V2V communication distance and 10% CDA vehicle penetration. A solution to this would be to change the control algorithm to eliminate the attempt to join the platoon once the single CDA vehicle is already in the target lane. This will be attempted in future efforts.

5.4.1.3.2 Impact of Weather Variation

The speed and acceleration fluctuations of the merging single CDA vehicles at different weather conditions (see Table 5-2 for the description of the weather conditions) are illustrated in Figure 5-23, and the corresponding RMSD values are provided in Table 5-7. It was observed that in sunny weather conditions, the vehicle performs the best merging behavior in terms of acceleration fluctuation and maintains steady speed reduction while merging.

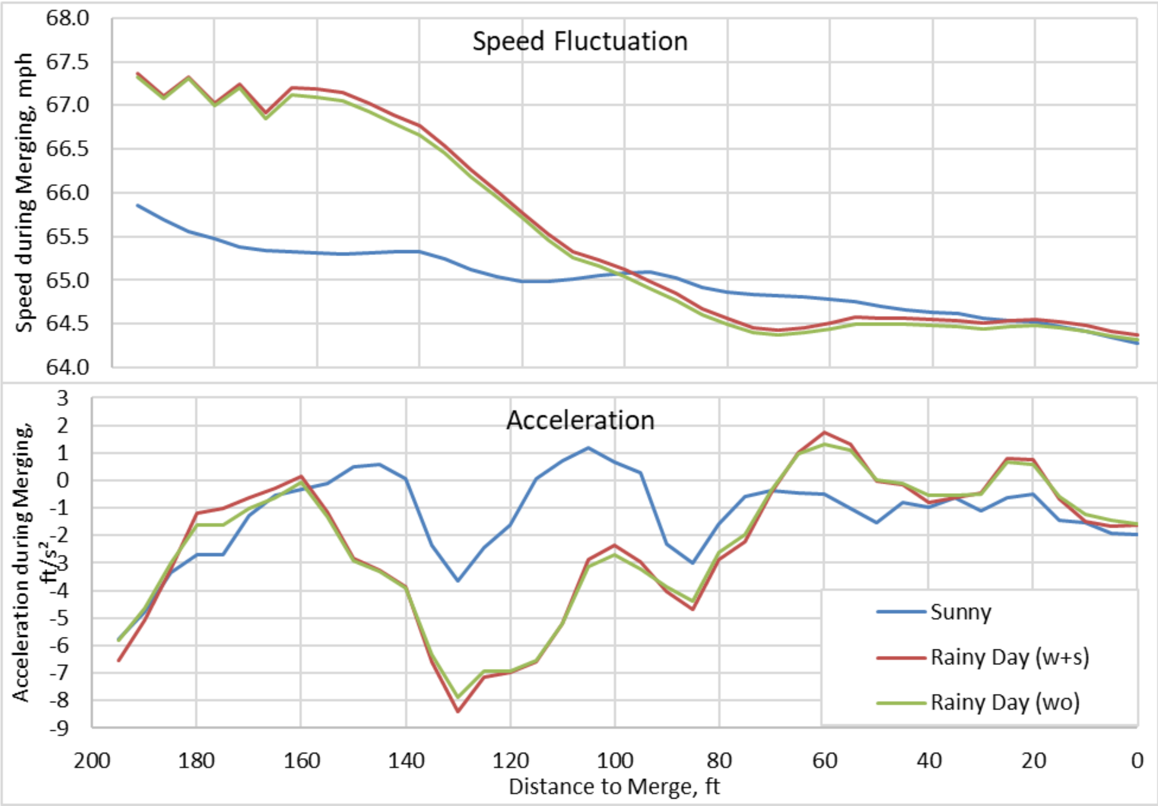


Figure 5-23 Acceleration and speed fluctuation of merging vehicle for last 200 ft before the merging point at different weather variation.

Unstable merging maneuvers are observed in rainy conditions during the day. The acceleration graphs show that merging vehicles performed abrupt acceleration and deceleration during merging with "Rainy Day (w+s)" condition, reaching the highest deceleration of 8.41 ft/s², where the highest deceleration was 5.78 ft/s² for sunny weather.

Table 5-7 RMSE of speed and acceleration fluctuation of the merging vehicle at different weather.

