Center for Advanced Multimodal Mobility Solutions and Education

Project ID: 2019 Project 04

TRAJECTORY OPTIMIZATION OF CONNECTED AND AUTONOMOUS VEHICLES (CAVS) AT SIGNALIZED INTERSECTIONS

Final Report

by

Wei Fan (ORCID ID: https://orcid.org/0000-0001-9815-710X)
Pengfei Liu (ORCID ID: https://orcid.org/0000-0001-7217-151X)

Wei Fan, Ph.D., P.E.
Professor, Department of Civil and Environmental Engineering
9201 University City Blvd, Charlotte, NC 28223.
Phone: 1-704-687-1222; Email: wfan7@uncc.edu

for

Center for Advanced Multimodal Mobility Solutions and Education
(CAMMSE @ UNC Charlotte)
The University of North Carolina at Charlotte
9201 University City Blvd
Charlotte, NC 28223

September 2020

ACKNOWLEDGEMENTS

This project was funded by the Center for Advanced Multimodal Mobility Solutions and Education (CAMMSE @ UNC Charlotte), one of the Tier I University Transportation Centers that were selected in this nationwide competition, by the Office of the Assistant Secretary for Research and Technology (OST-R), U.S. Department of Transportation (US DOT), under the FAST Act. The authors are also very grateful for all of the time and effort spent by DOT and industry professionals to provide project information that was critical for the successful completion of this study.

Table of Contents

List of Figures

List of Tables

EXECUTIVE SUMMARY

Connected and autonomous vehicle (CAV) technologies are among the most heavily researched advanced technologies. CAVs will revolutionize the transportation system by bringing a bunch of benefits including improved mobility for the elderly and disabled, enhanced connections to transit, and most importantly, improved safety. With the capability of vehicle to infrastructure (V2I) and infrastructure to vehicle (I2V) technologies, CAVs can receive real time information on surrounding vehicles (e.g., speed, acceleration rate, and location) as well as roadside infrastructures (e.g., signal timing and speed limit). With this information, CAVs can coordinate their maneuvers accordingly and therefore increase traffic efficiency of the roadway systems. For an intersection, CAVs can receive real time signal timing from intersections ahead through I2V technology. Therefore, they can adjust their speeds accordingly to arrive in green and pass the intersections without stopping. The optimized trajectories of CAVs approaching the signalized intersection will decrease the travel delay at the intersection as well as the vehicle emissions.

As the rapid development of CAV technologies, CAVs are anticipated to penetrate into the market in the near future, and as such, the impact that CAVs will bring to the transportation system should be evaluated. The impact of different CAV penetration rates in the highway system on various facilities under different scenarios should be examined. In order to be better prepared for both CAV planning and operations under varying levels of market penetration and traffic demand, there is a critical need to develop and establish new guidelines considering CAVs. This research will focus on quantifying the impact of CAVs on signalized intersections, and establishing new guidelines in order to be suitable for use in conducting various types of analyses involving CAV strategies at signalized intersections.

This research will develop guidelines and recommendations for estimating and predicting intersection efficiency in the presence of CAVs, and therefore will lead to a better understanding of how CAVs will improve mobility at signalized intersections. To better understand the impact of CAVs on the operation of signalized intersections, autonomous vehicles (AVs) are also involved in this study, so that a mixed traffic environment can be investigated including regular vehicles, AVs, and CAVs. A case study is conducted with a signalized intersection in Charlotte, North Carolina. The selected signalized intersection is simulated in VISSIM, a traffic microsimulation tool, to explore the impact of CAVs on the intersection. A speed advisory strategy is proposed to optimize CAVs' trajectory approaching the intersection. Simulation results are discussed in details. Overall, the results of this study can help traffic engineers and stakeholders better understand how different market penetration levels of CAVs influence traffic operation of signalized intersections and improve efficiency of signalized intersections.

