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Connected and Automated Vehicles in Urban Transportation Cyber-Physical Systems

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CONNECTED AND AUTOMATED VEHICLES IN URBAN TRANSPORTATION
CYBER-PHYSICAL SYSTEMS

A Dissertation
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy
Civil Engineering

by
Sakib Mahmud Khan
August 2019

Accepted by:
Dr. Mashrur Chowdhury, Committee Chair
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ABSTRACT

Understanding the components of Transportation Cyber-Physical Systems (TCPS), and inter-relation and interactions among these components are key factors to leverage the full potentials of Connected and Automated Vehicles (CAVs). In a connected environment, CAVs can communicate with other components of TCPS, which include other CAVs, other connected road users, and digital infrastructure. Deploying supporting infrastructure for TCPS, and developing and testing CAV-specific applications in a TCPS environment are mandatory to achieve the CAV potentials. This dissertation specifically focuses on the study of current TCPS infrastructure (Part 1), and the development and verification of CAV applications for an urban TCPS environment (Part 2).

Among the TCPS components, digital infrastructure bears sheer importance as without connected infrastructure, the Vehicle-to-Infrastructure (V2I) applications cannot be implemented. While focusing on the V2I applications in Part 1, this dissertation evaluates the current digital roadway infrastructure status. The dissertation presents a set of recommendations, based on a review of current practices and future needs.

In Part 2, To synergize the digital infrastructure deployment with CAV deployments, two V2I applications are developed for CAVs for an urban TCPS environment. At first, a real-time adaptive traffic signal control algorithm is developed, which utilizes CAV data to compute the signal timing parameters for an urban arterial in the near-congested traffic condition. The analysis reveals that the CAV-based adaptive signal control provides operational benefits to both CVs and non-CVs with limited data
from 5% CVs, with 5.6% average speed increase, and 66.7% and 32.4% average maximum queue length and stopped delay reduction, respectively, on a corridor compared to the actuated coordinated scenario.

The second application includes the development of a situation-aware left-turning CAV controller module, which optimizes CAV speed based on the follower driver’s aggressiveness. Existing autonomous vehicle controllers do not consider the surrounding driver’s behavior, which may lead to road rage, and rear-end crashes. The analysis shows that the average travel time reduction for the scenarios with 600, 800 and 1000 veh/hr/lane opposite traffic stream are 61%, 23%, and 41%, respectively, for the follower vehicles, if the follower driver’s behavior is considered by CAVs.
DEDICATION

I dedicate this dissertation to our beloved son, Taasbeeh.
ACKNOWLEDGMENTS

First and foremost, I would like to express my gratefulness to God Almighty for giving me the opportunity, ability and time to complete my dissertation.

I would like to express my deepest appreciation and gratitude to my advisor, Dr. Mashrur Chowdhury for his continuous assistance, guidance, and support throughout my graduate study. I could not have imagined having any better advisor and mentor for my graduate study. He gave me complete freedom to pursue challenging research questions which require critical thinking and innovative solutions. Also, I am grateful as he involved me in different research activities and projects.

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Staffs from the Glenn Department of Civil Engineering have helped me a lot during the process. I would like to acknowledge all of them. Last but not least, special thanks go to the Bangladeshi Community at Clemson.
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CHAPTER ONE

INTRODUCTION

1.1 Problem Statement

Transportation Cyber-Physical Systems (TCPS) can be defined as the integrations of feedback loop-enabled physical, networking and computation processes. Like any other cyber-physical systems, embedded computers and networks are available in TCPS which, with the help of feedback loops, monitor and manage the physical processes (Deka, Khan, Chowdhury, & Ayres, 2018). One critical component of future TCPS is the Connected and Automated Vehicles (CAVs), which requires seamless interconnection, efficient interaction and reliable inter-dependency of every other component of the TCPS environment. The components of TCPS for a CAV-incorporated urban environment include digital infrastructure (i.e., infrastructure with physical nodes having networking and computation capabilities), CAVs, connected road users and online media (Sakib Mahmud Khan, Chowdhury, Morris, & Deka, 2019) as shown in Figure 1-1. These components are connected via different wireless communication options, and required computations can be conducted in different layers, which include mobile (i.e., in-vehicle devices), fixed (i.e., roadside infrastructure), and system (i.e., backend infrastructure) layer. Also, legacy infrastructure components, such as traffic signals and roadway sensors, can be integrated with the CAVs using wireless communication. All components of urban TCPS work together to achieve the overarching goals of CAV applications, which are to provide safety, operational, environmental and energy-related benefits (M. A. Chowdhury, Apon, & Dey, 2017; Kakan C. Dey, Mishra, & Chowdhury, 2015; Sakib Mahmud Khan,
Dey, & Chowdhury, 2017; Sotelo, van Lint, Nunes, Vlacic, & Chowdhury, 2012). According to a study, in US cities the average cost of crash and congestion per person are $1,522 and $590, respectively (Cambridge Systematics, 2011). TCPS will be mainstreamed in the operations and business practices of transportation systems soon (Deka et al., 2018), and the TCPS applications can reduce the safety, operation, environmental and energy-related problems that exist in today’s transportation (UDSOT ITS JPO, 2019).

**Figure 1-1** Transportation cyber-physical systems components

The enormous benefits of CAVs can only be materialized if the CAV-incorporated TCPS is created with the required physical, networking and computation components. In this dissertation, the author has discussed the components of TCPS, and the required communication and computation options to create the CAV-incorporated TCPS environment. The digital infrastructure, which is intended to support CAVs, can also support Connected Vehicles (CVs), which only have communication capabilities. The
digital infrastructure is required to support the Vehicle-to-Infrastructure (V2I) applications, which is the focus of this dissertation. Particularly, the author is focusing on V2I applications in an urban area.

CAV operation in a TCPS environment is challenging, specifically in an urban area where mixed traffic scenarios exist. Urban arterials are controlled by traffic signals, which influences the traffic operations. In a CAV-incorporated TCPS environment, advanced traffic signal control strategy can be deployed using data from CAVs/CVs which can offer better operational performance for any congested/near-congested urban arterials. This dissertation focuses on the development and assessment of an adaptive traffic signal control system using data from a small penetration of CAVs/CVs. Demonstrating the operational benefits for any congested/near-congested urban arterial using the CAV/CV-incorporated adaptive traffic signal control will accelerate the rapid TCPS environment creation.

Another challenging part of CAV operation in a mixed traffic scenario is the development and assessment of the situation-awareness for CAVs. While operating on public roads, CAVs need to assess and act based on the surrounding non-CVs. Generally, CAVs demonstrate a defensive driving behavior, and CAVs expect other non-autonomous entities on the road will follow the traffic rules or common norms. However, the presence of aggressive human drivers in the surrounding environment, who may not follow traffic rules and behave abruptly, can lead to serious safety consequences. In this dissertation, the author will address the interaction by studying the situation-awareness module for left-turning CAV operation for an urban area.
1.2 Research Objectives

In order to accurately understand the fundamental and complex interaction of TCPS components and quantify benefits of CVA applications, the author has included two parts in this dissertation. In Part 1, the author has investigated the CAV-enabled TCPS environment for V2I applications. Part 2 includes the development and assessment of CAV/CV based applications for an urban environment with mixed traffic conditions. The specific objectives of this dissertation include:

1. Identify digital infrastructure investment trends to recommend future directions (Part 1)
2. Develop an adaptive traffic signal control algorithm with CVs and non-CVS (Part 2)
3. Develop a CAV controller module that reacts to aggressive human drivers (Part 2)

1.3 Research Contributions

The contributions of this research are outlined below:

1. The safety, mobility, environmental, energy, and economic benefits of CAV-incorporated TCPS are potentially significant. However, the realization of these benefits largely hinges on the timely integration of digital technology into the existing transportation infrastructure. CAVs must be enabled to broadcast and receive data to and from other CAVs (Vehicle-to-Vehicle, or V2V, communication), to and from infrastructure (Vehicle-to-Infrastructure, or V2I,
communication) and to and from other road users, such as bicyclists or pedestrians (Vehicle-to-Other road users communication). Further, for V2I-focused applications, the infrastructure and the transportation agencies that manage it must be able to collect, process, distribute, and archive these data quickly, reliably, and securely. This dissertation focuses on V2I applications and studies current digital roadway infrastructure initiatives. It highlights the importance of including digital infrastructure investment alongside investment in more traditional transportation infrastructure to keep up with the auto industry’s push towards connecting vehicles to other vehicles. By studying the current CV testbeds and Smart City initiatives, this dissertation identifies digital infrastructure components (i.e., communication options and computing infrastructure) being used by public agencies. It also examines public agencies’ limited budgeting for digital infrastructure and finds current expenditure is inadequate for realizing the potential benefits of V2I applications. Finally, the dissertation presents a set of recommendations, based on a review of current practices and future needs, designed to guide agencies responsible for transportation infrastructure. It stresses the importance of collaboration for establishing national and international platforms for the planning, deployment, and management of digital infrastructure to support connected transportation systems across political jurisdictions.

2. CAVs have the potential to revolutionize real-time transportation applications. In this dissertation, the author has developed a real-time adaptive traffic signal control algorithm, which utilizes only CAV/CV data to compute the signal timing
parameters for an urban arterial in the near-congested condition. This study develops a strategy for dynamically optimizing signal timing parameters for an urban near-congested corridor in real-time only using limited CAV/CV data (5% CV). The author has used a machine learning-based short-term traffic forecasting model to predict the overall traffic number in CAV/CV-based platoons. Using a multi-objective optimization technique, the green interval time is estimated for each intersection using CAV/CV-based platoons. Later, intersection offsets are dynamically adjusted in real-time so the vehicles in the major street can experience improved operational conditions compared to the loop-detector based actuated coordinated signal control.

3. One important aspect of CAV operation in the urban area is the situation-awareness for CAVs in a mixed traffic scenario. CAVs by default display defensive driving behavior, and they often create confusion for human drivers, particularly the aggressive drivers. Existing autonomous vehicle controllers do not consider other vehicles’ intents. In order to fill this gap, the author has developed and assessed a situation-aware CAV controller module which considers the intent of the following aggressive human drivers. The situation-aware CAV controller module can provide better operational performance compared to the scenario where autonomous vehicles do not consider the behavior of the following vehicle.

1.4 Dissertation Organizations

This dissertation has five chapters. The first chapter provides an overview of the
research problem, as well as objectives and contributions of this research. Chapter 2 discusses the components of TCPS for an urban area, current TCPS initiatives, and future directions to create CAV-enabled TCPS environment. Chapters 3 and 4 discuss two V2I applications for the TCPS environment. Chapter 3 discusses an adaptive signal control system based on limited CAV/CV data. In Chapter 4, the situation-aware CAV controller module is discussed for urban arterials. Chapter 5 concludes the dissertation and discusses the major findings, study limitations and future works for CAV applications in a TCPS environment.
CHAPTER TWO
DIGITAL INFRASTRUCTURE FOR TRANSPORTATION CYBER-PHYSICAL SYSTEMS

2.1 Introduction

Advances in communication technology and data processing capabilities furnish the potential for vehicles to “talk” to each other (via Vehicle-to-Vehicle communication, or V2V), to pedestrians (via Vehicle-to-Pedestrian communication, or V2P) as well as to transportation infrastructure (via Vehicle-to-Infrastructure communication, or V2I). Potential benefits from real-time communication between the elements of the transportation system are dramatic (Chang et al., 2015). For example, CAVs/CVs, which broadcast their data to infrastructure and other vehicles, could give drivers advance warning of impending collisions in time to avert dangerous circumstances, dramatically reducing crash damage, injuries, and fatalities. V2I connectivity between vehicles and “digital roadways,” which feature roadside devices and backend computation infrastructure, could ensure safe and efficient traffic management in real-time, which is not present on public roads today. In this chapter, the author will carry out the discussion with CVs, however, the digital infrastructure environment will serve both CVs and CAVs.

CVs can benefit the environment with 9,400 tons of annual emission savings for an area covering 45 kilometers (28-miles) of US-75 in Dallas, TX. As reported by Chang et al. (2015), about 27% of the delay can be reduced for six intersections in Anthem, AZ, and 11% of the fuel consumption can be eliminated for a 10.5 kilometer (6.5 mile) segment of El Camino Real, CA by V2I applications. Further, in the US, roughly 575,000 annual
crashes at intersections could be avoided with the use of V2I (Chang et al., 2015)s. Ultimately, the marriage of Automated Vehicle (AV) technology with advanced communication and data processing technology has the potential to revolutionize auto travel in ways not seen since the introduction of the auto itself (NHTSA, 2017; Shladover, 2013).

Figure 1-1 shows the typical roadway digital infrastructure components for a connected vehicular environment (M. Chowdhury et al., 2018b; Lu, Cheng, Zhang, Shen, & Mark, 2014). Such digital infrastructure is a component of TCPS. In an environment based on TCPS, CVs will wirelessly communicate with Roadside Units (RSU), which both communicate and process data. Based on the application requirements, additional processing units can be integrated with the RSUs to further increase their data processing capabilities. Such processing units may include commercial computation units such as Intel’s Next Unit of Computing (NUC), or ASUS’s VivoPC. Data from multiple RSUs will be forwarded to the backend infrastructure, which could be either cloud servers (e.g., Amazon AWS, Microsoft Azure, IBM cloud) or local Traffic Management Center (TMC) servers. These servers would have data storage, processing, and management tools to support CV applications. Data would include real-time, near real-time, and historical data.

Spurred by governments, automakers are rapidly moving toward incorporating communication technology in new vehicles. Communication options such as Long Term Evaluation (LTE) or Wi-Fi already exist in some vehicles. In the US, General Motors has already introduced Dedicated Short-Range Communication (DSRC) technology in its 2017 Cadillac CTS sedans for the purpose of V2V communications; Toyota will include DSRC
in Lexus cars from 2021 (Uhlemann, 2018). General Motors also provides the OnStar service, which is an in-vehicle two-way communication system using cellular networks to enhance safety, security, and entertainment (Z. He, Yang, Wang, & Zhang, 2017). Similar types of wireless communication services also exist for Ford (SYNC), Volkswagen (CarNet), and BMW (TeleService). Some brands, such as Audi, Chevrolet, Ford, and Buick, also provide wireless infotainment (i.e., in-vehicle Wi-Fi hotspots based on 4G LTE). In Europe, from April 2018 all new vehicles have the eCall facility to call emergency services in case of crashes (EU, 2015).

However, to realize the maximum potential of CVs, public agencies must keep pace with the auto industry. Roadway infrastructure must be upgraded with the digital communications infrastructure that evolves with increasing CV penetration levels. This will create an environment suitable for fostering beneficial V2I innovations, such as the V2I safety applications listed by the Connected Vehicle Reference Implementation Architecture (e.g., Curve Speed Warning, Pedestrian in Signalized Crosswalk Warning, Red Light Violation Warning, Warnings about Upcoming Work Zones, etc.) (CVRIA, 2018). To benefit from all V2I applications, public agencies need to decide on the type of computing infrastructure (i.e., centralized or distributed) and the communication options (e.g., DSRC, LTE, Wi-Fi) needed to implement a reliable, scalable and connected TCPS. With a centralized computing infrastructure, a TMC server can act as the single computing node/processor to process the CV application locally, whereas a distributed computing infrastructure requires the computation steps to be divided among the different nodes (i.e.,
RSUs, TMC servers, cloud servers) to minimize computation time and processing costs (Pourebrahimi, Pourebrahimi, Bertels, & Vassiliadis, 2005).

For digital infrastructure investment, proper planning, design, deployment, operations, and maintenance are needed. In terms of which phase presents the biggest obstacles, (Zmud, Goodin, Moran, Kalra, & Thorn, 2017) found maintenance cost to be the biggest unknown, as this may exceed the initial cost of the deployment of the technology.

Public transportation agencies need to allocate a budget to instrument roadways under their jurisdiction to capture data from CVs, such as traffic volume and speed data. This may not be easy, as expenditure on digital infrastructure must be justified by public agencies which operate in a constrained fiscal environment. In this dissertation, the author has discussed the reasons for investment in digital infrastructure for V2I applications, followed by a review of communication options for V2I applications, TCPS computing infrastructures, and existing testbeds. Finally, the author has highlighted current political, technical and investment challenges and future directions so that digital infrastructure deployment will succeed and provide maximum return on investment.

2.2 Why Invest In Connected And Computerized Vehicles And Roadway Infrastructure?

Even in the absence of vehicle automation, data connectivity in transportation systems promises myriad benefits for travelers and society as a whole. For example, V2I communication will lead to less time-consuming and more ecologically friendly driving. A federal report discussed an integrated eco-corridor management decision support system,
which could save 323,000 gallons of fuel annually on a 32 kilometer (20-mile) section of I-15 section in San Diego, CA, and 981,000 gallons on an area covering 45 kilometer (28-miles) of US-75 in Dallas, TX (Chang et al., 2015).

In the future, these savings will come from utilizing the real-time traffic condition information broadcasted from an increasing number of CVs, which will alert drivers, and ultimately their vehicle control systems when such technology exists. Existing studies have found upcoming congestion and incidents can be accurately identified using CV data (S.M. Khan, Dey, & Chowdhury, 2017; Ma, Chowdhury, Sadek, & Jeihani, 2012; Yongchang Ma, Chowdhury, Sadek, & Jeihani, 2009). Further benefits from V2I will include better traffic management in work zones (e.g., alerts to motorists to avoid congested routes), better data on infrastructure use for supporting the work of transportation planning and engineering agencies, more timely and accurate condition assessments of transportation infrastructure, and optimized route planning for wireless power transfer for connected electric vehicles. Table 2-1 provides examples of the potential benefits of receiving data through CV applications for different stakeholders. The applications listed in this table are V2I-based applications, however, a few also include V2V and V2P connectivity.
### Table 2-1 TCPS Stakeholders’ Benefits

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<th>Information Received</th>
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<th>Benefit</th>
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<td><strong>Drivers / CVs</strong></td>
<td>Information on potential collisions, harsh braking of vehicles in front, hazards at blind corners and intersections, and road obstructions such as construction zones for route planning</td>
<td>V2V and V2I</td>
<td>Automated braking with connected vehicle warning systems: fatality reduction of 37-86 percent in South Australia (simulation study) (ITS Benefits, 2018)</td>
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<td>Information on signal phase and timing to maintain an optimized speed through green phases</td>
<td>V2I</td>
<td>Predictive cruise control using traffic signal information: fuel consumption reduction of 24 percent (urban scenario) and 47 percent (suburban scenario) in South Carolina (simulation study) (ITS Benefits, 2018)</td>
</tr>
<tr>
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<td>Warnings about hazardous material and road conditions such as slippery surfaces, floods, potholes, etc.</td>
<td>V2V and V2I</td>
<td>Data networking and GPS tracking: benefit-cost ratio up to 7.2:1 for HAZMAT trucking in the US (field test) (ITS Benefits, 2018)</td>
</tr>
<tr>
<td></td>
<td>Information about points-of-interest such as parking, gas stations, restaurants, etc.</td>
<td>V2V and V2I</td>
<td>On-street parking space information: cruising time reduction by 5-10 percent (simulation study) (ITS Benefits, 2018)</td>
</tr>
<tr>
<td><strong>Automated vehicles</strong></td>
<td>Traffic signal information via V2I communication, vehicle information for Cooperative Adaptive Cruise Control (CACC)</td>
<td>V2V and V2I</td>
<td>91 percent delay reduction and 82 percent fuel saving for CACC application compared with conventional signal control without CACC (simulation study) (Zohdy, Kamalanathsharma, &amp; Rakha, 2012)</td>
</tr>
<tr>
<td><strong>Vulnerable Road Users (VRUs) such as pedestrians and cyclists</strong></td>
<td>Early warnings about potential collisions when VRUs approach crosswalks, blind corners or intersections with traffic signals</td>
<td>V2P, V2V, and V2I</td>
<td>Vehicle turn warning at crosswalk: 23 percent of 27 pedestrians avoided collision with a bus in Portland, Oregon (field test) (ITS Benefits, 2018)</td>
</tr>
<tr>
<td><strong>Traffic Management Centers (TMC)</strong></td>
<td>Information about current traffic conditions such as traffic flow, congestion, and accidents</td>
<td>V2V and V2I</td>
<td>Getting information from CVs may increase capacity by 273 percent (theoretical modeling and analysis) (ITS Benefits, 2018)</td>
</tr>
<tr>
<td></td>
<td>Information about broken down vehicles or incidents</td>
<td>V2I</td>
<td>Incident spot guidance and alerts to approaching connected vehicles and emergency responders: network delay reduction up to 14 percent in CA (simulation study) (ITS Benefits, 2018)</td>
</tr>
<tr>
<td></td>
<td>Information about emergency evacuation situations</td>
<td>V2I</td>
<td>Wireless route guidance during evacuation: congestion reduction of 20 percent in Louisiana (simulation study) (ITS Benefits, 2018)</td>
</tr>
<tr>
<td><strong>Government and city planners</strong></td>
<td>Information useful for planning bus and other public transport routes, road capacity improvements, etc.</td>
<td>V2I</td>
<td>More accurate network-level performance measures (compared to Bluetooth sensors and probe vehicles) and vehicle-level travel behavior data (compared to GPS units and mobile phone data) for transportation planning applications (field test) (Deering, 2016)</td>
</tr>
<tr>
<td></td>
<td>Information to effectively plan new land use developments</td>
<td>V2I</td>
<td></td>
</tr>
</tbody>
</table>
For these expected benefits to materialize, public transportation agencies need to accelerate CV application deployment efforts. As shown in Figure 2-1, according to a US survey conducted in 2016, 59 (out of 95) transportation agencies (including both state and local agencies) have shown interest in deploying CV applications for freeway management, and 95 (out of 274) agencies plan to deploy them for arterial management (ITS Deployment Tracking, 2018). It is noteworthy that a relatively higher percentage of agencies are interested in deploying CV applications for freeway management (62%) than on arterials (34%).