Weather Conditions	Speed RMSD	Acceleration RMSD	Maximum Deceleration, ft/s^2
Sunny	0.374	1.943	5.78
Rainy Day (wo)	1.134	3.392	7.88
Rainy Day (w+s)	1.133	3.503	8.41

5.4.2 Hardware-in-the-Loop Co-simulation

HIL integrates the OBU, RSU, CARLA simulator, and a real vehicle to create a co-simulation environment for testing and validating CACC-based vehicle platooning algorithms. In this system, the CARLA simulator manages virtual vehicles, while the real vehicle communicates with the simulator via a C-V2X connection facilitated by the RSU and OBU. The following insights were derived from the test results:

- **Event Delay:** Communication delay is one of the key observations noted during the HIL test. This communication delay is primarily caused by network latency during data transfer, the processing time required by both the real vehicle and the simulator, and the response time limitations of hardware components such as the driver-by-wire kit and the actuator. These factors contribute to delays in the real-time interaction between the physical and virtual systems. When conducting HIL co-simulation, it is important to closely monitor these delays to ensure they remain within tolerable limits for the specific test being performed.
- **Mimicking Target Velocity:** The real vehicle was unable to perfectly match the target velocity (please see Figure 5-24). This is due to unmodeled dynamics in the CARLA simulator, communication delays between the real vehicle and the CARLA simulator, and truncation of the control signal sent to the vehicle's actuators from the drive-by-wire kit. In this context, the target velocity refers to the velocity of the virtual leader vehicle in the platoon.

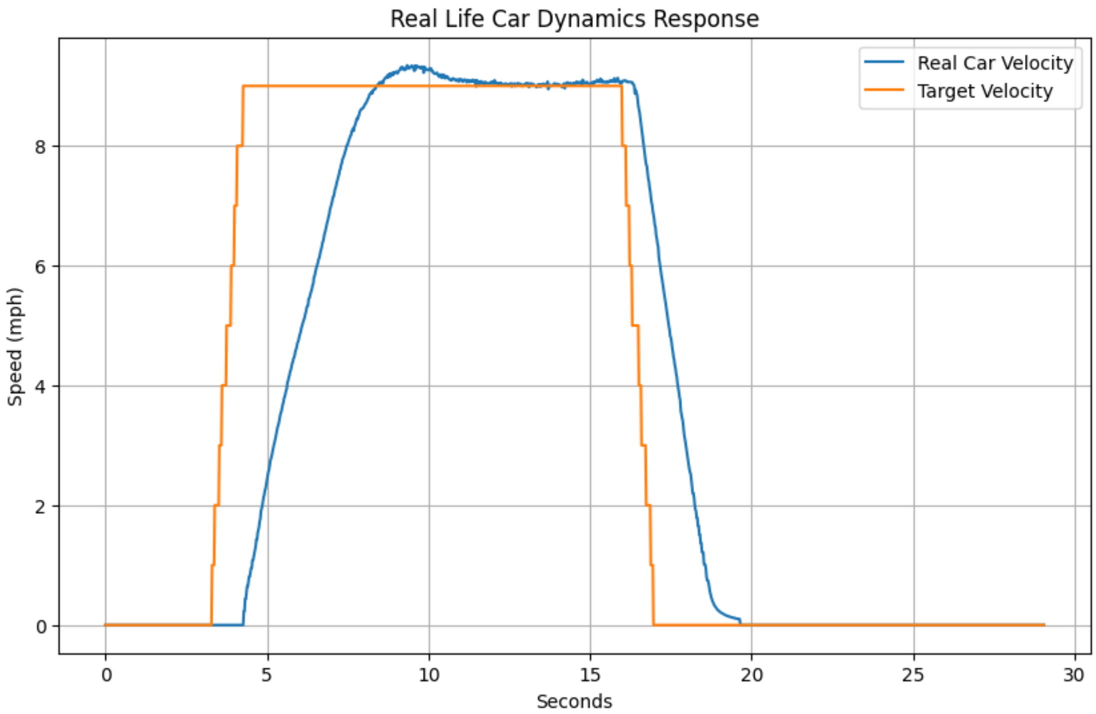


Figure 5-24 The deviation between the target and achieved velocities of the real-life vehicle.