Chapter 1. Introduction

1.1. Problem Statement

Connected and autonomous vehicle (CAV) technologies are known as an effective way to improve safety and mobility of the transportation system. As a combination technology of connected vehicle and autonomous vehicle, CAVs share real time traffic data with each other, such as position, speed, and acceleration. Also, CAVs enable the communication between vehicles and transportation infrastructures. The coordinated operations among CAVs and the communication between CAVs and traffic signals will improve the throughput at signalized intersections and lead to a higher intersection capacity. The coordinated through or turning maneuvers of CAVs may reduce crashes and minimize the total delay at an isolated signalized intersection. Traffic signals play an important role in urban traffic management. On the other hand, traffic signals increase travel time, gas emissions and fuel consumption of vehicles. Moreover, stop-and-go traffic increases the possibility of vehicle collisions and leads to economic cost as a result. With the increasing travel demand in recent years, traditional signalized intersections are generating more delays as well as gas emissions. There is an urgent need to increase mobility, intersection capacity and the throughput using the emerging CAV technologies.

With the rapid development of CAV technologies, CAVs equipped with dedicated short-range communications (DSRC) can communicate with both other CAVs and infrastructures. Traffic signal control framework becomes feasible and can achieve greater benefits regarding transportation system efficiency. Feng et al. (2018) investigated a joint control framework for isolated intersections. A two-stage optimization problem was modeled with signal optimization at the first stage and vehicle trajectory control at the second stage. The objective function for signal optimization was to minimize vehicle delay. And the vehicle trajectory control problem had an objective of minimizing fuel consumption and emissions. The simulation results showed that both vehicle delay and emissions can be reduced with the proposed joint control framework under different demand levels. Compared to fixed-time and adaptive signal controlled intersections, optimized vehicle trajectories can reduce vehicle delay and CO_2 emissions by as much as 24% and 13.8% respectively. Jiang et al. (2017) proposed an eco-driving system for an isolated signalized intersection under mixed traffic with CAVs. The system optimized the traffic flow by optimizing vehicle speed of CAVs using Pontryagin's Minimum Principle. According to the simulation results, with different market penetration rate of CAVs, system throughput benefits were up to 10.8% while fuel consumption benefits ranged from 2.02% to 58.01% and CO2 emissions benefits varied from 1.97% to 33.26% respectively. The results also showed that benefits are significant and grow along with the increase of market penetration level of CAVs up to 40%, which indicated that the proposed eco-driving system can be implemented with a low market penetration rate of CAVs in the near future.

Sun et al. (2017) proposed an innovative intersection operation scheme with automated vehicles which can maximize intersection capacity by utilizing all lanes on a road simultaneously. The lane assignment and green durations were optimized by solving a multi-objective non-linear programming mixed-integer problem. The numerical examples showed that the proposed intersection operation scheme can increase the intersection capacity by as much as

99.51% compared to the conventional signal operation scheme. Zhu and Ukkusuri (2015) developed a novel linear programming formulation for intersection control in connected vehicle environment. Using three numerical case studies, the authors confirmed that the autonomous intersection control outperforms the actuated signal control under different V/C ratio scenarios. And the results also showed that the difference between autonomous intersection control and actuated signal control is decreasing when the V/C ratio increases. Hashimoto et al. (2016) focused on the possible collision between a pedestrian and a turning vehicle at signalized intersections with connected vehicles. A probabilistic model based on the Dynamic Bayesian Network was developed to recognize the pedestrian crossing decision in a few seconds based on the traffic signal and pedestrian position information. The proposed model can find rushing pedestrians who might be in a turning driver's blind spots in order to reduce unnecessary waiting for pedestrians who might have already given up crossing.

Guler et al. (2014) investigated the delay savings of using connected vehicle technology for intersection control. The simulation results showed that the average delay can be reduced by up to 60% with the penetration rate ranging from 0% to 60%. The rate of reduction decreases after a penetration rate of 60%. Zheng and Liu (2017) estimated the traffic volume at signalized intersections using GPS trajectory data from connected vehicles under low market penetration rates. Comparing the manually collected volume data and data from loop detectors, the proposed methodology could utilize connected vehicle data for adjusting traffic signals effectively.