![Figure 2-1 US agencies willingness to deploy CV applications (data from (ITS Deployment Tracking, 2018)).](image)

To be sure, there is the potential for problems arising from CVs and CAVs. With improved mobility, more people will be attracted to the roads, which will increase Vehicle-Miles Traveled (VMT) (Hörl, Ciari, & Axhausen, 2016). Empty vehicles will travel in
between drop-offs and pickups for passengers and goods, adding to congestion. AV use may substitute for the use of transit, as the former will have no first mile/last mile issue. The potential impact of CAVs and CVs on land use is somewhat ambiguous, as they may encourage dense development in cities or sprawling development in the suburbs (Bagloee, Tavana, Asadi, & Oliver, 2016). If all connected vehicle drivers get the same navigation advice or ask for signal priority simultaneously, network efficiency will be adversely affected. Solutions for these problems are possible. For example, in a real-time connected environment, the potential of achieving system equilibrium, with increasing penetration levels of CVs and CAVs, will increase, which will reduce the risk of network overloading (Bagloee, Sarvi, Patriksson, & Rajabifard, 2017). Also, intelligent algorithms can address the problem of all CAVs taking the recommended route to avoid the congestion that could produce the unintentional consequence of further corridor-level or network-level delay. The authors in one study observed that the possibility of network-level congestion in their simulated network would be less if only 70% of vehicles could be routed to the first-choice route rather than all vehicles (Dai, Lu, Ding, & Lu, 2017). With proper planning, CVs and CAVs can be synergistically integrated with the non-connected vehicle stream in a sustainable fashion so that adverse impacts of CVs and CAVs could be mitigated. In another study, the authors have discussed how CVs can be integrated into the planning process by both state and local transportation agencies in a coordinated way so that CVs can provide positive benefits (Krechmer, Osborne, Bittner, Jensen, & Flanigan, 2015).

It must be stressed here that V2I connectivity is an enabler which will allow AVs to reach their full potential (Litman, 2017). Although AVs will likely need to be able to
operate without connectivity in order to be not dependent on external infrastructure for safe operations in case connectivity is not available, connectivity would dramatically improve AVs’ functioning. The United States Department of Transportation (USDOT) has highlighted the importance of connectivity between AVs and other vehicles and infrastructure in the Automated Vehicle Research webpage (ITSJPO, 2018). The fault tree analysis was used in an earlier study to study the risks inherent in the use of AV sensors (LIDAR and camera) and found that sensor failure would be the leading cause of pedestrian fatalities (Duran, Robinson, Kornecki, & Zalewski, 2013). Based on 2016 AV testing data provided by California Department of Motor Vehicles, AV sensor-related hardware and software failure caused five to eighteen percent of the total incidents that occurred during AV field testing (Bhavsar, Das, Paugh, Dey, & Chowdhury, 2017). Further, connectivity will lower failure rates of AVs by providing additional data beyond the coverage area of the AV sensors (e.g., LIDAR, camera). For example, tightly packed platoons of vehicles operating at high speeds will be possible in an AV environment, but the considerable safety challenges posed by this strategy would be dramatically reduced if vehicles at the front of the platoon communicated their speed and position to followers in real-time. By providing information about current and planned actions of leading connected AVs, connectivity will help follower AVs to take early and appropriate responses. In addition, intelligent intersections will feature signals which change phases based on current and future traffic conditions as determined by communications from oncoming CVs; this ultimately may even dispense with the need for traditional signals altogether (Fayazi & Vahidi, 2017), as vehicles can be woven through the intersection, dramatically increasing throughput. Also,
external connectivity, including connectivity with roadside or roadway infrastructure, will reduce the extent and cost of the sensors and computing systems AVs may be required to carry on-board. Connectivity can augment data captured by AV sensors, which will: (a) reduce the impact of AV sensor uncertainty, (b) limit processing lags for filtering AV sensor data, and (c) capture information beyond AV sensors’ coverage (Shladover, 2013). To truly maximize the benefits of AVs, then, connectivity is essential.

2.3 Research on CV Communication and Computing Infrastructure

The following subsections discuss the available communication and computing infrastructure for CV deployment.

2.3.1 Communication Options for V2I Applications

For V2I applications, digital infrastructure consists of embedded sensors and backend computation infrastructure, which can exchange real-time data between road management agencies or other data providers and users via a reliable communication network. Road management agencies can use any one of, or combinations of, several communication options: Dedicated Short-Range Communication (DSRC), Cellular technologies (such as 4G, 5G), Wireless Fidelity (Wi-Fi), Worldwide Interoperability for Microwave Access (WiMAX), Bluetooth, etc. Latency, bandwidth, cost, communication range, and the reliability of different communication options vary for different applications. In 2016, the ITS Joint Program Office conducted a survey on US public agencies’ communication technology adoption and received responses from 272 arterial management and 99 freeway management agencies (ITS Deployment Tracking, 2018; USDOT, 2018).
Figure 2-2 shows the options adopted by these agencies to enable communication between multiple ITS devices, or between ITS roadside devices and a central processing location. In general, cellular LTE is the most widely adopted wireless communication option. The other wireless options that have been adopted include Wi-Fi, WiMAX, DSRC, and microwave.

![Bar chart showing communication options adopted by US agencies](chart.png)

**Figure 2-2** Communication options deployed by US agencies (data from [ITS Deployment Tracking, 2018]).

Fifty-three of the 78 cities participating in the UDSOT Smart City Challenge proposed implementing DSRC connectivity to enable communications between vehicles and infrastructure (USDOT, 2016). On the other hand, downtown Kansas City features an intelligent Wi-Fi network (Boissevain, 2018; KCMO, 2016) which wirelessly connects and adjusts smart street lights based on pedestrian presence. Such wireless connectivity could provide monetary and environmental benefits once CVs are deployed (Chang et al., 2015).
Another option would be fifth-generation (5G) cellular communications systems, which feature greater range (up to 32 kilometers (20 miles)) and increased throughput compared with DSRC (Cordero, 2016). The cellular alternative to IEEE802.11p/DSRC is being heavily backed by vehicle manufacturers and network operators as is evident from establishment of the 5G Automotive Association (5GAA), which was set up in 2016 (5GAA, 2018).

**Table 2-2 Characteristics of Wireless Communication Networks**

<table>
<thead>
<tr>
<th>Communication Options</th>
<th>Single-hop Latency</th>
<th>Range</th>
<th>Spectrum</th>
</tr>
</thead>
<tbody>
<tr>
<td>DSRC</td>
<td>0.0002 sec</td>
<td>300 meter (1000 ft.)</td>
<td>5.85-5.925 GHz (US) 5.875-5.925 GHz (Europe) 5.77-5.85 GHz (Japan)</td>
</tr>
<tr>
<td>Cellular LTE 4G</td>
<td>0.01 – 0.02 sec</td>
<td>&lt; 29 kilo-meters (18 miles)</td>
<td>Different ranges between 450 MHz to 3.6 GHz</td>
</tr>
<tr>
<td>Cellular LTE 5G</td>
<td>0.0001 sec</td>
<td>32 kilo-meters (20 miles)</td>
<td>Different ranges between 600 MHz and 100 GHz</td>
</tr>
<tr>
<td>Wi-Fi (802.11)</td>
<td>0.006 sec (for 2.4 GHz) 0.0009 sec (for 5 GHz)</td>
<td>31 meters (100 ft.)</td>
<td>2.4 and 5 GHz</td>
</tr>
<tr>
<td>WIMAX</td>
<td>&lt; 0.01 sec</td>
<td>50 kilo-meters or 31 miles (with line of sight) 5.5-10 kilo-meters or 3.5-6 miles (with no line of sight)</td>
<td>2.3, 2.5, 5.8 GHz (US) 2.5, 3.5, 5.8 GHz (Europe)</td>
</tr>
</tbody>
</table>

Table 2-2 shows that different wireless communication options have different single-hop latency, range, and allocated spectrum (Chintapalli, Weragama, & Agrawal, 2013; de Carvalho, Veiga, Pacheco, & Reis, 2017; Ghadialy, 2015; Grigorik, 2018; J. Lee et al., 2018; Odiaga, Joussef, Medina, & Augusto, 2016; Remy & Letamendia, 2014; Shabbir & Kashif, 2009; Zhou et al., 2009). Because of the different strengths and weaknesses of the different technologies, it is recommended that a real-world connected TCPS makes use of a heterogeneous network which can support multiple applications at
the same time (Siegel, Erb, & Sarma, 2018). A Heterogeneous Wireless Communication Network (HetNet) permits selection of wireless network options (e.g., Wi-Fi, LTE and DSRC) to exchange data between data users and data providers based on communication delay, availability of communication options, communication coverage area, and communication reliability, considering the temporal and spatial requirements of the V2I applications. Prior research has studied the applicability of heterogeneous networking for TCPS (M. Chowdhury et al., 2018b; Kakan Chandra Dey, Rayamajhi, Chowdhury, Bhavsar, & Martin, 2016), which can be leveraged by public agencies.

2.3.2 TCPS Computation Options for V2I Applications

On-premise computing (e.g. Traffic Management Center (TMC) servers), cloud computing, and edge/fog computing are available for V2I applications. Robust and reliable algorithms for V2I applications often have to meet real-time and/or near-real-time processing requirements (Zheng, Zheng, Chatzimisios, Xiang, & Zhou, 2015). To make the TCPS scalable and resilient with increasing numbers of CVs, edge computing is a viable option for public agencies. An “edge” is any computing resource (e.g., an On-Board Unit (OBU), RSU, server) which can help with data storing, processing, and service request distribution along the path between CV data sources and CV data consumers (Shi, Cao, Zhang, Li, & Xu, 2016). Edge computing paradigm in a CV environment can be defined as computational services to run CV applications in computing devices, such as in RSUs, that are distributed by nature and close to the data sources (e.g., CVs), which facilitates low data loss and data communication latency between CV the data sources and computational services. By distributing the computation to different edges, edge computing
also ensures high bandwidth. As discussed by (M. Chowdhury et al., 2018a) on their work on the South Carolina CV Testbed (SC-CVT), mobile entities such as CVs and pedestrians with connected wearable devices, RSUs, and a backend server are different edges. These edges have different levels of computation capabilities and memory storage to support multiple CV application requirements with increasing CV penetration. A white paper by the (5GAA, 2017) demonstrates a number of diverse cases where edge computing will be particularly effective.

2.4 Current Digital Infrastructure Initiatives in CV

The following sub-sections discuss the characteristics of existing CV testbeds and smart cities.

2.4.1 CV Testbeds and Initiatives

V2I applications will require common standards to ensure interoperability, whether across different makes of vehicles or across the infrastructure in different political jurisdictions. Some progress has been made on this. In the US, pilot digital infrastructure initiatives have been mostly led by state agencies and academic institutions with industry collaboration. The Mcity initiative, a testbed for V2V and V2I development run under the aegis of the University of Michigan in Ann Arbor, is an example of government, academia and industry collaboration; it enables CV testing to be done in a safe and controlled environment before deployment in a public environment (Mcity, 2019). The USDOT has also supported research on centralized digital infrastructure by sponsoring several CV research projects. In a program funded by the USDOT, New York, Florida and Wyoming
have been selected as CV pilot sites in the year 2015. The instrumentation descriptions for these and other CV deployment sites are shown in Table 2-3 (Cregger & Wallace, 2012; Dickey, Dulmage, Huang, & Sengupta, 2010; Misener & Shladover, 2006). These pilot sites’ instrumentation requirements include deploying RSUs, connecting RSUs with back-end computational infrastructure via wired/wireless communication networks, and developing computing infrastructure to store and process the data.
**Table 2-3 CV Deployments in the US**

<table>
<thead>
<tr>
<th>State</th>
<th>Project Name</th>
<th>State DOT Role</th>
<th>Deployment Site</th>
<th>Deployment Description</th>
<th>Transportation Applications</th>
<th>Communication Options Used</th>
<th>Computing Infrastructure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Virginia</td>
<td>Virginia Connected Corridors</td>
<td>Partnered with Virginia Tech Transportation Institute and Virginia Transportation Research Council</td>
<td>Smart Road near Blacksburg, VA: 3.5 kilometers (2.2 miles) two-lane road from Transportation Research Drive to Wilson Creek Bridge Fairfax in Northern Virginia, including sections of Interstate 66, Interstate 495, U.S. 29, and U.S. 50</td>
<td>10 RSUs</td>
<td>Weather impact on transportation, OEM-desired applications</td>
<td>DSRC, Fiber Optic</td>
<td>Cloud-based centralized system</td>
</tr>
<tr>
<td>California</td>
<td>California Connected Vehicle Test Bed</td>
<td>Owner</td>
<td>16 kilometers (10 miles) segments of 2 routes (in Palo Alto and near the San Francisco Airport), encompassing US 101 and State Route 82</td>
<td>9 RSUs along SR-82</td>
<td>Intersection safety applications, intelligent on-ramp metering, travel time data to vehicles, work zone safety warnings, taking curves over-speed warnings</td>
<td>DSRC, LTE</td>
<td>Centralized data management system</td>
</tr>
<tr>
<td>Colorado</td>
<td>E-470 Toll Plaza</td>
<td>Not involved (tested furnished by Kapsch)</td>
<td>3 lanes next to an existing E-470 highway toll collection system in Aurora, CO</td>
<td>RSUs, 27 instrumented vehicles, cameras, laser units</td>
<td>Road tolling and enforcement.</td>
<td>DSRC</td>
<td>No information available</td>
</tr>
<tr>
<td>New York</td>
<td>NYC CV pilot deployment</td>
<td>Owner</td>
<td>Manhattan arterials (within 14th and 67th street), Brooklyn Flashback Avenue, Manhattan FDR freeway</td>
<td>320 RSUs, 10,000 vehicles with after-market safety devices</td>
<td>Collision warning, blind-spot warning, curve speed compliance, pedestrian in signalized intersection warning</td>
<td>DSRC, cellular (NYCWIN), fiber optic</td>
<td>TMC-based centralized system</td>
</tr>
<tr>
<td>State</td>
<td>Project Name</td>
<td>State DOT Role</td>
<td>Deployment Site</td>
<td>Deployment Description</td>
<td>Transportation Applications</td>
<td>Communication Options Used</td>
<td>Computing Infrastructure</td>
</tr>
<tr>
<td>------------</td>
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</tr>
<tr>
<td>Florida</td>
<td>Florida Test Bed</td>
<td>Owner</td>
<td>Corridor in Orlando along I-4 and along with John Young Parkway/ International Drive/Universal Boulevard</td>
<td>11 RSUs along I-4 and 16 RSUs at other locations, 41 vehicles</td>
<td>Traffic management</td>
<td>DSRC, Fiber Optic</td>
<td>TMC-based centralized system</td>
</tr>
<tr>
<td></td>
<td>Tampa CV Pilot Deployment</td>
<td>Partnered with Tampa Hillsborough Expressway Authority (THEA), USDOT, City of Tampa, etc.</td>
<td>Downtown Tampa</td>
<td>46 RSUs, 1600 private cars, 10 buses, 10 streetcars, 500 pedestrians</td>
<td>Traffic backup warning, wrong-way warning, transit signal priority, traffic flow optimization</td>
<td>DSRC, Wi-Fi, LTE</td>
<td>TMC-based centralized system</td>
</tr>
<tr>
<td>Osceola County Connected Vehicle Deployment</td>
<td>Partnered with Osceola County and FHWA</td>
<td>Osceola Pkwy. and Orange Blossom Trail intersection, and Orange Blossom Trail and Poinciana intersection in Kissimmee</td>
<td>2 RSUs (with the capability to run signal phase and timing applications)</td>
<td>Showing Signal Phasing and Timing (SPaT) information on OBUs</td>
<td>DSRC, Fiber Optic</td>
<td>TMC-based centralized system</td>
<td></td>
</tr>
<tr>
<td>Michigan</td>
<td>Ann Arbor Connected Vehicle Test Site</td>
<td>USDOT partnered with the University of Michigan Transportation Research Institute</td>
<td>117 kilometers (73 miles) of roadway in the northwestern part of Ann Arbor</td>
<td>29 RSUs, 2836 vehicles</td>
<td>Safety benefits of connected vehicles</td>
<td>DSRC, LTE, Fiber Optic</td>
<td>No information available</td>
</tr>
<tr>
<td>Southeast Michigan Connected Vehicle Testbed</td>
<td>USDOT-sponsored</td>
<td>Sections of I-96, I-94 (Ann Arbor-metro Detroit), and U.S. 23 (Ann Arbor-Brighton)</td>
<td>50 RSUs, 9 vehicles</td>
<td>Signal phasing and timing, security credential management system</td>
<td>DSRC, Fiber Optic</td>
<td>Situation data processing center-based centralized system</td>
<td></td>
</tr>
<tr>
<td>Wyoming</td>
<td>Wyoming CV Pilot Deployment</td>
<td>Owner</td>
<td>I-80 corridor</td>
<td>75 RSUs, 400 vehicles</td>
<td>Forward collision warning, work zone warning, spot weather impact warning</td>
<td>DSRC, WyoLink Radio Network, LTE, Wi-Fi</td>
<td>TMC-based centralized system</td>
</tr>
<tr>
<td>Arizona</td>
<td>Arizona Connected Vehicle Test Bed</td>
<td>Partnered with Maricopa County, DOT,</td>
<td>3.7 kilometers (2.3 miles) on arterial, 11 signalized</td>
<td>12 RSUs, 2 MCDOT REACT</td>
<td>Traffic signal control priority for electric vehicles and transit, traffic signal priority applications</td>
<td>DSRC, Wi-Fi, Bluetooth, Fiber Optic</td>
<td>TMC-based distributed system</td>
</tr>
<tr>
<td>State</td>
<td>Project Name</td>
<td>State DOT Role</td>
<td>Deployment Site</td>
<td>Deployment Description</td>
<td>Transportation Applications</td>
<td>Communication Options Used</td>
<td>Computing Infrastructure</td>
</tr>
<tr>
<td>--------------</td>
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<td>--------------------------------------------------------------------------------</td>
<td>------------------------</td>
<td>------------------------------------------------------</td>
<td>-------------------------------------------------------</td>
<td>--------------------------</td>
</tr>
<tr>
<td>Minnesota</td>
<td>Minnesota Connected Vehicle (CV) Pilot Deployment</td>
<td>Owner</td>
<td>I-35W southwest of Minneapolis</td>
<td>6 RSUs, 600+ vehicles</td>
<td>Maintenance activities</td>
<td>LTE, DSRC</td>
<td>TMC-based centralized system</td>
</tr>
<tr>
<td>Pennsylvania</td>
<td>CMU Cranberry Township and Pittsburgh Test Bed</td>
<td>Partnered with Carnegie Mellon University (CMU), Cranberry Township, and the City of Pittsburgh</td>
<td>2.9 kilometers (1.8 miles) stretch along Route 19 corridor</td>
<td>11 RSUs</td>
<td>Traffic signal-related applications</td>
<td>DSRC</td>
<td>No information available</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Partnered with FHWA</td>
<td>Baum Boulevard (state route) and Centre Avenue (city road) corridors</td>
<td>24 RSUs</td>
<td></td>
<td>No information available</td>
<td>No information available</td>
</tr>
<tr>
<td></td>
<td>PennDOT Ross Township Test Bed</td>
<td>Partnered with FHWA</td>
<td>Along McKnight Road (SR 4003) from I-279 to Perrymont Rd/Babcock Blvd in Pittsburgh, PA</td>
<td>11 RSUs</td>
<td>Traffic signal related applications</td>
<td>DSRC</td>
<td>No information available</td>
</tr>
<tr>
<td>South Carolina</td>
<td>South Carolina Connected Vehicle Testbed</td>
<td>USDOT sponsored</td>
<td>3.2 kilometers (2 miles) long stretch along Perimeter Road, Clemson SC</td>
<td>3 RSUs, 20 vehicles</td>
<td>Queue warning, speed harmonization, heterogeneous network testing</td>
<td>DSRC, Wi-Fi, LTE, Fiber Optic</td>
<td>TMC-based distributed system</td>
</tr>
<tr>
<td>Utah</td>
<td>UDOT Redwood Road DSRC Corridor</td>
<td>Owner</td>
<td>Redwood Road, 400 South Street to 8040 South Street</td>
<td>30 RSUs, 4 buses</td>
<td>Transit signal priority</td>
<td>DSRC, Fiber Optic</td>
<td>TMC-based distributed system</td>
</tr>
</tbody>
</table>
In addition to funding several pilot projects, the USDOT has provided guidance through its Connected Vehicle Reference Implementation Architecture program (USDOT, 2017). This initiative aims to support standards development for data collection and communication networks. It has shown how different transportation components, such as vehicles, roadway infrastructure, and data storage and processing infrastructure should exchange data and what types of data should be exchanged. This program serves as an important roadmap towards the future.