6 Summary and Recommendation

6.1 Summary

The project started by conducting a systematic review of the existing literature on CDA sensing technologies. In addition, the research team hosted several stakeholder meetings to identify gaps in existing CDA vehicle technologies and infrastructure features by discussing critical questions. The literature review and stakeholder discussions indicate that as CDA technology evolves, infrastructure must adapt for safe and efficient operations. Initially, it should support both CDA and human-driven vehicles with consistent visibility and reliable sensors. As adoption increases, dedicated infrastructure, including advanced communication devices and sensor networks, enhances safety and fuel efficiency. In the mature phase, advanced systems can replace or simplify existing components. Stakeholders also emphasized the need for field experiments, such as platooning and pedestrian interactions, to guide future developments.

6.1.1 Evaluation of CDA Vehicle Sensing Technologies

The research team evaluated automated vehicle (AV) sensing functions and identified several performance limitations. Cameras effectively detected traffic signs, lane markings, and traffic lights, but performance degraded at night and was hindered by obstructions, fading signs, unclear markings, and curved roads. Lidar struggled with elevated traffic light detection but excelled in detecting stop signs across different conditions. Traffic light detection via V2X technology proved less reliable than camera-based systems, which also faced occasional inaccuracies. Collision avoidance systems (e.g., Forward, Blind-Spot, and Rear Cross-Traffic Detection) relied on radar and cameras, with performance generally better during the day due to camera limitations in low-light conditions. Adaptive Cruise Control (ACC) with Stop & Go functions demonstrated reliable daytime performance, aided by multi-sensor fusion, but rain and low visibility impacted cameras and radar. Full Self-Driving systems utilizing multiple cameras handled diverse driving scenarios with robust performance under all lighting conditions. C-V2X communication tests revealed a non-linear relationship between packet error rate (PER) and inter-packet gap (IPG) with distance, influenced by environmental urban structures.

6.1.2 Evaluation of Infrastructure Features for CDA Sensing

The compatibility of current infrastructure with CDA sensing is also investigated, identifying elements that hinder effective vehicle detection or connectivity. This includes lane marking, static signs, and traffic signals.

Lane Markings: The study reveals significant challenges in lane detection for commercial vehicles under conditions such as unclear markings, curves, merging and diverging lanes, rainy days, and nighttime.

Static Message Signs: The research identifies key factors impacting traffic sign detection performance, including obstruction, fading, dirt, rainy days, and nighttime.

Traffic Signal: The interaction between vehicles and traffic signals highlights the need for infrastructure improvements to optimize detection and communication capabilities.

Dynamic Traffic Message Signs were not evaluated due to the inability of tested commercial and lab vehicles to interact with them, though future evaluations may be possible with technological advancements. The research team acknowledges certain limitations, including the use of smartphones for scene capture, which may not accurately represent low-light or nighttime conditions due to automatic lighting adjustments. Additionally, the scope of testing is limited and not exhaustive, emphasizing that partial successes, such as detecting lanes in 4 out of 10 tests, should not be interpreted as a definitive accuracy rate.

6.1.3 Platooning Field Experiment Design Guideline

The Platooning Field Experiment Design Guideline provides a structured approach for planning and conducting freeway platooning experiments. It begins by outlining key objectives, such as testing vehicle-to-vehicle (V2V) communication efficiency, evaluating the impact of infrastructure on platooning, and assessing safety and performance metrics. The document emphasizes the importance of selecting appropriate experimental variables, including independent factors like platoon size and inter-vehicle distance, dependent metrics such as fuel consumption and safety indicators, and control variables to maintain test consistency.

The guideline details the selection of a suitable test environment, emphasizing controlled freeway segments with diverse road conditions. It highlights vehicle and equipment preparation, ensuring all test vehicles are equipped with necessary sensors, communication devices, and automated driving features. Calibration and data collection mechanisms are crucial for capturing accurate measurements of vehicle dynamics, environmental factors, and communication efficiency. Additionally, structured test scenarios are recommended, incorporating varied traffic conditions, merging and demerging maneuvers, and randomized executions to enhance result reliability.