Vehicle to Infrastructure (V2I) communication is another focus for signalized intersection mobility analysis (Ubiergo and Jin, 2016; Xie and Wang, 2018). Through V2I communications, the system can not only ensure traffic safety and improve mobility by reducing unnecessary stops at the intersection but also reduce fuel consumption and greenhouse gas emissions. CAV technologies have also been implemented at unsignalized intersections. The impact of CAVs on safety and mobility of unsignalized intersection was investigated (Xu et al., 2018; Mirheli et al., 2018).

This research will develop guidelines and recommendations for estimating and predicting intersection efficiency in the presence of CAVs, and therefore will lead to a better understanding of how CAVs will improve mobility at signalized intersections. To better understand the impact of CAVs on the operation of signalized intersections, autonomous vehicles (AVs) are also involved in this study, so that mixed traffic environment can be investigated including regular vehicles, AVs, and CAVs. A case study is conducted with a signalized intersection in Charlotte, North Carolina. The selected signalized intersection is simulated in VISSIM, a traffic microsimulation tool, to explore the impact of CAVs on the intersection. To obtain valid results, various driving behavior parameters such as standstill distance and minimum headway between vehicles are adjusted for AVs and CAVs. Simulation results are discussed in details. Overall, the results of this study can help traffic engineers and stakeholders better understand how different market penetration levels of CAVs influence traffic operation of signalized intersections and improve efficiency of signalized intersections.

1.2. Objectives

The main objective of this research project is to investigate the impact of CAV technologies on intersection efficiency at different market penetration levels. The objectives of this project are to:

1. To conduct a comprehensive review of the state-of-the-art and state-of-the-practice CAV technologies;

2. To identify and develop suitable intersections as potential scenarios;

3. To use simulation methods to measure intersection efficiency at different CAV penetration levels;

4. To analyze the impact of the CAV technologies at signalized intersections and provide recommendations on future research directions.

1.3. Expected Contributions

In order to quantify the impact of CAVs at signalized intersections and develop the guidelines, modeling and simulation of CAVs are conducted in this research. The expected contributions from this research are summarized as follows:

1. A review of CAV technologies and signalized intersection mobility analysis considering different level of CAV penetration;

2. Identification and development of signalized intersection scenarios and collect the characteristics of each scenario;

3. Guidelines on traffic delay at signalized intersections at different CAV penetration levels.

1.4. Report Overview

The research will be structured as shown in Figure 1.1. In this chapter, the background and motivation of the study have been discussed, followed by the research objectives and expected contributions.

Chapter 2 presents a comprehensive literature review of the current state-of-the-art and state-of-the-practice CAV technologies and various methodological approaches to analyze traffic efficiency at signalized intersections with or without CAVs. This chapter gives a clear picture of existing intersection efficiency analysis methods with consideration of CAVs, possible modeling scenarios, and suitable parameters to estimate the traffic delay. To get a better understanding of the capability and feasibility of the simulation methods, several previous studies using simulation methods for signalized intersection analysis are investigated and presented in as well.

Chapter 3 presents potential signalized intersections and necessary data related to the selected intersections. A signalized intersection is selected at Charlotte, North Carolina. The city of Charlotte provides the historical traffic data as well as the signal plan of the selected intersection. A consolidated historical traffic data is collected in each direction of the intersection. With the information collected on traffic data and signal plan, researchers can conduct research on the selected signalized intersection, evaluate intersection performance, and make better decisions on intersection operations.

Chapter 4 discusses the procedure of the microscopic traffic simulation model. VISSIM uses the Wiedemann's car following model to capture the physical and human components of vehicles. In order to observe valid modeling results, the parameters of the microscopic traffic simulation model should be adjusted for both AVs and CAVs. Also, the proposed methodology of trajectory optimization for CAVs is presented. VISSIM cannot simulate operations of CAVs with its internal driver model. However, VISSIM uses the Component Object Model (COM) interface to give access to data and functions contained in other programs. The speed advisory strategy for CAVs is written in Python. The optimal speed for CAVs will assure that the CAVs arrive at a green traffic light and pass the intersection without stopping.