Outside the US, Asian and European countries are also active in conducting research and deploying pilot projects involving CVs (Sakib M. Khan, Rahman, Apon, & Chowdhury, 2017). In Europe, there has been an accelerating effort to deploy CV technologies and make the roads ready for connected vehicles. Table 2-4 outlines some existing CV deployment sites outside the US. Among other initiatives, the European Commission, through its Europe on the Move strategy, has recently completed its agenda on safe mobility (using mandatory advanced driving features and smarter roads to move toward a goal of zero road fatalities by 2050), clean mobility (with new CO₂ emission standards for heavy-duty trucks aiming at a 30% reduction in emissions by 2030), and connected and automated mobility. Four hundred and fifty million euros are being invested to achieve these goals (European Commission, 2018). There is a current investment program in the UK that is allocating £11 billion between 2015 and 2021 for the creation and upgrading of “smart motorways” (England, 2017). These motorways will automatically keep track of congestion to dynamically change speed limits, as well as open hard shoulders as traffic lanes to mitigate congested conditions. While this investment is
commendable and has been successful in terms of reducing congestion, a more forward-looking investment would include CV technologies. Comprehensive detail of UK’s 2018 projects can be found at (CCAV, 2018).

Table 2-4 CV Deployments outside US

<table>
<thead>
<tr>
<th>Country</th>
<th>Deployment Site</th>
<th>Deployment Description</th>
<th>Transportation Applications</th>
<th>Year</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiple countries from European Union (EU)</td>
<td>7 intersection sites in 7 participating countries</td>
<td>150 RSUs, 662 vehicles</td>
<td>Traffic signal violation warning, roadway hazard warning, and intersection energy efficiency improvement</td>
<td>2013-2015</td>
<td>(Compass4D, 2017)</td>
</tr>
<tr>
<td>Multiple countries from EU</td>
<td>Application deployed in intersections and within emergency vehicles, other participating vehicles, and road work sites</td>
<td>Cellular based 3G-4G/LTE mobile communication networks (for C-Roads Belgium)</td>
<td>Emergency vehicle approaching, road works warning, in-vehicle speed limit, intersection safety, weather conditions, and in-vehicle signage</td>
<td>Ongoing</td>
<td>(CRoads, 2017)</td>
</tr>
<tr>
<td>France</td>
<td>Ile-de-France, Paris-Strasbourg highway, Isère, the ring road of Bordeaux, Bretagne</td>
<td>3000 vehicles, RSUs at 5 sites (almost 2011 kilometers (1250 miles) of road)</td>
<td>Slippery road warning, road work information</td>
<td>Ongoing</td>
<td>(Scoop, 2017)</td>
</tr>
<tr>
<td>Austria</td>
<td>Almost 45 kilometers (28 miles) long corridor close to the motorway junctions A2/A23-A4-S1 in Vienna; belongs to the Telematics Consortium</td>
<td>46 roadside communication points, including 10 traffic lights</td>
<td>Traffic safety and traffic management</td>
<td>2013</td>
<td>(ECoAt, 2017)</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>Two sites in the UK including 90 kilometers (56 miles) of roads</td>
<td>5G emulation, data storage, controlled to the semi-controlled urban environment along 90 kilometers (56 miles) of roads</td>
<td>All aspects of real-world CV operation including Mobility-as-a-Service and social impacts</td>
<td>2019</td>
<td>(Millbrook, 2018)</td>
</tr>
</tbody>
</table>

To motivate public and private stakeholders to adopt common standards which would allow for interoperability, the European Commission has created a common platform to facilitate deployment of CV technologies called the Cooperative Intelligent
Transport Systems (C-ITS) initiative. This program, initiated in November 2014, brings together key public and private stakeholders (e.g., government authorities, auto manufacturers, suppliers, service providers, and telecommunication companies) to adopt a common vision and accelerate innovation and deployment of CV technology. Created in consultation with various stakeholders, the C-ITS platform addresses technical, legal and policy issues, such as the underlying communication medium, security and certification, the data integration platform, privacy and liability issues (arising from data sharing and usage), standardization, interoperability among stakeholders (particularly across political borders), effective business models, and more. Although the C-ITS platform has been developed, substantial investment and development are required for both vehicles and infrastructure before many socio-economic benefits can be reaped; it has recommended that governments must continue to invest in V2I technology deployment so that private companies see clear benefits and continue investing in in-vehicle technology. C-ITS stresses that since CV technology is currently ready for adoption, and since vehicle manufacturers aim to deploy CV-enabled vehicles in the EU by 2019, setting up the technical and legal infrastructure is urgent (IEEE, 2015).

While industry, academia, and governments in the US and Europe aim to be at the forefront of the advancement of the CV technology, there is a marked difference in their approaches. In the US, policymakers have left it to industry to decide which connectivity option to adopt for CVs, and the majority of the automakers and network operators have recently put their support behind cellular technology for V2I communication (terming it Cellular Vehicle-to-Everything, or V2X). This gained traction with the formation of the
5G Automotive Association (5GAA) (5GAA, 2018) in 2016. On the other hand, across the Atlantic, the approach is more prescriptive and standards tend to be set more by government, though stakeholders influence policy. The European Commission plans to leverage both Intelligent Transport Systems-G5 (ITS-G5), a wireless communication option similar to DSRC, and cellular communications for vehicular connectivity (5G America, 2018). Based on these communication options, the European Commission plans to finalize the legal framework soon for the implementation of cooperative intelligent transportation systems by 2019.

2.4.2 Connected Transportation and Smart Cities

Connectivity in transportation is a key element of the “Smart Cities” concept, or, as a recent report from the USDOT (2014) calls it, the “Smart/Connected Cities” concept (Cuddy et al., 2014). USDOT foresees Smart/Connected Cities as interconnected networks of systems including employment, transportation, public services, buildings, energy distribution, and more. These are referred to as systems of systems, which are linked together by Information and Communications Technologies (ICT). Within the Smart/Connected City, ICTs broadcast and process data about different activities. The Smart/Connected City will use intelligent infrastructure that translates the state of the physical world into data through devices that sense their environment and collects, exchanges and analyzes that data through advances in ICT such as crowdsourcing, Big Data analysis, and gamification. Big Data is characterized by volume (i.e., large data size which cannot be analysed with traditional data analysis software), velocity (i.e., data coming in real-time, or a certain interval), veracity (i.e., trustworthiness of the data), variety
(i.e., data having different formats, and types), and value (i.e., worth or efficacy of the data) (Sakib M. Khan et al., 2017). In addition to collecting and transmitting data, infrastructure will sometimes receive instructions for action. The goal is to create synergies between smart and programmable infrastructure systems, such as the electricity grid, waste disposal, water distribution, healthcare, and more. Connected transportation is a major element of Smart Cities, as is shown in Figure 2-3. The digital infrastructure may process information not only on traffic flows and road conditions, but also on related systems such as energy systems (e.g., fuel consumption by vehicles), the environment (e.g., vehicle emissions, hazardous material exposure), and the community (e.g., traveler information, traveler satisfaction).

**Figure 2-3** Overview of smart city components.
The USDOT has laid out a research agenda to make the Smart/Connected City—particularly its transportation element—a reality. This includes not only developing a connected transportation system but exploring how this system will interface with other aspects of a Smart City such as the Smart Grid, Smart Homes, etc.; how the system can be used to influence traveler behavior while ensuring sustainability and a reduced carbon footprint; what role the Internet and mobile devices can play in a Smart/Connected City system; what actors (such as, travelers, private and public agencies) must be engaged to make the Smart/Connected City a reality; and what the social, political, environmental, and economic benefits of a Smart/Connected City maybe.

Innovative initiatives around the globe are currently making the Smart/Connected City, with a strong transportation element, a reality. In 2016, USDOT held a Smart City challenge and selected Columbus, OH, as the winner. The Smart City plan for the City of Columbus the use a number of new technologies, such as connected infrastructure, electric vehicle charging infrastructure, an integrated data platform, and autonomous vehicles to meet the current and future challenges in different areas including transportation, residential and commercial. The European Innovation Partnership on Smart Cities and Communities (EIP-SCC) (European Commission, 2015) brought together cities, residents and industries to develop a number of solutions that have found their way into commercially viable products, start-ups and services, such as the SuperHub tailor-made mobility solution, which suggests to people the most eco-friendly mobility option (European Commission, 2017). In the United Kingdom, a multi-million pound Smart/Connected City project has been launched in the city of Bristol to upgrade the
existing infrastructure with the latest sensors and connectivity technology, turning the city into a live laboratory to test and deploy solutions for combating air pollution and traffic congestion while helping to assist the elderly and support the city’s trial of AVs (Bristol, 2017). Rio de Janeiro has the world’s largest “smart” operations center, created in collaboration with IBM. It collects and analyzes data from myriad sources to optimize city services. The initial focus was on disaster prediction and response, but the program has grown to include transportation, with data being drawn from traffic and transit navigation apps. Another example of a Smart City is Songdo, South Korea, where CISCO, a private company, demonstrated the connected community concept by connecting offices, residences and other buildings (Angelidou, 2014). With the help of remote control systems, residents have the capability to control different functionalities in their homes. This compact city also has an accessible transportation system with the widespread provision of public transit, biking, and walking facilities, and the whole city is under surveillance for real-time traffic management. In Amsterdam, an open data platform has been developed with the help of public agencies, utility companies and other data providers to visualize the energy consumption of the local residents (Loibl et al., 2014; van den Buuse & Kolk, 2019). The open platform provides data for decision-making regarding energy management and is used by the local agencies. Perhaps the world’s leading Smart City is Singapore, where a highly developed data-gathering and analysis system, including sensors, cameras, and GPS devices provides information on traffic and congestion to aid navigation, transit operations, and the congestion tolling program. For more on these cities, see (Cuddy et al., 2014).
2.5 Investment Trends in Digital Infrastructure by Public Transportation Agencies

However, notwithstanding all of these initiatives, public agencies’ limited investment in digital infrastructure is clear when examining agencies’ ITS deployment and improvement funding. For example, for the fiscal year 2019 the total operating budget requested for Arizona DOT is $33 million more than 2018, yet for statewide Intelligent Transportation Systems (ITS) upgrades and maintenance the requested budget increment is only $2 million (only 0.6% of the total highway budget increment) (ADOT, 2017). This additional funding is requested mainly for replacing and updating statewide Closed Circuit TV (CCTV) cameras, Dynamic Message Signs (DMS), and Road Weather Information Systems (RWIS). Arizona DOT is currently under-funded by $500,000 per year for the statewide ITS infrastructure (ADOT, 2017). For the Wisconsin DOT, the total proposed allocation for its ITS program, according to the 2015 biennium funding request, is only 0.67% of the total state transportation funding request (WisDOT, 2015). Although the funding request is higher than in prior years, it is not sufficient to implement ITS infrastructure on selected corridors, which includes the installation, replacement, and rehabilitation of traffic signals, CCTV, DMS, ramp meters, and related communication networks. According to the State Transportation Improvement Program for the Massachusetts DOT, the proportion of the budget devoted to ITS is very small, at only 1.61 percent (MassDOT, 2017). For ITS programs, the budget includes the cost of traffic sensors, CCTV, and DMSs. For the Colorado DOT (CDOT), ITS devices include CCTV, radar devices, RWIS, travel time readers, ramp meters, and automated traffic recorders. According to the proposed budget plan, 2% (i.e., $33.5 million) of the total DOT budget is
allocated to ITS programs in 2018 (CDOT, 2018). As these data suggest, the ITS program budget in many US states is not sufficient to implement the widespread digital infrastructure for the V2I applications of the future.

In the UK, while investment in ITS infrastructure has recently increased (since 2015 there has been over £1.5 billion in ITS investment in England for upgrading the motorways), much of it is limited to the trunk roads and motorways, primarily in “traditional ITS” technology such as CCTV, DMS and traffic control centres (Trans Scot, 2017). In addition, there have been a number of small pots of investment under the C-ITS project funded by the Department of Transport.

2.6 Future Directions to Overcome Challenges Impeding V2I Deployment

The author has identified three major challenges which are obstructing the V2I deployment, and these challenges are: political, technical and investment-related challenges. Future directions to overcome these three challenges are discussed below.

2.6.1 Political Challenges and Opportunities

This lack of resources for V2I comes in the context of increasingly constrained funds for transportation in the US. Although the United States was a world pioneer in terms of funding and building a massive highway system, in recent decades a lack of funding and political will has precluded dramatic new investment in highway infrastructure. For some time, observers have noted that the condition of US roadway infrastructure is suboptimal and declining. The American Society of Civil Engineers issues an annual “Report Card” on the state of roads and bridges in the US: currently, the road system receives a grade of
“D” (i.e., poor-fair condition with many roadways approaching the end of their service lives), while bridge infrastructure receives a “C+” (i.e., fair-good condition with many bridges exhibiting signs of general deterioration) (ASCE, 2017). The 2017-2018 Global Competitiveness Index, available from the World Economic Forum, ranks the US only tenth for overall road quality (World Economic Forum, 2017). Several national-level assessments have called for immediate action and fresh investment in order to repair and upgrade American transportation infrastructure (Pisarski & Reno, 2015; Roundtable, 2015). A severe infrastructure and transit funding shortfall in the US has thus been identified, worth $846 billion for the seven-year (2013-2020) planning timeframe (Zmud et al., 2017).

Clearly, if resources are lacking even to keep pavement in good condition, questions abound about funding for digital infrastructure. This is unfortunate because the technology exists, and has been proven feasible as well as highly beneficial, to integrate travelers, such as drivers, cyclists, and pedestrians, and infrastructures, such as traffic lights, open-road tolling facilities, DMS boards, highway onramp meters, and regional traffic control centers. Thus far, despite promising pilot programs, the political will to deploy this technology on a large scale has proven elusive. This lack of willingness is evident from the funding shortfall and discrepancy between automotive R&D and public investment in traffic management infrastructure. In 2015, global automotive R&D expenditure for 92 auto companies was $109 billion (PWC, 2015), while the global traffic management system market was only $4.12 billion (Market Research, 2016). Such an
investment mismatch may lead to an environment where the benefits of a smart, connected ecosystem will never fully reach fruition.

In addition to a lack of financial resources, several other hurdles must be surmounted in order to proceed from the research phase to the actual deployment of V2I technologies by the public sector. According to the United Nations Economic Commission for Europe, the impediments inhibiting ITS deployment include a lack of political will, a lack of harmonized ITS deployment policies, and a lack of coordination between public agencies and the private sector (UNECE, 2012). Based on prior experience, different agencies/stakeholders will have different perspectives on who should take the lead in investing in, operating, and maintaining digitally connected infrastructure. Identifying the roles and responsibilities of stakeholders (as shown in Table 2-5), and developing a consensus regarding the investment, deployment, operations, and maintenance of the digital infrastructure, are the most critical steps in mainstreaming CV technology.

Table 2-5 US Agency Responsibilities for Digital Infrastructure Deployments

<table>
<thead>
<tr>
<th>Tasks</th>
<th>Federal Transportation Agency</th>
<th>Regional Transportation Agency</th>
<th>Private Actors</th>
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<tbody>
<tr>
<td>Standards development</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Device specification development</td>
<td></td>
<td>X</td>
<td></td>
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<tr>
<td>Device interoperability checking</td>
<td>X</td>
<td>X</td>
<td></td>
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<tr>
<td>Security and privacy control</td>
<td>X</td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>Communication mandate</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Device and software manufacture</td>
<td></td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>Digital infrastructure deployment and management</td>
<td></td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Outreach program and staff training</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
</tbody>
</table>
Finally, the legal implications of the digital infrastructure must be addressed at the political level. Responsibilities of various stakeholders must be assigned; for example, legal liability for safety events and security and privacy breaches must be sorted out. In one report published for the European Commission, the authors also identified liability, standardization, and government roles as challenges facing vehicle and roadway automation (Brizzolara & Flament, 2017).

2.6.2 Technical Challenges and Opportunities

Although the technology has come a long way, some of the technical hurdles still facing V2I remain somewhat daunting. Once CV technology is deployed, the sheer number of vehicles and the extent of transportation infrastructure will generate a tremendous volume of data, and existing facilities come nowhere close to having the capacity to communicate, store and analyze such an unprecedented amount of information. To illustrate, California’s freeway Performance Monitoring System (PeMS) is a repository for all fixed-location loop detector data in the state. From the more than 23,000 loops statewide, 2 GB of data is collected by PeMS per day (Choe, Skabardonis, & Varaiya, 2002). In contrast, a single CV can produce 25 GB of data per hour (Hitachi, 2015), and AVs can produce more than 165 GB per hour (Geonovum, 2017). This enormous disconnect calls for dramatic investment to upgrade existing information technology infrastructure to make it fully capable of handling Big Data from both vehicles and infrastructure. National, state, regional and local-level edge computing guidelines need to be established to successfully handle the data generated by CVs.
Other concerns must be addressed before CV digital infrastructure will become “public ready.” For example, the security of the digital infrastructure and privacy of the users must be guaranteed. Earlier studies have investigated the cyber-security aspect of V2I applications for different public infrastructure components like RSUs (Islam, Chowdhury, Li, & Hu, 2018) and connected traffic signal controllers. USDOT has also developed the Security and Credential Management Systems to protect privacy among the communicating devices, thus ensuring security, which can be used by public agencies for digital infrastructure deployments. As shown in Figure 2-4, many US agencies have cybersecurity policies in place for ITS devices, but for V2I applications these policies will not be sufficient, as the number of externally connected devices will be higher than exist today. Public agencies should collaborate with industry and academia to develop a resilient cyber-security framework for TCPS. Further, as the author has noted, the standardization of these technologies across political jurisdictions must be established in order to facilitate interoperability and provide the requisite levels of both efficiency and security.
Finally, there are issues in terms of the wireless communication network. For example, as the author has noted, HetNet is required for multiple V2I applications (including safety, mobility, and environmental applications). In HetNet, DSRC could provide low latency within a limited range for safety-critical applications such as collision warnings, while for applications that require longer range but where higher latency is acceptable, such as queue warnings to vehicles not within a DSRC limited range, other options such as LTE may be more appropriate (Kakan C. Dey et al., 2015). However, once deployed and incorporated in HetNet, the cellular 5G network could support the early rollout of CV and Smart City initiatives. 5G will provide more data at a higher transmission rate for an increased number of simultaneous users in larger portions of the coverage area compared to the cellular 4G network (Rappaport et al., 2013). However, there is no
mandate about specific communication options from the Federal Government for V2I applications in the US, as was discussed earlier. All these technical gaps have slowed digital infrastructure investment in the transportation system.

2.6.3 Investment Challenges and Opportunities

To ensure that digital infrastructure investment is made wisely, collaboration across jurisdictions will be essential. Agencies responsible for deploying, managing and maintaining transportation infrastructure must participate in national and international platforms to plan, implement, and manage the digital infrastructure in their own jurisdictions. These plans could include national intelligent transportation plans and/or architectures, which both the US and Europe have developed. Such architectures would ensure interoperability across products, jurisdictions, and regions. Failure to adopt common standards may result in a haphazard deployment that would limit the efficacy of CVs.