Safety protocols and risk management strategies form a critical component of the guidelines. The document stresses the need for thorough safety assessments, driver roles in emergencies, and clear communication procedures. Post-experiment analysis, including data processing, statistical evaluations, and validation through simulations, ensures comprehensive insights. The guideline also underscores regulatory compliance, ethical considerations, and continuous improvement through iterative testing, making it a valuable resource for advancing freeway platooning research.

6.1.4 Co-Simulation Use to Support Testing

The co-simulations are conducted at SIL and HIL levels. The literature review indicates the interest and potential for the use of both software-in-the-loop simulation and hardware-in-the-loop simulation in the testing. Two open-source software-in-the-loop co-simulation platforms, CARMA and OpenCDA, were investigated for use in this study. The CARMA XIL platform was first selected, but the research team faced difficulty in addressing the issues with the platform considering the time frame of the project. Thus, an alternative open-source platform

(OpenCDA) was selected for this study.

Next, to demonstrate the use of co-simulation in testing CDA applications at the SIL level, this study developed a detailed test plan for a use case involving CDA vehicles approaching a freeway work zone, developed following IEEE standards. The test plan includes a description of the use case, tested units, operational design domain, selected performance metrics, test scenarios, and test procedures. The case focuses on merging maneuvers of single CDA-equipped vehicles into either a CDA platoon or a traffic stream of HVs in the vicinity of a freeway work zone. The impact of various factors—including weather conditions, V2V communication distance, merging advisory distances, and CDA market penetration—on both traffic-level and vehicle-level performance was investigated. The application of the test plan to the use case illustrates the ability of the selected co-simulation platform to evaluate CDA and its impacts on traffic-level and vehicle-level measures.

The study examines the ability to simulate the detection ranges of different types of sensors, showing that when specifying the same detection range of lidar and RADAR in the input to CARLA, a follower CDA vehicle with a simulated RADAR responded earlier than a follower with lidar. A follower CDA vehicle with a combination of camera and lidar allowed the fastest response when compared with followers equipped with lidar only or RADAR only. Merging is also the smoothest when the follower vehicles are equipped with lidar and a camera compared to the other two alternatives. This study also investigated if the impact of weather on sensor performance could be simulated by the platforms. The weather impacts were investigated using two alternatives: 1) modifying the weather parameters in CARLA, or 2) modifying both the weather impacts in CARLA and the sensor's detection range input to CARLA based on the findings of previous studies that investigated the impact of weather on sensors using real-world data. The differences in car following performance were observed with the second alternative but not the first. For example, the follower started following the leader 2.3 seconds or 151.93 ft later with RADAR and 1.5 seconds or 122.93 ft later with lidar compared to the sunny conditions later compared to sunny weather. The above indicates that the RADAR was more impacted than the lidar by rain. This is interesting since the percentage reduction in the sensor range specified in the input to CARLA was higher. This needs to be investigated.

The results indicate that the penetration rate of CDA vehicles significantly affected the traffic-level measures as indicated by the average traffic speed. Higher CDA penetration led to higher average speeds. The impact is expected to be even higher with increasing the traffic demand beyond the traffic demand investigated in this study.

For a given CDA penetration rate, the V2V communication distance did not substantially influence overall traffic performance but did have an impact on individual vehicle behavior, specifically in terms of speed and acceleration measures, which reflect vehicle oscillations that can impact traffic performance in terms of traffic-based measures (with higher demands) and safety.

In the study, two merging strategies—early merge and late merge—were tested to assess the impacts of these strategies on the performance. The results showed that the late merge strategy was more effective at improving overall traffic flow speed, with the highest investigated market penetration (20%). This improvement with late merge could be attributed to higher proportions of platoons allowing CDA vehicles to merge later in into these platoons and increasing the number of gaps available in the right lane for the merging of the HV vehicles.

When setting the communication distance at which the single CDA vehicles started communicating with the platoons, it appears that there is an optimal distance that reduces the number of oscillations depending on the market penetrations of CDA vehicles.   A travel behavior was observed with OpenCDA where CDA vehicles change in and out of the lane that has the platoon to merge into the platoon due to the competition with HV on occupying the gaps in the lane that has the platoon.   This appears to be due to OpenCDA treatment of this situation and indicates the need to reexamine and potentially fix this treatment.