Chapter 5 describes the results of the simulation in detail. The intersection performance at the signalized intersection under different combinations of regular vehicles, AVs, and CAVs is discussed. The improvement of vehicle emissions due to the penetration of AVs and CAVs is presented, and the impact of different market penetration levels of CAVs at signalized intersections is also quantified.

Chapter 6 will conclude the report with a summary of the simulation results. Direction for future work will also be provided.

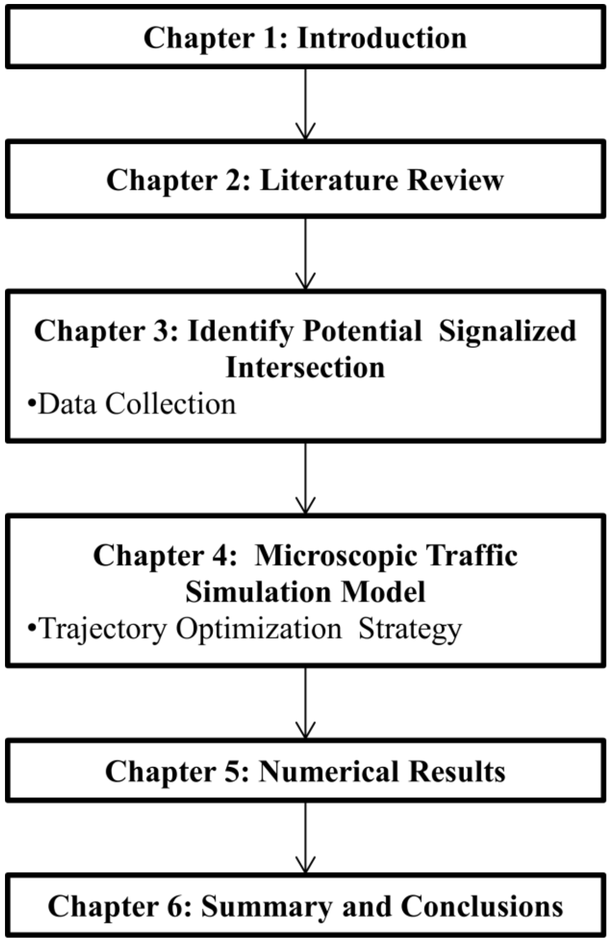

Figure 1.1 Research structure

Chapter 2. Literature Review

2.1. Introduction

This chapter provides a comprehensive review of the current state-of-the-art and state-of-the-practice CAV technologies and various methodological approaches to analyzing intersection efficiency with or without CAVs. This should give a clear picture of existing intersection analysis methods with consideration of CAVs, possible modeling scenarios, and suitable parameters to estimate the intersection efficiency.

The following sections are organized as follows. Section 2.2 presents definitions of vehicle to infrastructure (V2I) and infrastructure to vehicle (I2V) technologies, followed by current technologies in use and benefits of CAVs. Section 2.3 details existing intersection analysis methods with consideration of CAVs. Particular attention will be given to trajectory optimization approaches as they are helpful in improving and measuring intersection mobility under different modeling scenarios. A suite of possible intersection modeling scenarios and a variety of suitable parameters that can be used to assess the mobility of signalized intersections are presented in section 2.4, respectively, with consideration of different CAV penetration levels. To get a better understanding of the capability and feasibility of the simulation methods, several previous studies using simulation methods for intersection mobility analyses are investigated and presented in as well. Finally, section 2.5 concludes this chapter with a summary.

2.2. Vehicle to Infrastructure (V2I) and Infrastructure to Vehicle (I2V) Technologies

2.2.1. Definition of V2I and I2V Technologies

The USDOT has not adopted an official definition of a “connected vehicle,” and the term has evolved to include various modes of telecommunications, numerous automation levels, and differing information processes. The term connected vehicle is defined as “combining leading edge technologies - advanced wireless communications, onboard computer processing, advanced vehicle-sensors, Global Positioning System (GPS) navigation, smart infrastructure, and others - to provide the capability for vehicles to identify threats, hazards, and delays on the roadway and to communicate information over wireless networks to provide drivers with alerts, warnings, and real-time road network information.” Although there are several components of connected vehicle technology, this research focuses on V2I communication and applications.