Another strategy should involve transportation agencies following the existing CV and Smart City pilot sites’ instrumentation experience (i.e., RSUs, back-end computational infrastructure, and wired/wireless communication options), moving toward deploying similar, albeit improved, technology on public roadways. Moreover, all stakeholders involved in the creation of this digital infrastructure must squarely address the remaining political, legal, and technical challenges, such as security and privacy, which have the potential to slow the development of CVs. According to a recent study, among 115 DOT personnel in Oregon, 14% thought that Oregon DOT needs to invest in legislation and
regulatory actions update before allowing AVs (Bertini, Wang, Knudson, Carstens, & Rios, 2016).

There have been efforts to surmounting these challenges. To gain useful insights about the ITS devices’ collected data, MassDOT organized “Hackathon” as a part of their Open Data initiative (MassDOT, 2014). New York City followed the Open Data Government program to create a citywide open data portal where all city government agencies publish data under their jurisdiction (Dawes, Vidiasova, & Parkhimovich, 2016). Based on the available data, developers can create an application for citizens. Also, New York City has established annual ‘BigAppsNYC’ competitions to encourage local entrepreneurs and researchers to develop applications. Creating such outreach programs and other similar competition/training activities will help agencies to realize the maximum benefits from V2I applications, and provide blueprints for programs that can be adopted by other cities.

Public agencies need to justify the investment in digital infrastructure to successfully implement V2I applications. At first, agencies should identify the critical areas under their jurisdiction where V2I applications will bring the maximum benefit. Based on agency requirements and application criteria, the key design considerations (i.e., computing infrastructure, communication technology) can vary. Existing literature provides sufficient data about the costs and benefits of digital infrastructure components, which can be used by public agencies to help justify funding requests (Co-pilot, 2015; ITS Benefits, 2018; Williges, Volodin, Garrett, & Azizi, 2018).
Financing digital infrastructure investment for CVs is, of course, a major challenge. Traditional means (e.g. fuel taxes, subsidies from general funds, and tolls) may be used to generate the necessary revenue. Public-private partnerships, which have been gaining momentum worldwide, are also a promising potential mechanism to deal with upfront investment costs. Some programs are addressing this issue: for example, the American Association of State Highway and Transportation Officials (AASHTO), along with the ITS America, and Institute of Transportation Engineers (ITE), has announced the AASHTO Signal Phase and Timing (SPaT) Challenge. This encourages transportation agencies to deploy DSRC-enabled infrastructure in 20 intersections in each of the 50 states by 2020, and maintain its operations for a minimum of 10 years (Zmud et al., 2017). With this challenge, AASHTO wants not only to provide technical resources with implementation guidelines but to identify funding sources for the participating agencies.

Whatever financing methods are chosen, the path forward for mainstreaming digital roadway infrastructure necessitates creating strong partnerships between all CV stakeholders, particularly private industry and public agencies. With foresight, commitment, and cooperation, V2I may engender a unique public/private collaboration, with private industry developing the in-vehicle components of a CV system and public agencies equipping the infrastructure with complementary technology. Such collaboration will be mutually beneficial.

2.7 Conclusions

The benefits of CV technology are clear, multifaceted, and potentially dramatic. Travelers, automakers, insurers, public agencies, and the general public all stand to reap
the rewards from an environment featuring V2I communication, including improved safety, enhanced environmental sustainability, increased mobility, and much else.

Unfortunately, the investment and regulation that are required to reach this potential are lagging. Although automakers are beginning to commit resources to CV technology for V2V communications, they are understandably reluctant to depend on public agencies given that the current public infrastructure is not ready to interact with connected vehicles. In the US, there have been federal investments, especially in the research, development, and pilot deployment of V2I infrastructure. However, investment is lacking at the state and local levels. There must be regional, national, and international collaboration to engage private and public stakeholders in planning and implementing the digital infrastructure. The products of this collaboration must include platforms that will allow public and private stakeholders to cooperate in CV deployment, with common architecture and standards which would allow for interoperability between vehicles, infrastructure, and devices across political jurisdictions. This, in turn, will benefit private enterprise through the success of its products, as well as government entities which will be better able to provide the public improved safety and mobility across the infrastructure they operate and manage. Failure to adopt common standards may result in a haphazard deployment that would limit the efficacy of CVs.

Transportation agencies should imitate the existing CV and Smart City pilot sites’ instrumentation strategies, moving toward deploying similar, albeit improved, technology on public roadways. Moreover, all stakeholders involved in the creation of this digital infrastructure must squarely address the remaining political, legal, and technical
challenges, such as security and privacy, which have the potential to slow the development of CVs.

A unique public/private collaboration can be helpful for future TCPS, where the private industry will develop the in-vehicle and infrastructure components of a CV system and public agencies will deploy the digital infrastructure. Another option could be the total privatization of the digital infrastructure. Such efforts, either private/public collaboration or privatization, could greatly benefit not only the stakeholders but society as a whole.
CHAPTER THREE

CONNECTED VEHICLE SUPPORTED ADAPTIVE TRAFFIC CONTROL FOR NEAR-CONGESTED CONDITION IN A MIXED TRAFFIC STREAM

3.1 Introduction

In this chapter the author has conducted research using the connected vehicle data, however, similar benefits can be achieved by CAVs. Connected Vehicles (CVs) are wirelessly connected mobile nodes that communicate with the surrounding connected vehicles, other connected road users (e.g., pedestrian, cyclists) and infrastructure (i.e., traffic signal, roadside unit) using any available communication option, and provide data based on vehicle movement, and interactions with the surrounding environment. Although many research-based or market-focused studies have predicted the rapid penetration of CVs into the regular vehicle fleet, challenges exist to develop an efficient transportation system considering both CV and regular vehicles (non-CVs). In this research, the author has considered the mixed traffic scenario while developing an adaptive traffic control algorithm for urban arterials. In urban arterials, traffic signal control is used to control and manage traffic operations. The signal controller ensures smooth traffic operations by reducing the delay and conflicts on urban arterials, and the controller collects data from different traffic data collection sensors. Widely used traditional traffic data collection sensors include inductive loop detectors, video camera, RADAR, and/or ultrasonic sensors. However, the emerging CVs have the potential to provide the data required by the traffic signal controllers, and thus it can help to reduce or even eliminate the need for traditional traffic sensors. In this research, CV based data and upstream traffic signal status are used
to collect traffic flow information in the corridor, estimate existing queue length near the signalized intersections, and estimate the traffic signal timing parameters.

Adaptive traffic signal control is the most advanced strategy for signalized intersection operation and it promises to offer better operational, safety, environmental and economic performance compared to the fixed/pre-timed and actuated traffic signal control. Adaptive traffic signal control algorithms collect real-time data and they dynamically estimate traffic signal timing parameters satisfying different objectives (e.g., reduction of travel time, delay, and/or queue length, or increase in average speed), which ensures better performance compared to the actuated and pre-timed traffic control. Using data only from a limited number of CVs in a mixed traffic stream, estimating traffic signal timing parameters is inherently challenging as complexities can arise while estimating aggregated data (e.g., total vehicle count, average queue length, average speed) from microscopic data from CVs that are a small proportion of the total traffic streams. An earlier study conducted by (Goodall, Smith, & Park, 2014) could not achieve better operational performance with limited CV penetration (i.e., less than 25% CV) compared to the coordinated actuated traffic signal control. Another challenging aspect of traffic signal design for an urban arterial is the establishment of proper signal coordination. Signalized intersections are closely spaced in urban areas, therefore the traffic signals are often coordinated to make the vehicle progression smooth in the coordinated direction. Offset is one of the important parameters for the signalized intersection coordination. Traffic engineers use the term ‘offset’ to refer to the time lapse between the start of green times between two successive coordinated, signalized intersections. Offset is a common parameter for actuated
coordinated signals, however most existing actuated coordinated signals have fixed offset values. During rush hour traffic, if there is a huge fluctuation in the directional traffic flow, having fixed offset values may not provide the desired operational benefits due to the varying traffic demands. Another concern for the existing legacy adaptive signal control algorithms is that the green signal interval does not update in real-time based on the traffic demand on the coordinated direction (Shelby et al., 2008). Earlier studies have estimated a fixed green signal interval for the intersections in the coordinated direction. However during a complete cycle time (i.e., the time required to complete all phases in an intersection), traffic volume can fluctuate in the coordinated direction, thus having a volume-responsive green interval time can help to dynamically adjust the green time for the coordinated direction in response to the existing demand.

In order to overcome the aforementioned limitations, the author has developed a CV-based adaptive traffic signal control algorithm with three distinct capabilities. First, the algorithm can estimate traffic signal timing parameters based on the limited CV data in a mixed traffic environment. Second, the algorithm can do dynamic offset adjustments based on the existing congestion condition in the signalized intersections. Third, the algorithm can do dynamic adjustment in the green time interval for the coordinated directions based on the traffic demand in those directions. A machine learning-based short-term traffic forecasting model is used to predict future traffic counts. Based on the predicted counts, the author has identified vehicle platoons going through the intersections and used a multi-objective optimization framework with Mixed Integer Linear Programming (MILP) models to estimate signal split time for each intersection. The author has extended the
major street green splits based on the available cycle time if there is no call from the minor street. At the last step, another Mixed-Integer Non-Linear Programming (MINLP) model is used to dynamically estimate the offset values for each signalized intersection. The author has evaluated the CV-based adaptive signal control’s performance using a simulation network of US 29, Greenville SC. The motivation is to improve the operational performance on the coordinated major streets with limited CV data. The author has discussed the related studies, CV-based adaptive signal control algorithm, experimental design, analysis and discussion in the following sections.

3.2 Related Study

In the following subsections, the author has discussed the related studies on short-term traffic prediction, CV-based adaptive signal control, and traffic signal coordination.

3.2.1 Short-Term Traffic Prediction and Platoon Identification

Common input variables for any vehicle-responsive traffic control systems (including the adaptive traffic signal control system) include vehicle arrival time, traffic count, queue length, time gap between vehicles, and detector occupancy (Gershenson, 2004; Q. He, Head, & Ding, 2012; Ki, Keffer, Atkison, & Hainen, 2017; Xie, Barlow, Smith, & Rubenstein, 2011; Yulianto, 2018). The author has used traffic counts as an input parameter for the adaptive traffic control system in this study. In addition, the author has used a short-term time-series forecasting model to predict traffic count in the future based on the existing CV data. In a review study by (Vlahogianni, Karlaftis, & Golias, 2014), the authors identified challenges associated with the short-term traffic forecasting models. The
traffic forecasting models for arterials are found to be more complicated than that of freeways, as traffic signals have a direct impact on arterial operations. Using data from a low penetration level of probe vehicles and identifying proper data aggregation interval for forecasting are two main challenges for traffic forecasting, which the author has addressed in this study. The different state of the art approaches including the Auto-Regressive Integrated Moving Average or ARIMA model, state-space models, univariate and multivariate methods have been used by (Chatfield, 2005) for time series prediction. An earlier study has established the machine learning-based models as viable options for short-term traffic forecasting (Vlahogianni et al., 2014). Among the machine learning-based models, Recurrent Neural Network (RNN) model is one of the widely used models for the sequence prediction. The layers of the neural networks have internal feedback connections, which are used to update the network weights until the model converges to reduce the difference between the actual data and predicted data. In their use of Long Short-Term Memory (LSTM) to predict traffic flow at a specific detector location, the authors in (Kang, Lv, & Chen, 2018) found that the inclusion of speed and occupancy from upstream and downstream location can improve the prediction accuracy. In another study, (Tian & Pan, 2015) found LSTM model outperforms Random Walk, Feed Forward Neural Network, Support Vector Machine and Stacked Auto-encoder to predict traffic flow for different prediction intervals.

3.2.2 CV-based Adaptive Traffic Signal Control

Different studies have investigated the CV-enabled adaptive traffic control systems (Ban & Li, 2018; Beak, Head, & Feng, 2017; Feng, Head, Khoshmagham, & Zamanipour,
2015; Goodall et al., 2014; Guo, Li, & (Jeff) Ban, 2019; Li & Ban, 2018). In (Goodall et al., 2014), the authors used simulation to predict traffic over a 15-second time horizon, and estimated signal timing for a decentralized adaptive signal that satisfied objective functions (both single-variable and multivariable objectives) for the predicted traffic. The single-variable objective function was the minimization of cumulative vehicle delay for the simulated corridor with four intersections in Virginia. With 50% or more penetration levels, the delay reduction and speed improvements occurred. For the adaptive signal system, when the degree of saturation was lower than 0.9 and CV penetration was 100%, the operational performance improved or did not significantly alter compared to the coordinated actuated signal control. Using multi-variable objective function (i.e., with delay, negative acceleration, and the number of stops), the operational performance did not improve compared to the single-variable objective scenario. (Feng et al., 2015) evaluated their algorithm in a simulation environment where signal controller estimated position and speed of the non-CVs in three specific regions. Non-CVs were identified in the queuing, slow-down and free-flow regions using queue propagation speed, relative acceleration difference of CVs, and number of CVs with CV penetration rate, respectively. For left-turn lanes, stop line detector was used to detect left-turning vehicles. Once information about both CVs and non-CVs were known, the controller predicted the vehicle arrival times and used two-level optimization (with two separate objectives: to minimize total vehicle delay or minimize queue length) of the vehicles for a prediction horizon of 80 seconds. The simulation result showed that reductions in average delay for each phase occurred with 50% or more CVs for both objective functions in one intersection. (Beak et al., 2017)
extended the study of (Feng et al., 2015) by including coordination strategy (for a corridor with five signalized intersections) with the intersection-level control. The authors in (Beak et al., 2017) developed a platoon flow model based on the platoon dispersion model and simulation generated data. The link performance function used the platoon flow model as an input. Using data from both CVs and the stop bar detectors, adaptive signal control reduced the average delay and the average number of stops by 6% and 3%, respectively in the coordinated direction with 25% CV penetration compared to the actuated coordinated control.

For the intersection-level traffic signal control, (Li & Ban, 2018) used a dynamic programming model to calculate signal timing using CV speed and location data. In order to ensure a fixed cycle length using dynamic programming, the authors used a penalty function and a branch-and-bound method. The authors developed a framework to reduce fuel consumption and travel time for an environment with 100% CV penetration. For different traffic demands (250, 650 and 800 vph), the dynamic programming-based signal control model outperformed the performance of SYNCHRO based actuated traffic control but did not outperform the MATLAB NOMAD-solver based signal control. However, the authors suggested using dynamic programming based signal control as it was computationally feasible than the NOMAD-solver based control. In their review study, (Guo et al., 2019) discussed two approaches used by researchers while developing signal control frameworks, which are: deterministic (i.e., shockwave and kinetic equation-based approach) and stochastic approaches (i.e., uniform or Poisson distribution, machine learning) to derive traffic flow measures. Vehicle trajectory estimation is gaining more
momentum to improve traffic signal performance. Based on the variations of prediction data, three different control methods were identified: (1) CAV-enabled actuated signal control, (2) platoon-based signal control, and (3) planning-based signal control (i.e., using data from each vehicle, predict traffic state for a future time horizon and optimize traffic signal time for that horizon).

For traffic signal timing estimations, creating platoons can help to reduce the computation complexities of a signal timing algorithm. Platoon, representing a group of vehicles, is a form of a disaggregated unit that the signal timing algorithm can consider while assessing vehicle progression. The authors in (Bashiri & Fleming, 2017) discussed a platoon-based scheduling strategy for such scenario where all vehicles were Connected Automated Vehicles or CAVs, and platoons communicated with the intersection controller. When connectivity is incorporated with the automated/autonomous vehicles (i.e., vehicles having partial automation/full automation), the vehicles are referred to as Connected Automated Vehicles (CAVs). In an earlier study, once the controller knew the platoons arrival sequence, it implemented a greedy algorithm to reduce the waiting time of the arriving platoons (Bashiri & Fleming, 2017). For a four-legged intersection, the controller with platoon based delay minimization objective achieved almost 50% less delay compared to the stop-controlled intersection for vehicle flows ranging between 500 to 2000 veh/hour.

3.2.3 Traffic Signal Control Coordination

(C. M. Day et al., 2017) considered CV trajectory data in a mixed traffic scenario to optimize the intersection offsets. With 1% CV penetration level, the authors constructed
vehicle arrival profile from the CV data using virtual detectors (i.e., hypothetical detectors to identify CVs) and compared the findings with the physical detector-based method (i.e., inductive loop detector to identify all vehicles). Using an earlier offset optimizer algorithm developed in (C. Day & Bullock, 2012), the authors computed the offset for both virtual and physical detectors and implemented the offsets separately for one week time period. Using CV-based virtual detectors, the authors achieved similar operational performance. Using sensitivity analysis, at a 90% confidence level, the authors found that 2 weeks sampling period with the CV-based virtual detector method provided similar vehicle arrival profile with the physical detector-based method. For offset optimization in urban areas, (Aoki, Niimi, & Kamijo, 2013) considered arriving vehicles’ profiles and traffic signal timing parameters (i.e., cycle length, split and offset values from adjacent intersections) to maximize the green time overlap. At first, the authors estimated the phase start and end time for the next cycle based on the phase end time of the current cycle, current phase split and reference cycle length. Later, they constructed the vehicle arrival profiles and using the profiles they maximized the green overlap time. Using different traffic demands, the green overlap maximization with vehicle arrival profiles was found to reduce the number of stops and delay for a grid network with 25 intersections, while compared with the Split Cycle Offset Optimisation Technique (SCOOT) and decentralized-SCOOT techniques. (J. Zhang, Cheng, He, & Ran, 2016) developed a probe trajectory-based real-time offset estimation method based on vehicle state information (i.e., queue dissipation, queue formation, free flow). Using vehicle speed and location data, the free flow area (i.e., area where vehicle speed does not change more than 10% of the historical free-flow speed),
queue forming area (i.e., area starting from the point where vehicle speed is less than 3 mph) and queue dissipation area (i.e., area starting after the point where vehicle speed is less than 3 mph) are detected. The optimal offset is calculated as the difference between the time required by a free-flowing vehicle to traverse the corridor, and the time to dissipate the standing queue in the downstream intersection. For a simulated corridor with two intersections, the probe-vehicle based offset tuning method reduced the average delay under fluctuating traffic while compared with the model without offset tuning. But when there was no fluctuation the in traffic demand, the average delay did not improve with the real-time offset tuning method. (Jiao, Wang, & Sun, 2014) developed a real-time coordinated signal control system for urban arterials by estimating turning flows and cycle length at each intersection, and finally calculating split and offset for the arterials. Using loop detectors, the authors collected entering and exiting vehicle counts, and, using those counts, estimated the intersection cycle time to minimize the average delay.

For a simulated corridor with three intersections, the real-time coordinated control outperformed the existing MAXBAND method (i.e., a method to maximize the green wave band) by generating 16.7% less mean queue length, 6.4% less mean delay and 7.7% less number of stops. (Daganzo, Lehe, & Argote-Cabanero, 2018) used only average traffic density to optimize the signal offsets for one-way streets while keeping the intersection green ratios same. If the target corridor’s density was greater than the optimum density, backward progression (i.e., adjusting offsets based on the backward moving observer) was used. If the density was lower than the optimum density, forward progression (i.e., adjusting offsets based on the forward-moving observer) was used. The real-time offset
optimization method generated better operational performance with large roadway sections, compared to short corridors. However, the authors created a hypothetical simulation environment (e.g., one-way street with uniformly spaced intersections), which was favorable for adaptive offset optimization. Further investigations in the complicated, real-world environment are needed to validate the framework for real-world implementation.

3.3 Research Considerations for CV-Enabled Adaptive Signal Control

In this study, the author has developed a CV-based adaptive traffic control system for urban arterials. It is assumed that the urban arterial is instrumented with wireless communication devices (i.e., Roadside Units or RSUs) with computation capabilities required to estimate signal parameters in real-time. Urban arterials are characterized by multiple, closely spaced intersections, and multiple RSUs are required to establish proper coverage to receive real-time CV data. CVs will generate Basic Safety Messages (BSMs) which include time, location, speed, direction, etc. The author has used these CV generated BSMs and upstream traffic signal status to estimate the signal timing parameters. In addition, the author has not considered the effect of driveway traffic on the mainline traffic in the case study.