Furthermore, HIL co-simulation is also conducted. In the HIL co-simulation setup, a CARLA simulation PC is connected to a Cohda Mk6 RSU, which transmits target velocity data to a real vehicle using C-V2X communication. This enabled the HIL system to test and validate CACC platooning at a reduced cost while enhancing safety by closely replicating real-world conditions. However, challenges such as uncommunication delays, caused by network latency, processing times, and hardware response limitations are observed. In addition, unmodeled dynamics in the CARLA simulator and truncated control signals sent to the vehicle's actuators are also affecting HIL simulation. All of these challenges play a role in the real vehicle struggling to precisely match the target velocity of the virtual leader. Despite these issues, HIL

6.2 Recommendation

6.2.1 Evaluation of CDA Vehicle Sensing Technologies

Based on the tests conducted on CDA vehicle sensing technologies, integrating advanced sensors (e.g., infrared or thermal cameras) and optimizing sensor fusion have potential to enhance detection in low visibility or adverse conditions. In addition, Utilize V2X technology and leverage AI for improved CDA vehicle sensing capability.

6.2.2 Evaluation of Infrastructure Features for CDA Sensing

Reliable infrastructure is essential for the safety of both human-driven and autonomous vehicles. The following recommendations will strengthen infrastructure features for CDA sensing.

Lane Marking: Enhancing lane marking effectiveness requires a multifaceted approach to ensure detectability and functionality under varying conditions. Regular inspections and maintenance are essential to keep markings clear and visible, while high-contrast, durable resistance to weather and traffic wear can significantly improve longevity and performance. Integrating reflective materials into the paint enhances visibility during both day and night, making markings easier for vehicles to detect. For curved lanes, increasing the density of markings and using broader or more reflective patterns can aid in lane predictability. Curve-specific signage provides advanced warnings, giving both drivers and vehicles more time to respond. Distinctive patterns for merging and diverging lanes help alert users to structural lane changes, while advanced warning signs with flashing lights or V2X technology can provide additional guidance. Nighttime visibility can be improved through strategically placed streetlights or innovative solutions like LED lane markers and illuminated signs, which ensure consistent visibility regardless of ambient lighting. Furthermore, integrating onboard map data and GPS technology enhances lane detection accuracy, offering vehicles additional information to navigate challenging conditions. High-contrast pavement markings and retroreflective materials are particularly effective in low-light scenarios, provided they avoid excessive glare that may interfere with vehicle cameras. Together, these measures contribute to safer and more reliable navigation for both manual and autonomous systems.

Figure 6-1 The first highway with glow-in-the-dark markings opens in the Netherlands.
(Image courtesy to: https://newatlas.com/smart-highway-glowing-lines/34363/)

Figure 6-2 LEDs embedded in the road.
(Image courtesy to: https://www.researchgate.net/figure/Embedded-roadway-lighting-These-LED-lights-installed-in-the-pavement-are-not-visible-to_fig24_305720851)

Static Traffic Signs: To ensure the visibility and effectiveness of traffic signs, several measures must be implemented. Traffic signs should be positioned in unobstructed locations where they are visible to both manual drivers and CAV systems. Regular inspections are necessary to remove vegetation or adjust infrastructural elements that obscure signs, and establishing clear zones around signs can help prevent future obstructions. Using durable, high-quality materials with UV-protective coating extends the lifespan of signs and maintains their clarity. Routine evaluations and cleaning protocols should be enforced, with the potential use of hydrophobic or dirt-repellent coatings to minimize cleaning frequency. For nighttime visibility, retroreflective materials are highly effective, and additional lighting solutions, such as ground-mounted or overhead fixtures aimed at signs, can further enhance detection. Targeted lighting directed at the signage reduces glare for drivers while illuminating the signs while selecting light sources with an optimal color temperature and ensuring uniform light distribution prevents dark spots. Dimming controls can adjust brightness based on ambient light levels, reducing light pollution during darker hours. Incorporating LED technology for self-illuminating signs ensures consistent visibility independent of external lighting conditions. These strategies collectively improve traffic sign visibility, enhance road safety, and support advanced vehicle systems.