In a similar manner, this research uses a broader context of V2I communication to mean both V2I communication and I2V communication. Normally, one-way communication is distinguished by labeling the initiator of the communications first - vehicle communication from a vehicle to the infrastructure’s receiver is called V2I, while infrastructure communication sent to the vehicle’s receiver is called I2V. Hence, the two-way communications between vehicles and infrastructure will be designated as V2I in this research.

V2I technology is a communication framework that enables several vehicles to share information with a variety of devices supporting the highway system of a particular country.

These devices consist of RFID readers, signage, cameras, lane makers, streetlights, and parking meters among others. Enabled by a network of hardware, software, and firmware, the V2I technology is typically wireless and bi-directional: information from infrastructure devices is easily transmitted to the vehicle through an ad-hoc network and vice versa. Similarly to the vehicle to vehicle (V2V) technology, the V2I employs dedicated short-range communication (DSRC) frequencies in the transmission of data.

V2I sensors are used in intelligent transportation system (ITS) to capture data and issue road users with real-time advisories about various incidents on the road such as traffic congestions, construction sites, road conditions, and parking zones. The technology is employed in traffic management supervision systems to set speed limits and modify signal phase and timing (SPaT) to improve fuel economy as well as flow of traffic.

As the internet of things improves around the globe, the automobile industry is preparing for monumental advancement in both private and public transportation. Regarding the realism that over 80% of road accidents could be avoided by adopting advanced vehicle connectivity, technology firms and automakers are gearing up to develop V2V and V2I systems to improve safety and sanity on the roads. These technologies have the capacity to advance transportation in various ways: from prevention of collisions to the improvement of energy efficiency. With today's automation systems, the commonly used technologies include sensors, radar, and cameras to enable drivers to look and analyze the surroundings. While these technologies are valuable, they cannot monitor hidden objectives and surprisingly, what is happening in other vehicles. V2V and V2I technologies allow vehicles to share data with each other in real time, enabling them to predict what is coming.

With the increasing development of connected devices around the globe, the automobile industry is taking full advantage of the available information to improve its products. By fitting vehicles with the V2I technology capable of transmitting, receiving and processing pertinent information, the effect on safety, mobility, and convenience is significant. The US Department of Transportation (USDOT) admits that approximately 80 percent of vehicle accidents can be avoided will advanced vehicle connectivity. Moreover, USDOT confirms that more than 10 percent of time spent on roads is wasted due to traffic congestion, and approximately 12 percent of urban traffic is created by a driver trying to park their vehicles, and about 17 percent of fuel is wasted due to the failure of traffic lights. V2I technologies greatly mitigate these problems.

In recent years, roadways have become a stage for revolution. Self-driving vehicles, which were long dreamed of, are now being manufactured. The race to make safe autonomous vehicles is on, with automakers and technology companies entering the competition. The public attention espouses automakers as their autonomous products move from potency to mischance and back again. The truth is that giant automakers around the globe will produce self-driven vehicles sooner than most people would expect. This advancement will come with tremendous benefits such as reducing more than 90 percent of road fatalities and saving about $190 billion annually due to accidents.

The main objective of V2I is to create a communication network between several vehicles on roads and between the vehicles and roadside components/devices (infrastructure) to improve safety, convenience, and efficiency. This technology enables a direct connectivity between several vehicles and infrastructure within the defined vicinity. Safety is the main objective of implementing V2I systems on the road which enables avoidance or collisions hence saving lives. With this technology, automated emergency maneuver such as steering, decelerating, and braking is easily affected. Since V2I is essentially a concept, upon its implementation, road fatalities would be significantly reduced as well as costs incurred on health care.