3.4 CV-based Adaptive Signal Control Algorithm

The CV-based adaptive signal control algorithm follows three steps. First, the author identifies the CV-based platoons on both major and minor directions to estimate the required green time intervals. Second, once an understanding about the approaching
platoons is obtained, the author computes the signal timing parameters for each intersection. Third, while doing that, the author also estimates the offset in real-time in the coordinated direction. The author has discussed all these steps in detail in the following subsections.

3.4.1 Vehicle Platoon Identification and Count Prediction

The first step of the CV-based adaptive signal control algorithm is to identify the vehicle platoons and estimate the number of CVs and non-CVs in the estimated platoon, which is discussed in the following subsections.

3.4.1.1 Vehicle Platoon Identification

![Figure 3-1 Platoon identification with CV and non-CV](image)

The input of the adaptive signal system is the CV data and upstream traffic signal phase. Using only the CV data and upstream signal phase, the author updates the traffic signal timing parameters (i.e., signal split, sequence, and offset). At first, the author
identifies the vehicle platoons on each corridor segment based on the spatial distribution of the CVs, as shown in Figure 3-1 with the dotted bounding box. Here, the ‘corridor segment’ is defined as the roadway section in each direction between two successive traffic signalized intersections (for the major road), or the side street sections considered for this analysis (for the minor road). On each single corridor segment, the author identifies platoons in two separate areas. The first one is the queued platoon which forms inside the expected queue zone, and the next one is the queued platoon which forms beyond the expected queue zone. The expected queue zone is the area near a traffic signal where the queue is typically formed due to the signal yellow and red time. The author locates this area either based on CV data when any CV is queued due to the traffic signal, or based on previous queue length data (i.e., based on historical observations) when there is no queued CV. If two vehicles are moving beyond the expected queue zone, the author forms platoon using two successive CVs. Any non-CVs inside the two successive CVs will be considered as a part of the platoon. If there is only one CV, the author only considers one platoon, which has only that CV. The author similarly forms platoons with CVs inside the expected queue zone, but the platoons from both zones are not merged together.

3.4.1.2 Total Traffic Count Prediction Model

In order to estimate traffic signal timing for the next time horizon, the total traffic count (including both CVs and non-CVs) for a certain time horizon needs to be predicted. Based on this total traffic count, the intersection specific green time intervals and corridor-specific offsets will be optimized. The author predicts the total traffic count for each corridor segment using the Long Short-term Memory or LSTM models. The author has
derived the LSTM batch size (i.e., the size of the data that will be forwarded together in
the learning step), epoch number (i.e., defining how many times the entire dataset will go
forward and backward through the network), neuron number, and weights initially from a
large group of parameters for 20 corridors segments (randomly selected). Based on 20
models’ result, the author has filtered the parameter group and made a small group to figure
out the batch size and neuron number for each corridor-specific LSTM model for different
CV penetration. Using Python Keras (Chollet, 2015) library, the author has implemented
the framework, and estimated the parameters with cross-validation using the Clemson
University Palmetto Cluster computing infrastructure. Using the cluster-computing
environment the computation time is significantly reduced, and the optimized parameters
are derived. While deriving the optimal parameter values, the author has used 70% of the
training data to train, and 30% of the training data to validate the LSTM models. The author
has estimated the accuracy of different prediction time windows to figure out which time-
window based prediction gives the most accurate result.

The authors have used an iterative process (as shown in Figure 3-2) which uses Eq. 1
to estimate the required number of data in the training set, assuming that the underlying
data is normally distributed. Here n is the number of samples. In this process, the author
has estimated the sample size which satisfies the required number of sample runs. Using
Root Mean Square Error or RMSE, the author has calculated the accuracy of the LSTM
prediction as shown in Eq. 2. The low RMSE value means the predicted total traffic count
(including both CVs and non-CVs) are very close to the actual total traffic count.
\[ n = \left( \frac{Z_{\alpha} \cdot \sigma}{E} \right)^2 \] \hspace{1cm} (1)

\[ RMSE = \sqrt{\frac{\sum_{i=1}^{T}(y_{i,act} - y_{i,pre})^2}{T}} \] \hspace{1cm} (2)

where, \( Z_{\alpha} = 1.96 \) (at a 95% confidence interval)

\( \sigma = \) Standard deviation of simulation travel time

\( E = \) Tolerance (i.e., 10% of the average travel time captured from the field)

\( n = \) Number of simulation runs

\( T = \) Total number of samples

\( y_{i,act} = \) Actual data for \( i^{th} \) observation

\( y_{i,pre} = \) Predicted data for \( i^{th} \) observation

**Figure 3-2**: Estimation of the required sample run.

3.4.2 *Real-time Intersection Signal Timing Parameters Optimization*

In this section, the author has discussed the signal timing parameter estimation
method for each intersection. First, the author has discussed the green interval estimation process, followed by a discussion on queue dissipation time based on shockwave theory. The queue dissipation time is used to identify which platoon will be affected by the existing queue in the intersection. Later, the author discusses the minor street green time calculation step. The last subsection discusses the multi-objective optimization formulation step to estimate the intersection-specific signal timing parameters.

3.4.2.1 Traffic Signal Timing Estimation

Based on the LSTM-derived total traffic count for each street, the author has calculated the critical lane volume to derive maximum green time for non-coordinated phases. The following shows the equations, notations, and values to estimate the signal timing parameters for both coordinated (e.g., phase 2 and 6) and non-coordinated phases (e.g., phase 4 and 8). For the CV-based adaptive signal control, the author has only used coordination for one direction in the major street, which is the west-to-east direction (referred as the ‘coordinated direction in the later sections) for the case study area. The author has not adjusted offsets based on the traffic on the opposite direction (east-to-west direction, referred to as the ‘non-coordinated direction in the later sections) on the major road. The maximum and minimum green time can be estimated based on different traffic engineering manuals and experience based on engineering practices (FHWA, 2017; HCM, 2010; MnDOT, 2013; UDOT, 2017). In this study, for the maximum green time in the non-coordinated phases, the author has considered the minimum of the SYNCHRO calculated the maximum green time for that phase and the required green time based on the real-time traffic condition in the side street. Based on the peak hour volume, the maximum green
time can be calculated in SYNCHRO, which is a fixed value.

Coordinated Phases

\[ g_{\text{coord}, \text{max}} = C - P_{\text{coord}} - \sum_{i=1}^{P} (g_{\text{non-coord}, \text{min},i} + P_{C_{\text{non-coord}, \text{min},i}}) \]  \hspace{1cm} (3)

Non-coordinated Phases

\[ g_{\text{non-coord}, \text{max}} = \min (g_{\text{non-coord,max,fixed}}, (C-\text{L}) \frac{V_{C_{\text{non-coord}}}}{V_{C}}) \]  \hspace{1cm} (4)

where, C = Cycle time (sec.)

i = Non-coordinated phase

P = Total number of non-coordinated phases

PC_{\text{non-coord}} = Phase clearance time the non-coordinated phase (sec.)

L = Total lost time (sec.)

\[ V_{C_{\text{non-coord}}} \] = Critical lane volume for the non-coordinated phase (veh/hr)

\[ V_{C} \] = Sum of critical lane volume (veh/hr)

\[ g_{\text{coord/non-coord, max}} \] = Maximum green time for the coordinated/non-coordinated phase (sec.)

\[ g_{\text{non-coord, min}} \] = Minimum green time for the non-coordinated phase (sec.) (4 sec. is considered as the minimum green for all phases)
\( g_{\text{non-coord, max, fixed}} \) = Maximum fixed green time for the non-coord phase derived from manuals or traffic engineering software (sec.)

3.4.2.2 Queue Dissipation Time Estimation for Major Approaches

For each signalized intersection, the author needs to estimate the queue dissipation time for both approaches in the major direction. After the green interval ends, vehicles in the major direction start to form the queue. If \( L_Q \) is the maximum queue length (as shown in Figure 3-3 (a)), with the following two logics \( L_Q \) can be estimated.

If CVs-based platoons exist close to the traffic signal, and the platoon speed is less than 5 mph, the author considers the rear-point location of the CV-based platoons as the extent of \( L_Q \).

If no CV exists in the queued area in the major approaches, due to the low penetration level of CVs, the author considers \( L_Q \) for a certain approach as the typical queue length for that approach based on the historical observations.

Once the authors knows \( L_Q \), the corridor segment can be divided into two sections: congested section and uncongested section, as shown in Figure 3-3 (b). The author has derived the jam density \( (k_j) \) for each approach based on the following Eq. 5.

\[
k_a - k_j = \frac{Rq_a}{L_Q}
\]

where, \( R = \) Inter-green time (sec.)

\( L_Q = \) Maximum queue length (mile)
\( k_a = \text{Uncongested section density (veh/mile)} \)

\( q_a = \text{Uncongested section flow rate (veh/hour)} \)

After estimating the jam density, the backward forming shockwave speed \( (v_{bf}) \) and backward recovery shockwave speed \( (v_{br}) \) can be calculated using Eq. 6 and 7.

\[
v_{bf} = \frac{0 - q_a}{k_j - k_a} \quad (6)
\]

\[
v_{br} = \frac{L_Q}{T_{Sq}} \quad (7)
\]

where, \( T_{Sq} = \text{Time when last queued vehicle starts to move after the signal turns green (measured from the simulation case study: 1.5 seconds for each successive vehicles)} \)

Once \( v_{bf} \) and \( v_{br} \) is available, the queue dissipation time \( (T_Q) \) is calculated using the following Eq. 8. \( T_Q \) cannot be more than the cycle time, as any network spillover is not expected to occur.

\[
T_Q = \frac{R v_{bf}}{v_{bf} - v_{br}} \quad (8)
\]
3.4.2.3 Minor Road Green Activation Time

Using Eq. 4, the author has estimated the upper bound of the green time for non-coordinated phases. In order to initiate the green time for the minor approaches, the author has to monitor the queue length on both sides of the minor approaches. As illustrated in Figure 3-4, the minor direction queue starts to form when the signal is red in that direction. Based on historical observations, the author has the maximum allowable queue length data for both sides of the minor approach. Here two scenarios could happen. The first scenario applies when CV-based platoons are present in the queue. By tracking the movement of the CVs, if moving platoons are found within the maximum allowable queue length, the green time for minor approach is not initiated. If queued platoons (based on CV platoons speed) are found beyond the length of the maximum allowable queue length, the minor
direction green time is initiated. In the second scenario, if only non-CVs exist on the minor approach, the queue length can be calculated based on the predicted total traffic count on the side street for the amount of time passed from the start of the inter-green time. If the number of vehicles queued for a certain time interval is found to exceed the allowable queue length, the green time for the minor approach is initiated.

**Figure 3-4** Green activation time for minor approaches

3.4.2.4 Multi-objective MILP Formulation for the Intersection

The author has developed the multi-objective MILP formulation for each individual intersection to minimize the vehicle waiting time (due to pre-existing queue and inter-green time interval), and to maximize the number of progressing platoons. For this step, three different scenarios are considered, which are discussed here.
In the first scenario, the author considers vehicle-waiting time due to the inter-green interval in the major approaches. As shown in Figure 3-5 (a), the platoon progression is affected due to the end of green time, as a fraction of the platoon cannot cross the intersection. The hashed bounding box in Figure 3-5 (a) shows the inter-green time-affected portion of the platoon, which needs to wait for the inter-green time, and the time required to clear the portion of the platoon is $T_s$. $T_s$ is calculated using the following Eq. 9. Here $f_r$ is one of the decision variables of the MILP framework.

$$T_s = IG_{cor} + \sum_{l=1}^{M} \frac{d_{p_l}(1-f_{rl})Nh_s}{L}$$ \hspace{1cm} (9)$$

where, $f_{rl}$ = Fraction of the $i^{th}$ platoon that is allowed to go

$h_s$ = Saturation headway (sec)

$d_{p_l}$ = Length of the $i^{th}$ platoon (mile)
IG\text{cor} = \text{Inter-green time of coordinated phase (sec)}

N = \text{Number of vehicles in the specific approach of the corridor segment}

M = \text{Total number of platoons in the specific approach of the corridor segment}

L = \text{Length of the corridor (mile)}

The second scenario includes a situation where a platoon progression, in the major approaches, is affected by the pre-existing queue at the intersection stop-line during the green time. As shown in Figure 3-5 (b), the approaching platoon could cross the intersection in a shorter time period (shown with blue colored time duration) if there is no platoon queued in the intersection, compared to the scenario when queued platoon exists (shown with yellow-colored time duration). Following Eq. 10 (without queue consideration) and 11 (with queue consideration) show the equation to calculate the time to clear the queue due to pre-existing queue/congestion ($Tq$) for this second scenario:

$$
T_q = T_{h1} + T_{l1} + \sum_{i=2}^{M} (T_{h_i} + T_{l_i}) - (T_{h_{i-1}} + T_{l_{i-1}})
$$

(10)

$$
T_q = Q_d + \sum_{i \in A} \sum_{i=1}^{M} (d_{p_i} f_{r_i} + d_{\text{ahead}})/V_{a_i} + \sum_{i \in B} \sum_{i=1}^{M} (T_{h_i} + T_{l_i})
$$

(11)

where, $V_{a_i} = \text{Average speed of the } i^{th} \text{ platoon (mph)}$

A = \text{Set of approaching platoons affected by the queue}

B = \text{Set of approaching platoons not affected by the queue}

d_{\text{ahead}} = \text{Distance of the front vehicle of a queued platoon from the intersection stop}
line (mile)

\[ g = \text{Green time for the major approaches (sec.)} \]

\[ Q_0 = \text{Time to clear the pre-existing queue (sec.)} \]

\[ T_{hi} = \text{Time required for the first vehicle of the } i^{th} \text{ platoon to reach the stop line if no queue existed (sec.)} \]

\[ T_{li} = \text{Time required for the last vehicle of the } i^{th} \text{ platoon to reach the stop line (sec.)} \]

\[ = \frac{(d_{pi}f_{ri})}{V_{ai}} \]

The third scenario is for the platoons, which are not allowed to pass the intersection during the current cycle. These platoons need to wait for the whole cycle time, and the waiting time required by these platoons needs to be reduced. The waiting time for these platoons \( (T_p) \) can be estimated using the following Eq. 12.

\[ T_p = \sum_{i=1}^{M} C \delta N_{non} \]  
\[ (12) \]

where, \( N_{non} = \text{Number of vehicles in non-selected platoons} \)

\[ = \sum_{i=1}^{P} \left( \#CV_i + \frac{(d_i-10)N}{L} \right) \]

\( \#CV_i = \text{Number of CV in the } i^{th} \text{ platoon} \)

\[ \delta = \begin{cases} 1 & \text{if } fr = 0 \\ 0 & \text{if } fr \neq 0 \end{cases} \]
Based on these three scenarios, the MILP multi-objective optimization model is developed as shown in Eq. 13 and 14.

Multi-objective functions:

\[
\text{Minimize } \sum (T_q + T_s + T_p) 
\]

\[
\text{Maximize } \sum_{i \in A, B} \left( CV_i + \frac{(d_i - 10)N_{fr_i}}{L} \right) 
\]

Subject to:

Inequality Constraints:

\[ T_q \leq g \]

\[ g_{\text{min}} \leq g \leq g_{\text{max}} \]

\[ 0 \leq f_{r_i} \leq 1 \]

Equality Constraints:

\[ g_{\text{cor}} + y_{\text{cor}} + r_{\text{cor}} + g_{\text{non-cor}} + y_{\text{non-cor}} + r_{\text{non-cor}} = C \]

Decision Variables:

\[ f_{r_i}, g_{\text{cor}}, g_{\text{non-cor}} \]

\[ g_{\text{cor}} \text{ and } g_{\text{non-cor}} \text{ are integers} \]

where, \( g_{\text{cor}} \) = Green time for the coordinated approach
\( y_{\text{cor}} = \text{Yellow time for the coordinated approach} \)

\( r_{\text{cor}} = \text{Red time for the coordinated approach} \)

\( g_{\text{non-cor}} = \text{Green time for the non-coordinated approach} \)

\( y_{\text{non-cor}} = \text{Yellow time for the non-coordinated approach} \)

\( r_{\text{non-cor}} = \text{Red time for the non-coordinated approach} \)

The optimization problem is solved in real-time based on the demand in the coordinated approach. As shown in Figure 3-6, while the signal in coordinated approach turns green from red, the optimization algorithm computes the green time required by the platoons (including CVs and non-CVs based on the predicted total vehicle count) to cross the corridor in the coordinated approach. It simultaneously computes the maximum green time required by the side street following Eq. 4. The author has used the concept of ‘grace period’ for the major approaches, which means that a certain amount of green time is allocated to the major direction at the start of the green time. In case of limited CV penetration, and/or limited traffic in the major direction for one single intersection, if no CV-based platoon is found to compute green (at the start of the green) in the side street, it can have an adverse impact on the coordination. Allowing green time for a certain grace period gives us the opportunity to wait for a certain time interval to find a CV-based platoon in the major approach, and perform the optimization. This grace period is equivalent to ‘yield point’ of actuated-coordinated signal, where the green is provided for a certain time period on the coordinated direction. If the green time required by the platoons in the
coordinated direction is higher than the signal timing split with the maximum green time for the minor direction, the process of allowing side-street green based on side-street queue length needs to be initiated (as discussed in Section 3.4.2.3). This simply means that the sufficient green time is provided in the coordinated major approaches for a certain cycle length C, and now the side street queue needs to be monitored to initiate the side street green time. However, if the green time required by the platoons in the coordinated direction is lower than the signal timing split with the maximum green time for the minor direction and if there is no call from the side street, more green time can be allowed to the major approaches. In this case, the author looks for the CV-based platoons in the major coordinated approaches for a certain time period before the previously calculated green time ends (10 seconds considered in this research). If any platoon is found in that interval, the optimization is conducted again to re-compute green time for both directions for the remaining cycle time. If no platoon is found, the side-street green is initiated. In any case, the green time not used by the non-coordinated phases is used by the phases in the coordinated direction. The author has used MIDACO solver (Schlueter, Erb, Gerdts, Kemble, & Rückmann, 2013) to perform all MILP optimization. Using the multi-processing capability of MIDACO, the author has reduced the real-time computation time.
3.4.3 Real-time Offset Optimization

In this step, the offset optimization strategy is discussed for a corridor using Figure 3-7. The purpose of this step is to distribute signal timing parameters in such a way that the platoons which will start moving from an upstream intersection will not face queue in the downstream intersection. In order to compute the real-time offsets, the author has used the upstream vehicle flow rates from the side streets (i.e., $Q_{s1}$ and $Q_{s2}$ from two side streets), and the main street (i.e., $Q_{up}$ for upstream intersection and $Q_{dis}$ for downstream intersection) as shown in Figure 3-7 (a).
As shown in Figure 3-7 (b), the platoon, which will start from the upstream intersection, will face a delay if there is a pre-existing queue in the downstream intersection, and that delay is due to the area of ABC. The MINLP formulation is shown in Eq. 15.

\[
\text{Minimize } \text{Delay} = \frac{\text{Area of ABC}}{h} = \frac{AB \cdot d_1}{2h} = \frac{(T_2 + T_4 - T_3) \cdot (T_{req} \cdot Q_{up} \cdot h)}{2h} \tag{15}
\]

Subject to:

Inequality Constraints:

\[
\frac{L}{V_{FFS} \cdot \alpha} \leq T_2 \leq \frac{L}{V_{FFS} \cdot \alpha}
\]

\[1 \leq T_1 \leq \frac{c}{2}\]

Equality Constraints:
\[ r_{n+1} = \vert r_n - T_1 \vert + T_2 \]

Integer Constraints:

\[ g_{cor}, g_{non-cor} \]

Decision Variables:

\( T_1, T_2 \) (integers)

where, \( r_n \) = Inter-green time for the upstream intersection (sec.)

\( r_{n+1} \) = Inter-green time for the downstream intersection (sec.)

\( L_w \) = Distance between downstream intersection stop line and platoon arrival point to join the queue (mile)

\( T_1 \) = Time interval between the start of inter-green times for two intersections (sec.)

\( T_2 \) = Time interval between the start of green times for two intersections (sec.)

\( T_3 \) = Time interval between the start of upstream intersection inter-green time and platoon arrival time to reach the downstream queue (sec.)

\( T_4 \) = Time interval between the start of upstream intersection green time and platoon arrival time to reach the downstream queue (sec.)