Traffic signals: To address discrepancies in vehicle performance with camera detection, particularly between day and night, infrastructure improvements are essential. Anti-reflective coatings on traffic signal lenses can reduce glare and enhance camera recognition, while standardizing the design and color brightness of traffic signals can minimize detection variability. For lidar-equipped vehicles, traffic signals must fall within the sensor's range and detection angle, necessitating adjustments to signal placement or orientation. The integration of connectivity technology for traffic signals also requires refinement, with a hybrid approach recommended. This approach combines onboard sensors with connectivity technology to validate signal statuses, ensuring reliable and informed decision-making. Additionally, regular inspections of devices used to transmit or display traffic signals are crucial to maintaining their functionality and effectiveness. These measures collectively enhance vehicle interaction with traffic signals, supporting safer and more efficient navigation.

Vehicle and V2X: Improving vehicles with V2I technology requires targeted infrastructure enhancements, such as upgrading roadside units (RSUs) with advanced hardware and software and expanding V2I network coverage in areas with weak signal strength. Ensuring all RSU installation requirements, including both software and hardware, is essential for seamless operation. Compatibility between onboard units (OBUs) and RSUs must be prioritized to avoid connectivity issues. Additionally, considering vision-based V2I solutions is crucial for future CAVs that may lack full connectivity capabilities, ensuring their ability to interact effectively with infrastructure. These measures collectively enhance the reliability and functionality of V2I systems, supporting safer and more efficient vehicle operations.

Urban Planning: Throughout testing, problems have been noticed with urban planning design such as lane curvatures and clarity of lane markings. A second phase of this project would investigate the development of a quantitative method to guide FDOT's urban planning and development. Metrics to quantify the safety of lane curvatures, road altitudes, placement of signage, and other traffic engineering considerations will help guide FDOT to develop AV-friendly infrastructure.

6.2.3 Platooning Field Experiment Design Guideline

The freeway platooning tests led the research team to identify areas for improvement. The Platooning Field Experiment can be enhanced with the following recommendations.

Geofencing Measures for C-V2X: Proper methods for geofencing should be developed to ensure consistent communication. Geofencing is the practice of ensuring certain communications or actions only occur within some location. You could compare this to putting up a fence to keep your dog from running out of your yard into the street. A possible application could be geofencing a construction zone with a reduced speed limit that CAVs would obey.

Cellular signals can travel long distances and penetrate obstacles such as buildings, potentially causing vehicles that are not intended recipients to receive C-V2I packets inadvertently. To address this issue, a common approach involves the recipient vehicle verifying its location against the geofenced destination specified in the packet. This ensures that only vehicles within the intended area process the messages, thereby filtering out misdirected packets.

RSU Installation Guidelines: RSUs must be strategically placed to ensure optimal coverage of freeway gore points, particularly at merge areas and just before them. Proper placement is crucial for maintaining robust communication and providing timely information to merging vehicles. Additionally, RSUs need to communicate far enough in advance to provide adequate lead times during freeway ODDs, as vehicles travel at much higher speeds. This extended communication range is essential for delivering timely information to vehicles, ensuring safe and efficient merging maneuvers.

While cellular signals can penetrate objects, doing so can impede speed and data integrity. Therefore, RSUs should be mounted in locations with clear sightlines to minimize interference and maintain high-quality communication. Prioritizing such placements will enhance the effectiveness of the system.

In certain scenarios, vehicles on on-ramps or off-ramps may pass under overpasses or other aerial obstacles, which can disrupt GPS signals. To ensure continuous localization during GPS loss, vehicles must rely on alternative methods for accurate positioning. Maintaining good localization is essential for the effectiveness of geofencing measures within the existing infrastructure.

Additionally, if RSUs require GPS signals, they must be installed in locations with open-air access or have an antenna placed in an open-air position. This ensures that the RSUs can receive accurate GPS data, which is vital for their operation and the overall effectiveness of the traffic management system.

Deprecation of DSRC: During our testing, DSRC proved to be highly unreliable, frequently cutting out within just a few yards of distance. This inconsistency in maintaining a stable connection significantly hindered the effectiveness of the communication system, raising concerns about its reliability in real-world applications.

Given these findings, we do not recommend the use of DSRC for critical V2I communications. The frequent signal loss and limited range observed during testing suggest that alternative technologies should be considered to ensure robust and reliable communication, essential for the safe and efficient operation of cooperative driving systems.