\( h \) = Measured saturation headway= 2.5 sec (from simulation 4th-5th, 5th-6th vehicle)
\[ \alpha = \text{User-defined factor (0.8 considered in this research)} \]

Once the optimization is conducted, the value of \( L_w \) is derived using Eq. 16. After estimating \( L_w \), using the following Eq. 17 and 18, \( T_3 \) and \( T_4 \) are computed respectively.

\[ L_w = v_{bf} \star (\lvert r_n - T_1 \rvert + T_3) \quad (16) \]

\[ T_3 = \frac{L-L_w}{v_{FFS}} = \frac{L-v_{bf}(\lvert r_n - T_1 \rvert)}{v_{FFS} - v_{bf}} \quad (17) \]

\[ T_4 = \frac{(\lvert r_n - T_1 \rvert)(Q_{s1} + Q_{s2})}{Q_{dis}} \quad (18) \]

where, \( Q_{dis} = \text{Downstream Discharge Saturation flow rate in veh/hour green/ln unit} \)

\[ = \frac{3600}{h} \text{ veh/hg/ln} \]

As the impact of driveway traffic is not considered for simplifying the analytical framework, the downstream intersection discharge rate will be affected only by the upstream intersection incoming flow rate (from both side streets as \( Q_{s1} \) and \( Q_{s2} \), and main street as \( Q_{up} \)). This situation is valid if there is not significant driveway traffic demand for a corridor. According to the flow conservation, the following Eq. 19 can be derived. Here \( T_{req} \) is the time required to achieve a free-flow condition in the downstream intersection, meaning no signal related queue will be found in the major approach after this time. The value of \( T_{req} \) is calculated using Eq. 20.

\[ (\lvert r_n - T_1 \rvert)(Q_{s1} + Q_{s2}) + T_{req}Q_{up} = (T_{req} - T_2)Q_{dis} \quad (19) \]
\[
T_{req} = \frac{(r_n - T_1)(Q_{s1} + Q_{s2}) + T_2 Q_{dis}}{Q_{dis} - Q_{up}}
\]

(20)

3.5 Experimental Design

In this section, the author has discussed the study corridor for the CV-based signal control evaluation. Also, the author has included discussion for both actuated coordinated and adaptive signal control scenarios.

3.5.1 Study Corridor

In order to evaluate the performance of the CV-based adaptive traffic control framework, the author has used the US 29 corridor from Greenville, South Carolina. This selected corridor has 10 intersections, and the length of the study area is 3.2 miles. The yellow pinpoints in Figure 3-8 show the location of the signalized intersections along the US 29 corridor. The author has simulated the corridor using the ‘Simulation of Urban Mobility’ (SUMO).

![Figure 3-8 US 29 Wade Hampton study corridor from Greenville, SC](image)

The author has calibrated the simulation network with turning traffic counts from each intersection and travel time from peak hour traffic. For six intersection, the author has collected historic turning traffic counts for the afternoon peak hour from the South Carolina
Department of Transportation (SCDOT). The intersections include Rushmore Drive, Richbourg Drive, Arundel Road, East Lee Road, South Watson Road, and Edward Road. The author has collected turning counts for the other intersections, and travel time for both directions on the major corridor. Apart from collecting data for the four other intersections (i.e., West Lee Road, Vance Street, Tappan Road, and Rutherford Road), the author has collected data from East Lee and Edward Road to estimate the annual growth factor for the turning traffic comparing the SCDOT provided data and the field-collected data. The author has estimated the annual growth factor as 1.25% and applied this factor to estimate the turning traffic counts for the six intersections where the author has used data from SCDOT. The author has collected the existing signal timing plans from SCDOT to calibrate the model. The author has calibrated the simulation model so that the travel time from the simulation models resides within 10% of that from the real-world data. The author has used the Intelligent Driver Model (IDM) model as the car-following model for the vehicles in SUMO. For urban corridor, the author has used these parameters for the IDM model: Minimum Gap = 2m, Acceleration = 1 m/s\(^3\), Deceleration = 1.7 m/s\(^3\), Time Headway = 0.5 s, and Acceleration Exponent = 4.

Once the simulation model is calibrated, the author has increased the peak hour traffic for all intersections to achieve a congested scenario. The author has increased the intersection turning volumes so that the approach Level of Service for each intersection becomes C or worse, and the volume-by-capacity ratio becomes higher than 0.9. The author has not achieved such operational condition for Vance Street and North Watson eastbound approach on the major street direction, and Rutherford road major street direction as the
side street performance already deteriorates. Also, the author has used only a two-phase based signal control system for simplification, as discussed in Section 3.4.2. But the model can be applied to any scenario with more than two-phase signal control.

3.5.2 Actuated Coordinated Signal Control

In order to evaluate the CV-based signal control’s performance, the author has considered the actuated-coordinated signal control time from SYNCHRO software as the baseline. SYNCHRO is widely used, both by public and private agencies, to estimate traffic signal timing parameters. For the baseline scenario with SYNCHRO-based actuated-coordinated control, the coordination is done for both directions on the major road (for both phase 2 and 6). The cycle time, phase splits, maximum green time, and offset values for each intersection are optimized using SYNCHRO. In this scenario, all intersections have the same cycle length. Using the inductive loop detectors, the minor direction green is provided only if vehicles are detected in the minor direction. Otherwise green signal resumes in the major direction. The author has used fixed signal offset values in this scenario, based on the offsets derived from SYNCHRO.

3.5.3 CV-based Adaptive Signal Control

To evaluate the CV-based adaptive signal control’s performance, the author has considered two-phase signal control for an urban arterial without any protected or exclusive left-turn phase. However, in the future, additional phases can be added in the signal control framework to evaluate the signal control’s performance in more complex scenarios. As shown in Figure 3-9, Phase 2 and 6 are the phases for the major approach, and Phase 4 and
8 are the phases for the minor approach or side streets. The traffic signals are coordinated in the major approach. The author has considered two-phase signal control only for simplification, the algorithm can accommodate any higher number of phases for any given signal controller.

![Ring-barrier diagram for the two-phase intersection control](image)

**Figure 3-9** Ring-barrier diagram for the two-phase intersection control

In order to compare the performance of different signal controls, the author has used average speed, maximum queue length and stopped delay as the measures the effectiveness. Using the lane area detectors in SUMO, the author has measured the performance of different signal controls. In reality, the lane area detector is equivalent to a vehicle-tracking camera, where the vehicles can be tracked for a certain length along the corridor, specified by a start and endpoints. These detectors are not used by any traffic signal control strategy. The actuated coordinated signal control uses inductive loop detectors separately placed close to the intersections, while the CV-based signal control only uses CV-based data, and upstream signal phase. Using these lane area detectors, SUMO captures the length of the longest queued section during each time step to provide
the average of the maximum queue length. With this measure, the change in average queue
length in the adaptive signal control scenario can be compared to the actuated signal control
scenario.

3.6 Analysis and Discussion

The following subsections discuss the study findings. The author has used a short-
term traffic forecasting model, and the author has discussed the findings regarding the
model performance in the first subsection. The following subsections discuss the
evaluation of the CV-based adaptive signal control.

3.6.1 Total Vehicle Count Prediction

Based on Eq. 1, the author has found that the required number of samples for this
experiment is 32. For LSTM-based total traffic count prediction, the author has considered
32 training files and 8 test files, each with 1-hour data. The author has generated these all
files using the SUMO software with different random seed numbers for different
penetration levels of CV. The author has discarded the initial 900 seconds of the simulation
as the simulation warm-up time. The author has derived the LSTM hyperparameters (i.e.,
number of epoch, and batch size), layer number and neuron number in each layer based on
the cross-validation accuracy or RMSE value using 70-30 split of the training data (i.e.,
data from 32 training files) as training-validation data set. For the prediction of next time
interval, the LSTM input parameters (from each corridor segment) for a certain second are:
CV to CV distance (as shown in Figure 3-1), CV speed, CV Waiting time, Number of CV,
Upstream signal phase (if upstream intersection signal exists, otherwise not considered)
and CV Direction. The author has considered the upstream signal phase based on majority voting from a previous time window. If a 5-second prediction time horizon is considered, the majority voting system will help to identify the input signal phase that occurred for most of the times in that 5-second interval. Based on Pearson’s correlation coefficient, the author has found that the input parameters are not correlated. The LSTM model output is the total traffic count (including both CVs and non-CVs) for the next time interval. After multiple iterations, it is found that the Nadam optimizer works best for the total traffic count forecasting, and the parameters used in this research for the Nadam optimizer are: learning rate=0.001, epsilon=None, schedule decay=0.004, and exponential decay rate, beta_1 and beta_2 are 0.9 and 0.999, respectively.

The author has estimated the accuracy of the prediction time window and found that the 1-second prediction accuracy is higher than the accuracy with 2s, 5s, or 10s prediction window. The small prediction time window allows checking the traffic condition at a very fine level as in real-life traffic is very dynamic, and the situation can change highly if the prediction time window is high. Figure 3-10 shows the performance of LSTM-based prediction models for the major approach. Here using the optimized LSTM parameters, the RMSE from 8 test files are shown for all corridor segments on US 29. With the increasing number of CVs, the RMSE value decreases. The RMSE with 5% CV penetration is 9.76, and with 100% CV is 5.66.
Figure 3-10 LSTM performance of total count prediction for the next second

Figure 3-11 shows the LSTM model’s performance for both 30% and 100% CV penetration for one corridor segment. At 30% CV penetration, the predicted total number of vehicle count (dotted line in Figure 3-11 (a)) is sometimes higher and sometimes lower than the actual count (solid line in Figure 3-11 (a)). For 100% CV penetration, the predicted total count (dotted line in Figure 3-11 (b)) is closely following the actual count (solid line in Figure 3-11 (b)).

Figure 3-11 Total count prediction for different CV penetration

3.6.2 Evaluation of CV-based Adaptive Signal Controls

The author has included discussion about the impacts of CV-based adaptive signal
control on both major and minor streets.

3.6.2.1 Major Street Impact Evaluation

The author has conducted the operational performance evaluation for all 10 intersections (as shown in Figure 3-8) using both actuated coordinated signal control and adaptive signal control. In the adaptive signal scenario, the green split for both major and minor directions are dynamically decided in real-time based on intersection approaching vehicles. The offset timings are also adjusted for each cycle so that the approaching vehicles from one intersection do not need to stop at the following intersection. The benefit of this system will be demonstrated with the time-space diagram in Figure 3-12. Figure 3-12 shows the trajectory of through traffic platoon throughout the corridor for both actuated-coordinated and adaptive signal control scenarios. For the adaptive coordinated direction (orange arrow trajectory in Figure 3-12) with 5% CV, the intermediate signal timings are synchronized in such a way that the platoon can reach the last intersection with a minimum interruption (#1 dotted box in Figure 3-12). #2 dotted box in Figure 3-12 shows that with fixed offset value in actuated coordinated control, the end section of the platoon reaches the last intersection after a longer time compared to the adaptive scenario. As the offset in the coordinated direction does not adjust in real-time, the platoon breaks down almost at the middle of the corridor (at intersection 4, shown with #5 box in Figure 3-12). In the opposite direction (meaning approaches with phase 6 which are not considered for adjusting offset), the end section of the platoons reach the end intersection almost at the same time (comparing #3 and #4 boxes in Figure 3-12).

Figure 3-13 shows the summary of the operational analysis for the actuated
coordinated and CV-based adaptive signal. The author has findings for both adaptive coordinated direction (i.e., approaches with phase 2) and opposite direction (i.e., approaches with phase 6), and the findings include the result for both CV and non-CVs. The numbers on the top of the bar charts show the average of 32 runs, and the bold numbers in percentage inside the bars show the relative increase (shown as ‘+’) and decrease (shown as ‘-’) in different CV penetration levels compared to the actuated coordinated scenario. The analysis shows that with the increasing number of CVs in the traffic stream, the average speed increases and the average of maximum queue length and average stopped delay reduce in the coordinated direction. With only 5% CV data, 5.6% average speed increase, and 66.7% and 32.4% reduction in average maximum queue length and stopped delay are derived, respectively, in the major direction compared to the actuated coordinated scenario. With 100% CV penetration, 8.1% average speed increase, and 70.2% and 41.4% reduction in average maximum queue length and stopped delay are obtained, respectively, in the major direction compared to the actuated coordinated scenario.

![Diagram of Through Traffic Trajectory in Adaptive and Actuated Signal Environments](image)

**Figure 3-12** Trajectory of CV-based platoons for 5% CV penetration
Figure 3-13 Summary operational impact findings for major streets
For opposite direction (i.e., approaches with phase 6) the improvement does not occur as high like those in the coordinated direction, however still relative improvement in the traffic operational condition are found compared to the actuated coordinated scenario. With only 5% CV data, 0.4% average speed increase and 28.9% and 12.9% reduction in average maximum queue length and stopped delay are found, respectively, in the major direction with phase 6 compared to the actuated coordinated scenario. With 100% CV penetration, 1.5% average speed increase and 32.5% and 15.3% reduction in average maximum queue length and stopped delay are found, respectively, in the major direction with phase 6 compared to the actuated coordinated scenario.

In summary, the CV-based adaptive signal control improves the operational condition of the corridor for both directions (i.e., adaptive coordinated direction with phase 2 and the opposite direction with phase 6) in the major street. Also using only CV data, the operational performance can be improved even for very low CV penetration (5% CV). The CV based adaptive signal control algorithm can even provide benefits to the non-CVs with the limited data from 5% CVs.

3.6.2.2 Minor Street Impact Analysis

The author has evaluated the impact of CV-based adaptive signal control on the minor street/side street direction using the average speed. The author has found that only 2 minor street approaches have experienced average speed increase among the total 18 minor street approaches in 10 intersections with 5% CV, whereas with 100% CV only 1 side street approach has experienced the speed improvement. In summary, the CV-based adaptive signal control does not improve the operational condition for all minor streets. Also with
increasing penetration, there is no trend observed in the effect of minor street traffic improvement.

3.7 Conclusions

With increasing connectivity and emerging digital infrastructure (i.e., connected infrastructure with communication and computation capabilities), CV data can be utilized to detect CV-based platoons and reduce the existing reliance on the legacy transportation sensors, such as inductive loop detectors or video cameras to detect approaching vehicles. The contribution of this research is unique as only CV data and upstream signal phase information are used for an adaptive signal control strategy to improve the traffic signal controller’s performance. Also by determining green split, and dynamically adjusting intersection offset in real-time, better operational performance is achieved compared to the traditional loop-detector based actuated-coordinated traffic signal. The CV-based adaptive signal control allows green time extension on the coordinated direction to satisfy the additional green time requirement in the case of fluctuating traffic demand. With LSTM models, the total number of vehicles can be reliably predicted on certain corridor segments (i.e., the roadway section in each direction between two successive traffic signalized intersections for major road or the side street sections considered for this analysis) for any penetration levels of CV. Once the information about the approaching CV-based platoons including non-CVs is known, the intersection signal timing parameters can be estimated. Based on the analysis, with only 5% CV data, 5.6% average speed increase and 66.7% and 32.4% reduction in maximum queue length and stopped delay are derived, respectively, in
the major coordinated direction (with phase 2) compared to the actuated coordinated scenario. With 100% CV penetration, 8.1% average speed increase and 70.2% and 41.4% reduction in maximum queue length and stopped delay are derived, respectively, in the major direction compared to the actuated coordinated scenario. Operational improvements occur in the major street opposite direction (with phase 6) too. However, for the minor streets, no distinct pattern is found about the impact of the CV-based adaptive signal control system.
CHAPTER FOUR

SITUATION-AWARE LEFT-TURNING CONNECTED AND AUTOMATED VEHICLE OPERATION AT SIGNALIZED INTERSECTIONS

4.1 Introduction

In this chapter, another TCPS application is discussed for an urban area with signalized intersections. With the emergence of innovative computation and networking solutions, and novel sensor technology, CAV will be mainstream in the future transportation systems. However, CAVs will have to co-exist with the non-CAVs (i.e., human-driven vehicles) in the foreseeable future, and interacting with humans for the shared roadway spaces can be challenging for CAVs. CAVs are operated by programmable controller software, and the logics embedded in the controller software are based on traffic rules and common norms/code of conduct. By default, CAVs are programmed to be ‘defensive’, which implies that the controllers are not allowed to violate any traffic rules. On the contrary, the driving behavior of different human drivers varies significantly. Based on the weather effects, and demography, psychology, and physical condition of the driver, humans can behave significantly different from each other. The driving behaviour can also change based on the surrounding road conditions (Ahmed, Karr, Rouphail, Chun, & Tanvir, 2019). In terms of aggressiveness, driver behavior can range anywhere from aggressive to non-aggressive and anything in-between. Due to the aggressive nature of human drivers, a human can accelerate/decelerate abruptly, and maintain very little headway while following vehicles in front of them. This behavior often results in road rages or serious crashes. In urban areas, the presence of traffic signal controls often leads to aggressive
driving behavior. Also, if the front vehicle does not make any turn during the permissive phase, the follower aggressive vehicle has to face longer waiting time, and this can lead to road rage.

This dissertation specifically focuses on scenarios in an urban TCPS environment where CAVs operate in the mixed traffic stream. In an urban TCPS, the physical components include CAV sensors and actuators, traffic signal controllers, roadside units, and video cameras. The cyber components include wireless communication, CAV controller software, and computing software in the roadside unit. Based on the in-vehicle sensor captured data about the surrounding environment, the CAV controller manages the CAV movement. The objective for this task is to design and evaluate a situation-aware CAV controller module, which will operate in response to an aggressive human driver and consider the intent of aggressiveness in the CAV decision-making module. As shown in Figure 4-1, a CAV controller module is developed in this study which will consider the following vehicle’s intent while making left-turn after finding the appropriate gap in the opposite traffic stream to accommodate abrupt braking of the following vehicle, and/or to minimize the waiting time of the following vehicles. Existing literature does not consider the intent of the follower vehicle for left-turning movement (Alhajyaseen, Asano, & Nakamura, 2012; Dias, Iryo-Asano, & Oguchi, 2017; Gu, Hashimoto, Hsu, Iryo-Asano, & Kamijo, 2017; Wolfermann, Alhajyaseen, & Nakamura, 2011). Existing CAV controllers do not assess the follower vehicle’s intent. Based on the 28-month Autonomous Vehicle Disengagement Reports Database (September 2014-January 2017), 89% of the total crashes for Autonomous Vehicles (AVs) occurred at intersections, 69% of the total crashes
occurred with AV speed less than 5mph, and 58% of the crashes were rear-end caused by following human drivers (Favarò, Nader, Eurich, Tripp, & Varadaraju, 2017). A 2016 survey found that 37% of Americans among 2264 participants were concerned about the interaction of AVs and non-AVs (Cox Automotive, 2016). This research focuses on developing a situation-aware CAV controller module that will enable safe and efficient left-turns at an intersection considering the following vehicle’s aggressiveness. The controller module avoids any abrupt braking incidents of the follower vehicle and minimizes the intersection wait time of the follower. Situation-aware CAVs dynamically identify the intent of the follower vehicle using sensor captured data, and adjust speed in real-time to reach the intersection. A video camera at the intersection will monitor the opposite traffic stream and, using Vehicle-to-Infrastructure or V2I communication, the information will be communicated to the CAVs. In the future, when all vehicles will be connected, the gap information can be derived from the connected vehicle data using Vehicle-to-Vehicle communication. CAVs will identify the appropriate gaps in the opposite traffic stream and accelerate/decelerate to reach the intersection to capture the appropriate gaps and clear the shared lane, which will be used by the following vehicle to move in through direction and clear the intersection. The later sections discuss related studies, and the evaluation scenario and findings from this research.
4.2 Related Study

The following subsections discuss the related studies about driver aggressiveness, rear-end collision mitigation approaches and situation-aware CAVs.