Guideline for Planning and Designing Field Experiments on Freeway Vehicle Platooning: Creating comprehensive guidelines for planning and designing field experiments on freeway vehicle platooning involves multiple considerations, including safety, data collection, vehicle coordination, and analysis methods. Below is a structured guideline to plan and design these experiments:

1. Define Experiment Objectives

Purpose: Clearly state the objectives of the experiment. This could include testing specific algorithms, measuring V2V communication efficiency, the readiness of existing infrastructures for platooning, or evaluating the performance of platooning under different traffic conditions.

Scope: Determine the scope, such as the number of vehicles involved, the length of the experiment, and the specific behaviors or maneuvers to be used in the test.

2. Select Experimental Variables

Independent Variables: Identify and define the variables you will manipulate, such as platoon size, inter-vehicle distance, vehicle speed, and communication protocols.

Dependent Variables: Determine the outcomes you will measure, such as performance metrics (e.g., fuel consumption, platoon stability, communication latency), safety metrics (e.g., headway time, headway distance), and cybersecurity metrics (e.g., false injunction data rejection).

Control Variables: Establish control variables to maintain consistency across tests, such as environmental conditions, vehicle types, and traffic scenarios.

3. Choose a Suitable Test Environment

Location: Select a freeway or a controlled test track that represents the real-world conditions under which the platooning system will operate.

Test Route: Define specific routes and segments of the freeway for testing, ensuring they include a variety of road conditions (e.g., straight sections, curves, slopes).

Safety Considerations: Assess the safety of the test environment, including emergency response plans, clear zones, and visibility. Ensure the test area is isolated from regular traffic if necessary.

4. Vehicle and Equipment Preparation

Vehicle Selection: Choose appropriate vehicles for the platooning experiment, ensuring they are equipped with necessary sensors, communication systems, and automated driving features.

Instrumentation: Equip the vehicles with V2V and V2I communication devices to enable seamless information exchange between vehicles and with the surrounding infrastructure. Additionally, integrating cameras, GPS, and other sensors to capture data on vehicle dynamics, communication signals, and environmental conditions. Ensure that the infrastructure is also outfitted with V2I equipment to transmit essential information to the vehicles. Furthermore, incorporate data logging systems to facilitate efficient data collection and exchange throughout the experiment.

Calibration: Calibrate all sensors and equipment before the experiment to ensure accurate data collection.

5. Develop Test Scenarios

Scenario Design: Create specific test scenarios that align with your objectives, such as merging and demerging vehicles, varying traffic densities, and different communication conditions.

Repetitions: Plan for multiple repetitions of each scenario to ensure data reliability and allow for statistical analysis.

Randomization: Introduce randomization in scenario execution (e.g., starting positions, vehicle order) to minimize bias.

6. Safety Protocols and Risk Management

Safety Analysis: Conduct a thorough safety analysis to identify potential hazards and implement mitigation strategies, such as safe following distances and speed limits.

Driver Roles: Clearly define the roles and responsibilities of human drivers (if involved), including emergency procedures and manual override protocols.

Emergency Procedures: Develop and communicate clear emergency procedures, including communication channels and roles during an emergency.

7. Data Collection and Management

Data Requirements: Define the types of data needed, such as vehicle speed, distance between vehicles, communication latencies, and fuel consumption.

Data Storage: Ensure data is securely stored and backed up, with appropriate access controls and data management procedures in place.

Synchronization: Implement time synchronization across all data collection systems to ensure consistency in the dataset.

8. Post-Experiment Analysis

Data Processing: Develop a plan for processing and cleaning the collected data, addressing issues such as missing data or outliers.

Analysis: Define statistical methods (such as ANOVA, regression analysis, or time-series analysis and algorithm analysis (such as safety, performance, security, and resilience)

Validation: Cross-validate the results by comparing them with simulations, theoretical models, or results from other experiments.

9. Reporting and Documentation

Experiment Report: Prepare a comprehensive report documenting the experiment design, execution, data analysis, and conclusions. Include detailed descriptions of scenarios, variables, and methods used.

Lessons Learned: Document any challenges faced during the experiment and suggest improvements for future experiments.

Compliance: Ensure the report complies with any relevant regulatory or organizational requirements.