4.2.1 Driver Aggressiveness Identification

The aggressive driver behavior was previously studied using data from the smartphone, where the authors identified the acceleration behavior of both aggressive and non-aggressive drivers to provide real-time feedback to the drivers about their driving behavior (Vaiana et al., 2014). The types of aggressive behavior included excess speeding, abrupt braking, and aggressive U-turns and lane changes. The authors in (Vaiana et al., 2014) considered the driver experience and road surface condition to identify the boundary values of acceptable longitudinal and lateral accelerations. The smartphone-based GPS sensor was used to obtain the real-time acceleration values of the vehicle, and when the acceleration exceeds the allowable threshold, drivers can be alerted about their aggressive
behavior in real-time. In another study, the aggressiveness behavior of a subject vehicle was identified based on the vehicle’s current lane deviation possibility, speed and estimated collision time with the front vehicle (Kumtepe, Akar, & Yuncu, 2016). The authors used both an in-vehicle sensor and camera sensor to collect the required data and trained a machine learning-based classifier (i.e., support vector machine) to identify aggressive driving behavior. The machine learning-based classifier achieved 93% accuracy to classify aggressive drivers. Vehicle trajectory data was also used in another study, where the authors used relative speed, average speed, distance to leading vehicles, longitudinal jerk and lane change data from the I80 corridor in California to identify driving behavior of a subject vehicle (Cheung, Bera, Kubin, Gray, & Manocha, 2018). The authors interviewed 100 participants (whose driving data were not included in the I80 database) to identify the driving behavior and level of attentiveness of the subject vehicle driver. The driving behavior identification module was incorporated into a simulated vehicle navigation system to ensure safe navigation. Both lateral and longitudinal acceleration and speed data were used to derive the mathematical model of driver aggressiveness in another study, where the authors used real-world data from vehicles (Rodriguez Gonzalez, Wilby, Vinagre Diaz, & Sanchez Avila, 2014). The authors developed a classifier using Gaussian Mixture Models and maximum-likelihood, which achieved a 92% accuracy to identify driver behavior. In another study, the authors used speed and acceleration of the leading vehicle, and the time gap between the leading vehicles and following vehicle to cluster different driving behavior (Y. Zhang, Ni, Li, Liu, & Yin, 2017). Based on the driving behavior and acceleration of the leading vehicle, the car-following behavior was found to
be linearly stable. Vehicle data from the I80 corridor in California, available via the Next Generation Simulation database, were used to develop the car-following model. In this research, the author has used the acceleration of the following vehicle, and time headway between the subject vehicle and following vehicle to identify the following vehicle’s aggressiveness. In an urban TCPS, with the following vehicle’s acceleration/deceleration rate (Wei, Dolan and Litkouhi, 2013; Rodriguez Gonzalez et al., 2014; Zhang et al., 2017), the follower vehicle’s intent to slow down while following the leader left-turning CAV can be directly assessed. However, time headway is another important parameter (Zhang et al., 2017), as with time headway we can monitor how closely the follower vehicle is following the leader CAV in the urban area. A closely-following follower vehicle is considered to be more aggressive, compared to a follower vehicle maintaining a high headway. Thus the author has used both the acceleration of the following vehicle and time headway between the subject vehicle and following vehicle to identify the following vehicle’s aggressiveness in this study.

4.2.2 Rear-end Collision Mitigation

The sudden brake by follower aggressive human drivers can increase the likelihood of rear-end crashes. The aggressive driving behavior (such as speeding) was the contributing factor in 26% of all traffic fatalities in 2017 (NHTSA, 2019). For autonomous vehicles, based on the 28-months Autonomous Vehicle Disengagement Reports Database (September 2014-January 2017), 58% of the crashes were rear-ended, where follower vehicles were human-driven (Favarò et al., 2017). In one study, the authors found tactile and audible collision warning systems can reduce the rear-end collision events for human
drivers by increasing the brake response time, while the drivers were engaged in a cell phone conversation (Mohebbi, Gray, & Tan, 2009). In a similar study, to identify the rear-end collision mitigation method for human drivers, the authors found that the audio and visual warning assisted to release the accelerator faster by the human drivers to avoid a potential rear-end crash (J. D. Lee, McGehee, Brown, & Reyes, 2002). Due to the faster accelerator release response, drivers could apply brakes gradually to avoid a collision. Another rear-end collision mitigation system for human drivers was the use of green signal countdown timer, which was found to reduce rear-end crashes during the yellow interval (Ni & Li, 2014). The rear-end collision anticipation warning can be provided using vehicle-to-vehicle communication. As the rear-end collision avoidance application needs to satisfy strict delay constraint, the authors in one study developed a rear-end collision avoidance strategy using IEEE 802.11 standard and multi-hop broadcast system (Ye, Adams, & Roy, 2008). Using simulated single-lane and multi-lane scenarios, the rear-end crash avoidance strategy reduced almost all read-end crashes for the following vehicles. AVs still lack a mechanism to avoid rear-end crashes when the follower vehicle is a human driver (Favarò et al., 2017). In this study, the author has developed such a control module for left-turning autonomous vehicles to reduce the rear-end crash possibility, or at least to reduce road-rage events.

4.2.3 Situation-aware CAV

Earlier research developed the situation-awareness for AVs based on Partially Observed Markov Decision Process, where an autonomous agent chooses a policy to take action, without knowing the system state, to maximize reward (Liu, Kim, Pendleton, &
Ang, 2015). The authors considered intention recognition and sensing uncertainties in the framework and measured the conflicting vehicle intention with respect to speed. Compared to the reactive approach, the situation-aware autonomous vehicle showed fewer failure rates in different scenarios (such as interacting at roadways with T-intersection and roundabout), meaning autonomous vehicles did not always purposefully give way to the conflicting vehicles. Rather, autonomous vehicles acted proactively to reduce the waiting time. A similar method was used in another research, where the authors used four parameters (i.e., distance to the intersection, yaw rate, speed, and acceleration) to identify all vehicle’s intent in an unsignalized intersection (Song, Xiong, & Chen, 2016). The reward function includes reward due to adherence to the traffic law, reduction in travel time and improvement in safety. Using Prescan software, the autonomous vehicles were modeled and using a driving simulator, research participants drove the human-driven cars. The analysis shows that, without considering the human intention, the autonomous vehicles were confused about whether to cross the intersection. In another study, the authors discussed the use of temporal domain prediction instead of spatial domain prediction to predict uncertainty in other agent’s intent (McAree, Aitken, & Veres, 2017). For autonomous agents, the authors showed that the required time to reach a destination, and maneuvering time can be designed as a Gaussian distribution. With Monte Carlo simulations, the authors demonstrated that the autonomous vehicle can safely maneuver through roundabouts while considering other vehicle’s predicted position in time. In order to reduce conflict among multiple agents, one study investigated the empathic autonomous agent which made decisions based on the utility function (this function depends on the
acceptability of any action by all agents, based on the action’s future consequences) of everyone in the environment (Kampik, Nieves, & Lindgren, 2019). Here, the empathic autonomous agent made the decision which was acceptable to everyone. In another study, autonomous vehicle considered the yielding intent of merging vehicles on the freeway entrance ramp (Wei, Dolan, & Litkouhi, 2013). Using the acceleration value of the merging vehicle, the intent of the merging vehicle was recognized. Upon recognizing the intent, an autonomous vehicle would generate candidate strategies to minimize a cost function which avoids conflict, passenger discomfort, excess fuel consumption, and undesirable operational outcome. If the merging vehicles did not show the intent to yield, autonomous vehicles would slow down to avoid conflict. In this research, the author has developed a situation-aware CAV controller module for one of the most critical interactions between CAVs and follower aggressive vehicles, which results in the most prominent crash type, i.e., rear-end crash, for real-life autonomous vehicles (Favarò et al., 2017).

4.3 Situation-aware Left-Turning CAV Operation

Steps associated with the situation-aware left-Turning CAV operation are shown in Figure 4-2. The situation-aware left-Turning CAV operates depending on the surrounding situation, which for this research is the aggressive behavior of the following vehicle. If the following vehicle’s intent is identified, CAV can operate accordingly to prevent or minimize negative consequences, which include abrupt hard braking, and increased waiting time for the follower vehicle. Predicting the future condition of the surrounding traffic helps to take proper actions. In this case, the opposing traffic stream’s future
condition will dictate the availability of the target gap at the intersection when the CAV will arrive on the intersection stop bar to initiate the left-turn maneuver. If the prediction is not accurate, the appropriate gap will not be available for the CAV. Finally, while taking the left turn, the CAV needs to make sure that adequate gaps are there so that there will be no direct conflict with the opposite through traffic stream and subject CAV. The four steps, as shown in Figure 4-2, are discussed in the following subsections.

**Figure 4-2** Steps for the CAV left turn decision module

Figure 4-3 shows the components for the situation-aware control module for left-turning CAVs. The sensors used by this module include a rear-view camera, a GPS sensor, and a V2I communication radio. Using these sensors, the intent of the following vehicle (from the rear-view camera) and gaps in the opposite through traffic stream (from V2I
communication radio using the analyzed intersection video feed from the roadside unit) are identified. Also, the GPS sensor is used to identify the location of the CAV. Using the rear-view camera, the relative position of the follower is identified. Based on that the relative position of the follower aggressive vehicle and the CAV’s own position, the position of the follower vehicle is identified. The planning sub-module predicts the future possible gap in the opposite traffic stream and identifies how CAV should operate based on the existing road traffic conditions, and traffic signal status, while also considering the speed limit of major and minor streets. This sub-module identifies the final speed to be achieved by the CAV to reach the intersection. Based on the criteria identified by the planning submodule, the control submodule runs the optimization to estimate the speed profile to be followed by the CAV.

Figure 4-3 Situation-aware left-turning CAV module components
4.3.1 Intent Recognition of Following Vehicles

As discussed earlier, the following vehicle can show either aggressive or non-aggressive behavior. In order to identify the intent, CAVs can consider the data about the following vehicle captured by the vehicle sensors. Different sensors can be used to obtain data from the following vehicle, and different types of data can be used. These sensors include radar, camera, LIDAR, etc. In this research, the author has considered the following vehicle acceleration and time headway between the CAV and following vehicle to identify the intent of the follower. The CAV follows a decision-making framework, shown in Figure 4-4, for the left-turn maneuver. At first, it detects if there is any follower vehicle or not. If the follower is present, CAV sensor captures the data of the relative position of the following vehicle \( \Delta p_{t1} \) at time \( t1 \). Based on its own position \( p_{t1} \) (captured by the GPS sensor available in the CAV), and \( \Delta p_{t1} \), the position of the follower vehicle \( p_{follow,t1} \) can be estimated using Eq. 21. Using the following vehicle position for two consecutive times, \( t1 \) and \( t2 \), the speed \( v_{t2} \) at time \( t2 \) can be estimated using Eq. 22. From the calculated speed \( v_{t2} \), the acceleration \( a_{t2} \) and time headway \( th_{t2} \) of the following vehicle at time \( t2 \) can be estimated using Eq. 23 and 24.

\[
p_{follow,t1} = p_{t1} + \Delta p_{t1} \tag{21}
\]

\[
v_{t2} = \frac{p_{follow,t2} - p_{follow,t1}}{t_2 - t_1} \tag{22}
\]

\[
a_{t2} = \frac{v_{t2} - v_{t1}}{t_2 - t_1} \tag{23}
\]
In order to identify the probability of the follower’s intent, the author has used Bayes Theorem. The following Eq. 25 and 26 can be used to derive the probability of aggressiveness (A) or non-aggressiveness (NA) based on the attitude (Att) of the follower.

\[
Pr(A|Att) = \frac{Pr(Att|A)Pr(A)}{Pr(Att|A)Pr(A) + Pr(Att|NA)Pr(NA)}
\]  \hspace{1cm} (25)

\[
Pr(NA|Att) = \frac{Pr(Att|NA)Pr(NA)}{Pr(Att|A)Pr(A) + Pr(Att|NA)Pr(NA)}
\]  \hspace{1cm} (26)

The assumption is that there is an equal amount of chance for the follower vehicle to be aggressive or non-aggressive. Thus Pr(A) and Pr(NA) is equal to 0.5. In order to get the Pr(A|Att) and Pr(NA|Att), the author has considered that the aggressive and non-aggressive behaviors follow the distribution as shown in Figure 4-5 and Figure 4-6. Studies conducted on urban arterials were reviewed to get the threshold values for both acceleration and time headway (Berry, 2010; Michael, Leeming, & Dwyer, 2000). In an urban area, 2ms\(^{-2}\) acceleration is considered to be aggressive (Berry, 2010). This value is considered
as the mean of the Gaussian distribution and the standard deviation is considered to be $\frac{4}{3} ms^{-2}$ (when the acceleration value is less than the mean). Beyond the mean acceleration, the follower vehicle will always be considered aggressive. As the CAV will have to decelerate, the follower vehicle should slow down, and the non-aggressive behavior would imply that the follower vehicle is also slowing down. Thus, the distribution with mean deceleration value of $−2ms^{-2}$ and standard deviation of $\frac{4}{3} ms^{-2}$ is considered to be non-aggressive (when the acceleration value is higher than the mean). With deceleration less than $−2ms^{-2}$, the follower vehicle will always be considered non-aggressive. For time headway, 1 sec time headway is considered to be the mean of aggressive behavior, while 2 sec time headway is for safe or non-aggressive behavior (Michael et al., 2000).

![Figure 4-5](image)

**Figure 4-5** Probability of aggressiveness based on acceleration and headway
4.3.2 Prediction of Future Vehicle State of Opposite Traffic Stream

Once the CAV identifies the intent of the follower vehicle, it will look for the appropriate gap in the opposite through traffic stream. The information about the opposite through traffic stream will be provided by the connected roadside unit, installed at the intersection via Dedicated Short-Range Communication, or DSRC. A camera installed at the intersection can be used to identify the gaps in the opposite through traffic and send them to the connected roadside unit for it to transmit to CAVs. In the future, when all vehicles will be connected, the gap information can be derived from the connected vehicle data using Vehicle-to-Vehicle communication. The assumption of the research is that the opposite through traffic stream will maintain a constant speed while reaching the intersection. However, this assumption is not valid where human drivers can take actions (i.e., accelerate, lane change) at any given time when they are close to the intersection. Thus, when the CAV is at the intersection with an intent to initiate the left-turn, the gap may not be there. In order to ensure a safe left-turn, the CAV will assess the intersection
condition after reaching the intersection, in real-time, based on the data from the camera about the approaching opposite traffic stream. Whenever the required amount of time is available, CAV will initiate the left turn to safely cross the intersection and to clear the path for the following vehicle.

4.3.3 Opposite Traffic Stream Gap Estimation

While taking a left-turn manoeuvre, two scenarios may exist. In the first one CAVs may not need to stop after reaching the intersection if there is a gap in the opposite traffic stream right at that moment. CAV can take a left-turn without colliding with any other vehicle after reaching the intersection at a minimum speed. This scenario can be handled by the CAV uninterrupted inflow and outflow speed profile, as shown in Figure 4-7. In the second scenario, the interrupted inflow and outflow speed profile will be active as the CAV will have to stop at the intersection due to the presence of approaching vehicles in the opposing through traffic stream. CAV will wait for the required gap to make a left-turn based on the arriving pattern of the opposing through vehicles and start the left-turn right away when the gap is available.
Figure 4-7 Speed profile for CAV making left-turn

For any two way corridor with ‘m’ number of opposite lanes and ‘n’ number of vehicles at a certain time period, the opposite direction lane can be annotated as ‘Opp’, and the same direction shared lane as ‘Same’. For the opposite direction lanes, the vehicles’ state is ‘Pass’ if they pass/clear the conflict area before the CAV is present at the intersection. The ‘App’ state means the vehicle from the opposite direction will approach the intersection conflict area, but it will not clear the conflict area before the CAV clears the conflict area. The author has defined the vehicle sets in Table 4-1 based on the vehicles’ current lane and state (App for vehicles approaching the conflict area, and Pass for vehicles that will pass the conflict area).
Table 4-1 Vehicle Set Explanation

<table>
<thead>
<tr>
<th>Vehicle Set</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_{A,P} := {x</td>
<td>\beta_x = \text{Opp}_1, S_x = \text{Pass}, x \in N}$</td>
</tr>
<tr>
<td>$N_{A,A} := {x</td>
<td>\beta_x = \text{Opp}_1, S_x = \text{App}, x \in N}$</td>
</tr>
<tr>
<td>$N_{B,P} := {x</td>
<td>\beta_x = \text{Opp}_2, S_x = \text{Pass}, x \in N}$</td>
</tr>
<tr>
<td>$N_{B,A} := {x</td>
<td>\beta_x = \text{Opp}_2, S_x = \text{App}, x \in N}$</td>
</tr>
<tr>
<td>$N_{C,P} := {x</td>
<td>\beta_x = \text{Opp}_m, S_x = \text{Pass}, x \in N}$</td>
</tr>
<tr>
<td>$N_{C,A} := {x</td>
<td>\beta_x = \text{Opp}_m, S_x = \text{App}, x \in N}$</td>
</tr>
<tr>
<td>$N_{D,A} := {x</td>
<td>\beta_x = \text{Same}, x \in N}$</td>
</tr>
</tbody>
</table>

Figure 4-8 shows the conflict areas in the intersection for the left-turn maneuver with red bounding boxes.
The author assumes that the CAV will follow a parabolic path while taking the left turn at the intersection. For a typical two-lane corridor, the distance from the intersection stop line to the conflict area of the opposite first lane is $L_2$, and the distance from the intersection stop line to the conflict area of the opposite first lane is $(L_1 + L_2)$, as shown in Figure 4-8. These distances can be computed with the Arc Length (AL) equation of the parabolic path, as shown in Eq. 27.

$$AL = \frac{1}{2} \sqrt{b^2 + 16a^2} + \frac{b^2}{8a} \ln \left( \frac{4a + \sqrt{b^2 + 16a^2}}{b} \right)$$ (27)

For a typical two-lane-two-way corridor, $a$ and $b$ can be calculated as $a = 2.5w_l$ and $b = 3w_l$. $w_l$ is the lane width, and $w_{car}$ is the vehicle width. Here $d_l$ is the distance between the CAV direction stop line and end of the conflict area. The author has defined $d_f$ as the distance between the CAV direction stop line and the start of the conflict area.
The author has defined a distance threshold for both sides of the conflict area compared to the parabolic path of the CAV. For the start and end of the conflict points, the distance thresholds are $\sigma$ and $\sigma + t$, as shown in Figure 4-8. Considering two way two lanes, both $d_l$ and $d_f$ from Figure 4-8 can be calculated from the following Eq. 28 to 31. Here the first lane means the closest opposite lane for the left-turning CAV, and the second lane means the farthest opposite lane, as shown in Figure 4-8.

\[
d_{l-second\ lane,i} = 1.41 \sqrt{w_l} - \frac{w_{car,i}}{2} - \sigma, i \in N_{A,P} \quad (28)
\]

\[
d_{f-second\ lane,i} = 1.41 \sqrt{w_l} + \frac{w_{car,i}}{2} + \sigma + t, i \in N_{A,A} \quad (29)
\]

\[
d_{l-first\ lane,i} = \sqrt{w_l} - \frac{w_{car,i}}{2} - \sigma, i \in N_{B,P} \quad (30)
\]

\[
d_{f-first\ lane,i} = \sqrt{w_l} + \frac{w_{car,i}}{2} + \sigma + t, i \in N_{B,A} \quad (31)
\]

### 4.3.4 Optimization of CAV Movement while Avoiding Conflicts

Once the follower vehicle intention is known and gaps from the opposite traffic stream are identified, the CAV controller module needs to identify the speed profile for the remaining distance. The CAV will follow the speed profile to clear the path for the follower vehicles, or at least to minimize the waiting time for the follower aggressive vehicle. To do so, the speed profile is optimized following the diagram as shown in Figure 4-7. The speed of the turning vehicle can be modeled as a function of time with the polynomial of third-degree (Wolfermann et al., 2011). The slope of a speed profile means acceleration, and slope of the acceleration profile is called a jerk. For an initial time, $t_o$ the author
expresses the speed, acceleration and jerk values as \( v_o \), \( a_o \) and \( J_o \). The author has defined the slopes of the vehicle jerk as \( \dot{j} \). The value of \( a_o \) is zero. For any time \( t \), the jerk, acceleration and speed can be calculated using the following Eq. 32, 33 and 34, respectively. The same equations can be applied to both inflow and outflow speed profiles.

\[
J_t = J_o + \dot{j}t \tag{32}
\]

\[
a_t = a_o + J_o t + \frac{1}{2} \dot{j} t^2 \tag{33}
\]

\[
v_t = v_o + a_o t + \frac{1}{2} J_o t^2 + \frac{1}{6} \dot{j} t^3 \tag{34}
\]

In order to get the optimal speed profile, the optimization is computed in two steps. In the first step, the inflow speed profile is optimized using the optimized \( \dot{j} \) for the inflow. In the second step, based on the output of the inflow optimization model, the outflow speed profile is optimized. The input of the optimization model is the initial inflow speed, \( v_o - \text{inflow} \). The speed at which the CAV will reach the intersection needs to be close to zero, so the target speed range is considered to be within 0.1 \( ms^{-1} \) to 2.5 \( ms^{-1} \). The initial jerk \( J_o \) is confined within the boundary of 1.5 \( ms^{-3} \), as that is defined as the limit of the comfortable jerk (Treiber & Kesting, 2013). The boundary values for the slope of jerk (\( \dot{j}_{\text{inflow}} \)) are derived from (Wolfermann et al., 2011). The optimization objective, constraints and decision variables are given below.