10. Review and Approval

Internal Review: Conduct an internal review of the experiment plan, involving key stakeholders such as safety officers, technical experts, and project managers.

External Approval: If required, seek approval from external bodies, such as regulatory agencies or ethics boards, before experimenting.

6.2.4 Co-Simulation Use to Support Testing

Based on test procedures test data analysis and results of co-simulation used to support testing, the research team recommends the following.

In cases of SIL co-simulation, the study was conducted under a single demand level, representing uncongested traffic conditions. As a potential extension, future studies could explore the effects of CDA applications under varying congestion levels. Exploring these scenarios would provide a more comprehensive understanding of CDA vehicle behavior and its impact on both traffic-level (e.g., throughput, delays) and vehicle-level (e.g., speed, acceleration) performance across diverse traffic conditions. This investigation should consider the required computer resources and running time, which is much more demanding when using co-simulation compared to traffic simulation.

For the HIL co-simulation, the following points are recommended for future research.

Vehicle Control Challenges: Enhancing vehicle dynamics in the CARLA simulation was crucial for replicating real-world conditions and improving control over vehicle responses. This would allow the simulation to better account for factors like friction, tire slip, and drifting, which were often simplified. Addressing these challenges will lead to more accurate testing and closer alignment between simulation and actual vehicle behavior. Future research should focus on advancing vehicle dynamics models and integrating real-time data from real vehicles to improve simulation accuracy and ensure smoother transitions between virtual and real-world testing.

Two-way Communication Benefits: Implementing two-way, closed-loop communication between simulation and real-life systems is vital for enhancing the accuracy and reliability of co-simulation results. This integration would allow real-time updates of the simulation based on the real vehicle’s responses, improving synchronization between physical and virtual environments. Overcoming technological compatibility issues, such as those between CARLA, drive-by-wire kits, and Cohda OBUs/RSUs, is also necessary to enable seamless communication architectures. These advancements will create more robust testing environments, aligning simulations more closely with real-world performance. Future research should prioritize developing efficient two-way communication methods and addressing compatibility challenges to maximize the potential of HIL testing in vehicle platooning systems

Investing in Alternative Simulation Software: It is recommended to investigate alternative simulation software options to reduce computation time, as CARLA’s higher processing demands can result in delays during real-time testing and affect system responsiveness. Future research should focus on evaluating other alternative simulation software that balance performance, accuracy, and processing efficiency for real-time applications in vehicle platooning and control systems.

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Appendix A

The vehicles used in the evaluation of infrastructure features for CDA sensing (i.e., Chapter 3) are the following.

Number	Brand	Model	Year
1	Toyota	Corolla	2022
2	Hyundai	Santa Fe	2022
3	Ford	Bronco	2022
4	Audi	Q5	2023
5	Honda	Accord	2022
6	Tesla	Model Y	2023
7	Mustang	Electric	2021
8 (Lab vehicle)	Lincoln	MKZ	2016
9	Tesla	Model 3	2022

Appendix B: Testing Schedule

Test Scenario	Testing Objective	Sector	Speed	Platoon Formation
Warmup	Ensure drivers' comfort in driving their vehicle and navigating the layout of the SunTrax facility.	East Straight	-	-
Low Speed ACC	Initial evaluation of OEM ACC systems in a platoon formation; warmup for later high speed ACC.	Oval Track	35 mph	XT5, Fusion, Mach-E
High Speed ACC	Initial evaluation of OEM ACC systems in a platoon formation; warmup for later platooning test.	Oval Track	65 mph	XT5, Fusion, Mach-E
CACC Integration Test	Test software stack for safety and functionality before conducting field experiments.	East Straight	35 mph	Fusion, Mach-E
Platooning	Pilot test on cooperative freeway experiments with mixed traffic; collection of a baseline data set to demonstrate evaluation framework.	Oval Track	55 mph	XT5, Fusion, Mach-E
RSU	Pilot test on V2I technologies as a method for speed regulation.	East Straight	40 mph	Fusion, Mach-E, XT5
Cooperative Merge	Pilot test on V2V technologies in a freeway context targeting cooperative freeway merging and diverging maneuvers.	East Straight	40 mph	Fusion, Mach-E, XT5