Optimization objective for inflow:

\[
\min (J_{T_{\text{min-inflow}}}) \tag{35}
\]
Subject to,

\[ 0.1 \text{ ms}^{-1} < v_{T_{\text{min}}-\text{inflow}} < 2.5 \text{ ms}^{-1} \]

\[-1.5 \text{ ms}^{-3} < J_{0-\text{inflow}} < 1.5 \text{ ms}^{-3} \]

\[ 0.1 \text{ ms}^{-4} < J_{\text{inflow}} < 0.8 \text{ ms}^{-4} \]

\[ 0 \text{ s} < T_{\text{min}}-\text{inflow} < T_{\text{min}}-\text{inflow,max} \]

\[ a_{T_{\text{min}}-\text{inflow}} = 0 \]

Decision variables,

\[ J_{\text{inflow}}, J_{0-\text{inflow}}, v_{T_{\text{min}}-\text{inflow}}, T_{\text{min}}-\text{inflow} \]

The maximum available time to reach the intersection stop line \((T_{\text{min}}-\text{inflow,max})\) can vary based on the corridor. Once the desired target speed \(v_{T_{\text{min}}-\text{inflow}}\) from the initial optimization is available, the second optimization is conducted for the outflow model. For this outflow, the optimization model is provided in the following Eq. 36. The boundary values for the slope of jerk \(J_{\text{outflow}}\) are derived from (Wolfermann et al., 2011).

Optimization objective for outflow:

\[
\min (J\_{T_{\text{min}}-\text{outflow}}) \tag{36}
\]

subject to,

\[ v_{T_{\text{min}}-\text{outflow,min}} < v_{T_{\text{min}}-\text{outflow}} < v_{T_{\text{min}}-\text{outflow,max}} \]

\[-1.5 \text{ ms}^{-3} < J_{0-\text{outflow}} < 1.5 \text{ ms}^{-3} \]
-0.2 \text{ ms}^{-4} < \dot{j}_{\text{outflow}} < -0.6 \text{ ms}^{-4}

\[ a_{T_{\text{min-outflow}}} = 0 \]

Decision variables,

\[ j_{\text{outflow}}, J_{o-outflow}, v_{T_{\text{min-outflow}}}, T_{\text{min-outflow}} \]

The maximum and minimum boundary values of the speed (after entering the side street) to be achieved by the CAVs \( (v_{T_{\text{min-outflow}, \text{min}}} \text{ and } v_{T_{\text{min-outflow}, \text{max}}}) \) depend on the speed limit of the side street. Once the optimization is done, the distance required to initiate CAV deceleration to reach the intersection stop line \( (d_{T_{\text{min-inflow}}}) \) can be estimated with the following Eq. 37, where \( d_o \) is zero.

\[
d_{T_{\text{min-inflow}}} = d_o + v_0 T_{\text{min-inflow}} + \frac{1}{2} a_o T_{\text{min-inflow}}^2 + \frac{1}{6} J_0 T_{\text{min-inflow}}^3 + \frac{1}{24} j T_{\text{min-inflow}}^4 \quad (37)
\]

The point from which the CAV needs to slow down is shown as 'Initial Point of Deceleration' in Figure 4-7. The distance between this initial point of deceleration and the intersection stop line is \( d_{T_{\text{min-inflow}}} \). In order to reach the initial point of deceleration, the CAV adjusts its speed to reach the point soon. The desired speed \( (v_{\text{des}}) \) to reach the slow down point can be calculated simply by dividing the current distance from the CAV to the initial point of deceleration with the available time. However, \( v_{\text{max}} \) is calculated to create a trapezoidal shape so that the CAV can smoothly increase its speed and slow down, as shown in Figure 4-9. The CAV chooses the appropriate gap which it can capture so that the speed to reach the initial point of deceleration, \( v_{\text{max}} \) does not exceed the speed threshold (i.e., speed limit + 5 mph).
Figure 4-9 CAV speed adjustment to reach the initial point of deceleration

4.4 Case Study

The author has evaluated the situation-aware left-turning module for CAVs using a case study. The following subsections discuss the case study area, base scenario, and situation-aware CAV module.

4.4.1 Study Area

A case study is conducted with a simulated intersection from Perimeter Road, Clemson to evaluate the performance of the situation-aware CAV controller module. To simulate the non-CAVs of the mixed traffic stream, the author has used Simulation of Urban Mobility (SUMO) software, while to simulate CAVs and communication-infrastructure, the author has used Webots. The major corridor of this intersection has two lanes, while the minor corridor has one lane. The author has evaluated the simulated network with multiple scenarios while varying the opposite direction traffic. The traffic signal phase for the shared lane is considered to be permissive green, meaning left-turning vehicles need to wait for the appropriate gaps in the opposite traffic stream. In this
experiment, the author has restricted the lane-changing capability of the follower vehicle. This scenario simply means that due to the presence of heavy traffic in the same direction, the follower aggressive vehicle cannot make any lane change. The author has considered 600, 800 and 1000 vehicle per hour per lane (vphpl) opposite through traffic. For the non-CAVs, the speed distribution is set up in such a way so that 95% of the vehicles drive within 70%-110% of the speed limit. The speed limit of the corridor is 30 mph. The comparison of the base scenario and situation-aware CAV is conducted based on 10 simulation runs for each scenario with different approaching through traffic volume from the opposite direction.

4.4.2 Base Scenario with Autonomous Vehicle

In this scenario, the AV does not have any communication capabilities and it does not have to consider the following vehicle’s intent (to yield or not yield) to make a left-turn at the intersection. The AV uses the front camera to detect the opposite approaching vehicle, and based on the distance between the AV and the opposing vehicles, the AV calculates the gap and evaluates if the gap is acceptable. In a study conducted in California, the authors studied the left-turn gap acceptance value from 1573 observations (Ragland, Arroyo, Shladover, Misener, & Chan, 2006). For human drivers, the authors found that the 15%, 50% and 80% of the accepted gap lengths were 4.1, 6 and 8.6 seconds, respectively. For this study, after trial-and-error with the simulated scenario, the author has found 5 seconds is the accepted gap for the AV left-turn maneuver. For gaps less than 5 seconds, a collision occurs between AVs and opposite through non-AVs. In this scenario, the follower vehicle starts the journey after 8 seconds of the leader AV.
4.4.3 Situation-aware CAV

The goal of the situation-aware CAV controller module is to clear the path from the shared lane for an aggressive through vehicle, so that the aggressive driver does not need to apply a hard brake. If no safe gap is available, the CAV will try to clear the path of the aggressive follower vehicle by making a left-turn as soon as possible. The author has considered the maximum available time to reach the intersection stop line \( T_{\text{min-inflow,max}} \) as 60 seconds for this analysis, and the maximum and minimum boundary values of the target speed (after entering the side street) to be achieved by the CAVs \( v_{\text{T-min-outflow,min}} \) and \( v_{\text{T-min-outflow,max}} \) as 6 m/s\(^{-1}\) and 7 m/s\(^{-1}\), respectively, based on the minor street speed limit from the study area. In this dissertation, the author has used the acceleration of the follower vehicle and time headway between the CAV and follower vehicle to identify the aggressiveness or non-aggressiveness of the follower. The CAV uses a back view camera to capture data related to the following vehicles, following Eq. 21 to Eq. 24. The range of cameras currently used in AVs can be up to 250 meters (Taraba, Adamec, Danko, & Drgona, 2018). In this research, the author has considered the range to be 200 meters. Figure 4-10 shows the rear camera window of a situation-aware CAV while tracking the follower vehicle. Similar to the base scenario, here the follower vehicle starts the journey after 8 seconds of the leader CAV. The author has used MIDACO solver to solve the optimization function in real-time (Schlueter et al., 2013).
The arrival time of the through traffic approaching from the opposite direction needs to be estimated. Here, one assumption is that a video camera will be installed in the intersection, and it will be used to monitor arrival times of the opposite vehicle stream. To identify the start and end of the conflict points in the opposite through traffic stream, $\sigma$ and $t$ values are considered to be 2 ft. and 4 ft. The roadside units, installed in the intersection, will share the camera captured data with the CAV using V2I communication. The intersection video camera will use V2I communication only to share the information about the approaching vehicle stream with the CAV. Similar data can be captured with V2V communication if all of the approaching vehicles are connected vehicles. After reaching the intersection, CAV utilizes data from the intersection camera about the approaching vehicles from the opposite direction; however, the CAV does not use its own camera to

**Figure 4-10** Situation-aware CAV tracking follower vehicle
find the gap in the opposing traffic stream.

4.5 Analysis and Findings

The following subsections discuss the findings for both leader CAV and the follower vehicle.

4.5.1 Abrupt Braking of Aggressive Follower Vehicle

The abrupt braking of the aggressive driver is characterized by a sudden reduction of speed in this research. The author has quantified the number of abrupt braking event reduction by the situation-aware CAVs. As shown in Figure 4-11, the situation-aware CAV controller module reduces 40% of the abrupt braking of the follower vehicle for the 600 vphln opposing through traffic, compared to the base scenario with AV without situation-awareness. With the higher number of opposite through traffic volume (i.e., 800 and 1000 vphln), the abrupt braking reduction decreases to 10%.
Figure 4-11 Abrupt braking reduction by situation-aware CAV

4.5.2 Travel Time for CAV and Follower Vehicle

The author has estimated the travel time for the subject vehicle from the start point of the initial corridor (i.e., the corridor from which the vehicle starts to move to the intersection) to the start point of the target corridor after taking the left turn. As shown with box plots in Figure 4-12, the situation-aware CAV controller module decreases the travel time for the vehicle itself for each scenario compared to the scenario without a situation-aware controller module. Also, for 1000 vphpln opposite through traffic, the travel time distribution is almost the same as the distribution for the 800 vphpln opposite traffic. This means that the situation-aware CAV controller module can provide the same benefit for the scenarios with high opposite through volume. Figure 4-13 shows the average travel time for both base scenario with AV, and situation-aware CAV. The bold texts inside the columns show the percent reduction of average travel time for the situation-aware CAV
compared to the base scenario with an equal number of opposite directional through traffic. It shows that the average travel time reductions for the 600, 800 and 1000 vphpln scenarios are 54%, 20%, and 38%, respectively. The average travel time savings become steady after 800 vphpln.

Similar results are derived by observing the follower vehicle, as shown in Figure 4-14 and Figure 4-15. The follower aggressive vehicle’s travel time is reduced by the situation-aware CAV controller module for each scenario with different opposite directional through traffic. In the situation-aware CAV scenario the travel time savings for the follower, compared to the base scenario with AV, are 61%, 23% and 41% for the 600, 800 and 1000 vphpln opposite through vehicle stream, respectively.

![Box plot of travel time variations of the leader AV/CAV](image)

**Figure 4-12** Travel time variations of the leader AV/CAV
Figure 4-13 Average travel time of the leader AV/CAV

Figure 4-14 Travel time variations of the follower vehicle
4.5.3 Aggressive Follower Vehicle Progression

One of the purposes of the situation-aware CAV controller module is to clear the path for the follower aggressive vehicle driver so that the follower does not need to wait for a long time. The following aggressive vehicle’s progression profile provides a clear picture of the impact of the situation-aware CAV controller module. Figure 4-16 shows the progression of the base AV and situation-aware CAV with time. It is evident from the progressions that the V2I communication enabled situation-aware CAV helps the follower aggressive vehicle to quickly progress through the intersection compared to the base scenario with AV (without V2I communication).

Figure 4-15 Average travel time of the follower vehicle
4.6 Discussion about Field Implementation of Situation-aware CAVs

In order to validate the situation-aware CAV controller in a real-world scenario, an edge-centric TCPS has to be used. In an edge-centric TCPS, as shown in Figure 4-17, different layers exist, and each layer has different tasks. In the mobile edge layer, the necessary computation happens inside the CAV controller to recognize the follower vehicle’s intent. Once the follower vehicle is identified as an aggressive driver, the
optimization-based controller module identifies the speed profile to be maintained by the CAVs. The CAV actuators operate to achieve the desired non-conflicting outcomes. In this V2I application, a roadside fixed layer can provide the gap information available in the opposite traffic stream. Here a DSRC-enabled communication and computation device (i.e., Intel NUC, ASUS VivoPC) will be included in the roadside layer to get the streaming video feed from the intersection camera and compute the gaps available in the future. Different object detection algorithms can be used in this step to identify the position and speed of the approaching through vehicles to identify future gaps (Islam et al., 2019). The DSRC enabled communication can provide the gap information to the approaching CAVs satisfying the delay requirement for the application when the CAV is inside the DSRC coverage area. Based on the previous field-evaluations, the author has found that DSRC-based communication satisfies the delay requirement of CAV applications inside the DSRC coverage range (M. Chowdhury et al., 2018b). DSRC will also be used to broadcast the traffic signal state to the CAVs. The top layer of an edge-centric TCPS is the system layer, which communicates and control multiple fixed and mobile layers. Here real-time information about the side-street will be stored, and this information will be communicated to the CAVs so that the CAVs can enter the side street with an optimal speed which does not lead to any further conflict. The communication between the system layer and CAVs can be conducted via long-range wireless communication, which includes LTE, WIMAX, etc.

Figure 4-18 shows the South Carolina CV Testbed (SC-CVT), where the application can be tested in the future. The fixed edges have the required computation and
communication capabilities to support multiple CV/CAV applications, and the testbed supports heterogeneous wireless communication environment (M. Chowdhury et al., 2018b). The analysis from this field evaluation will be helpful to validate the research findings for situation-aware CAVs.

**Figure 4-17** Situation-aware CAV operations in an urban TCPS
Figure 4-18 SC-CVT testbed

4.7 Conclusions

The presence of aggressive human drivers in a mixed traffic stream makes the operation of CAVs challenging, as aggressive drivers tend to follow the leader very closely. Any sudden movement change by the leader CAV has the potential to cause abrupt behavior by the follower vehicle, which may result in road rage and/or a rear-end crash. Also, human drivers often could take unethical advantages of the defensive driving behavior of autonomous cars. If CAVs can act based on surrounding situations, they can mimic human behavior more closely, which will reduce the confusion in the surrounding human drivers about the future actions of CAVs. In this study, the situation-aware CAV controller module is developed in such a way that it can work with only one autonomous agent in the environment. The CAV uses its own rear camera sensor to identify the
following vehicle’s intent. Once the CAV determines that the following vehicle is aggressive, it determines the appropriate gap in the opposite traffic stream, optimizes the speed profile and increases its speed to reach the initial point of deceleration to initiate the left-turn. If a safe gap is not available when the CAV reaches the intersection stop line, the CAV evaluates data from the roadside unit and prepares to make a left-turn immediately when the required gap is available. The overall decision-making module helps to clear the intersection as soon as possible to reduce the travel time of the following aggressive vehicle.

Based on the analysis conducted in this research, the author has found that the situation-aware CAV improves the operational condition compared to the base scenario with only AV (without any V2I communication) for different flow rates in the opposite vehicle stream. The situation-aware CAV controller module reduces the number of abrupt braking by 40%, 10% and 10% for opposite through traffic stream with 600, 800 and 1000 vphpln, respectively, compared to the base scenario without situational awareness. While assessing the travel time reduction, the situation-aware CAV scenario reduces travel time for the CAV, compared to the base scenario with AV, as much as 54%, 20% and 38% for the 600, 800 and 1000 vphpln opposite vehicle stream scenarios, respectively. Similar improvements are found for the follower vehicles with 61%, 23% and 41% travel time savings for the 600, 800 and 1000 vphpln opposite through vehicle stream scenarios, respectively.
CHAPTER FIVE

CONCLUSION

5.1 Introduction

CAV operations in an urban TCPS environment is challenging due to the high variation in traffic mixture (CAVs and non-CAVs). Also, the intersection control has a direct influence on the CAV operation. In order to properly implement the CAV safety, operational, environmental and energy-related applications, and obtain the expected outcome, the author has identified the components of the urban TCPS. Additionally, public agencies need to come forward to play a leading role in creating and managing the urban TCPS environment. This dissertation directly contributes by identifying the components of TCPS and showing the current trend of CAV-enabled TCPS investments by public agencies. Also, the Vehicle-to-Infrastructure, or V2I applications, developed and validated in this research, shows that CAV-enabled TCPS can help to improve the traffic operations in urban intersections with mixed traffic conditions.

5.2 Findings from the Research

From Part 1, after examining public agencies’ limited budget for digital infrastructure, the author finds current expenditure is inadequate for realizing the potential benefits of V2I applications. This dissertation stresses the importance of collaboration for establishing national and international platforms for the planning, deployment, and management of digital infrastructure to support connected transportation systems across political jurisdictions. Identifying the roles and responsibilities of stakeholders (as shown
in Table 2-5), and developing a consensus regarding the investment, deployment, operations, and maintenance of the digital infrastructure, are the most critical steps in mainstreaming CV technology.

In Part 2, the author has developed two V2I applications for urban TCPS. In this dissertation, the author has developed a real-time adaptive traffic signal control algorithm which utilizes CAV/CV data to compute the signal timing parameters for an urban arterial in a near-congested condition. Using a 3 mile long simulated corridor of US-29 in Greenville, SC, the CAV-based adaptive signal control’s performance is evaluated. The RMSE of total vehicle count prediction with 5% CV penetration is 9.76, and with 100% CV is 5.66. The analysis reveals that the CAV-based adaptive signal control provides operational benefits to both CVs and non-CVs with limited data from 5% CVs, with 5.6% average speed increase, and 66.7% and 32.4% reduction in average maximum queue length and stopped delay, respectively, in major street coordinated direction compared to the actuated coordinated scenario in the corresponding direction. With 100% CV penetration, the author has obtained 8.1% average speed increase, and 70.2% and 41.4% reduction in average maximum queue length and stopped delay, respectively, in the major direction compared to the actuated coordinated scenario in the corresponding directions.

For a situation-aware CAV, the controller module reduces 40% of the abrupt braking of the follower vehicle for the 600 vphpln scenario, compared to the base scenario with AV without situation-awareness. With the increase of opposite through traffic numbers with 800 and 1000 vphpln, the reduction decreases to 10%. The analysis shows that the average travel time reductions for the opposite through traffic scenarios with 600,
800 and 1000 vphln are 61%, 23%, and 41%, respectively, for the follower vehicles if the follower vehicle’s intent is considered in the CAV decision-making module.

5.3 Study Limitation and Future Research Directions

The study considered only V2I applications related to urban intersections. CAV-enabled TCPS should support numerous V2I, V2V or V2P applications running simultaneously. In the future, the CV-based adaptive signal control algorithm can be extended to incorporate more complex scenarios (i.e., protected left-turn phase, pedestrian phase, etc.) on urban arterials. The author will test the algorithm’s performance while including more traffic phases (e.g., protected left-turn phase, pedestrian phase). Also, different objective functions (e.g., energy efficiency improvement, safety improvement) can be included to enhance the algorithm. This CV-based adaptive signal’s performance is validated using a calibrated simulation network. In the future, field validation should be conducted to evaluate the performance of the adaptive signal system in the real-world.

The desired benefit may not be achieved if CAVs cannot be proactive to reduce potential conflicts due to responding to an aggressive follower non-CAV. With an increasing penetration level of CAVs, a cooperative movement can be enabled with CAVs in the opposing traffic stream to help a left-turning CAV find gap if a follower aggressive vehicle is present. Also, the human driver aggressiveness level can vary from person to person. Developing the situation-aware CAV module for a wide range of driver aggressiveness can help CAV take actions based on the characteristics of the specific follower driver. Finally, real-world evaluation of situation-aware CAV controller module
presented in this paper should be conducted to validate the operational benefits in real-life.
REFERENCES


Liu, W., Kim, S.-W., Pendleton, S., & Ang, M. H. (2015). Situation-aware decision making for autonomous driving on urban road using online POMDP. In *2015 IEEE Intelligent Vehicles Symposium (IV)* (pp. 1126–1133). IEEE. https://doi.org/10.1109/IVS.2015.7225835

Loibl, W., Vielguth, S., Peters-Anders, J., Möller, S., Jakutey-Walangitang, D.,


on MINLP space applications. *Advances in Space Research.*
https://doi.org/10.1016/j.asr.2012.11.006


https://doi.org/10.1109/JIOT.2016.2579198


https://doi.org/10.1109/ELEKTRO.2018.8398279

https://doi.org/10.1109/SmartCity.2015.63