2.2.2. Required Infrastructure and Wireless Technologies

The functional architecture of the V2I system is based upon certain performance requirements. There are numerous elements upon which the V2I system is built. There are two main components: an infrastructure application component which is housed in the infrastructure application platform and a vehicle application component which is housed in the vehicle application platform. These components integrate and process both the infrastructure and vehicle data to deliver a coordinated message to drivers. Data is shared through a wireless data interface. Several V2I architectures can be found in the different research papers. However, generally these systems consist of the same key components, on the basis of which a general framework can be defined. Such an architecture framework was defined by USDOT's ITS Joint Program Office. The minimal V2I system should contain the following parts:

- Vehicle On-Board Unit or Equipment (OBU or OBE)
- Roadside Unit or Equipment (RSU or RSE)
- Safe Communication Channel

The OBUs are the vehicle side of the V2I system. An OBU is logically composed of a radio transceiver (typically DSRC), a GPS system, an applications processor and interfaces to vehicle systems and the vehicle's human machine interface (HMI). OBUs provide the communications both between the vehicles and the RSUs, and between the vehicle and other nearby vehicles. The OBUs may regularly transmit status messages to other OBUs to support safety applications between vehicles. At intervals, the OBUs may also gather data to support public applications. The OBUs will accommodate storage of many snapshots of data, depending upon its memory and communications capacity. After some period of time, the oldest data is overwritten. The OBUs also assemble vehicle data together with GPS data as a series of snapshots for transmission to the RSU.

RSUs may be mounted at interchanges, intersections, and other locations (e.g. petrol stations) providing the interface to vehicles within their range. An RSU is composed of a radio transceiver (typically DSRC or WAVE), an application processor, and interface to the V2I communications network. It also has a GPS unit attached. Through an additional interface, it may support local infrastructure safety applications. The RSU is connected to the V2I communications network. Using its interface to the V2I communications network, it can send private data to and from the Original Equipment Manufacturers (OEMs). The RSU may also manage the prioritization of messages to and from the vehicle. Although the OBU has priorities set within its applications, prioritization must also be set within the RSU to ensure that available bandwidth is not exceeded. Local and vehicle-to-vehicle safety applications have the highest priority; and messages associated with various public and private network applications have lower priority. Entertainment messages will likely have the lowest priority.

Bluetooth technology is a wireless communications technology that is simple, secure, and can be found almost everywhere. One can find it in billions of devices ranging from mobile phones and computers to medical devices and home entertainment products. It is intended to replace the cables connecting devices, while maintaining high levels of security. Automotive applications of Bluetooth technology began with implementing the Hands Free Profile for mobile phones in cars. The development is coordinated by the Car Working Group (CWG) and has been ongoing ever since 2000 by implementing different profiles and new features. The Bluetooth Specification defines a uniform structure for a wide range of devices to connect and communicate with each other.

In V2I systems Bluetooth can be used to provide communication channel between the car and the traffic signal systems. Nowadays several manufacturers offer Bluetooth capable traffic control devices. It is capable for privileging the public transport at the intersections or measuring the traffic and pedestrian flows with the help of the electronic devices installed with Bluetooth radio (such as smart phones, tablets, navigation units). These systems detect anonymous Bluetooth signals transmitted by visible Bluetooth devices located inside vehicles and carried by pedestrians. This data is then used to calculate traffic journey times and movements. It reads the unique Media Access Control (MAC) address of Bluetooth devices that are passing to and in the system. By matching the MAC addresses of Bluetooth devices at two different locations, not only the accurate journey time is measured, but also privacy concerns typically associated with probe systems are minimized.

2.2.3. Applications of V2I and I2V Technologies

The infrastructure application platform offers a support interface for exchange of data with various data systems, local user systems, traffic signal controllers, and roadside signage systems. The infrastructure application component relays alerts via dynamic message signs that are visible by approaching vehicles. On the other hand, the vehicle application platform offers a support interface for a collection of information from the various vehicle and driver warning systems via a driver-vehicle interface display. Vehicle application component relay messages via the driver warning interface that is vehicle-specific or similar to the messages displayed by static roadside signs. The safety application of the V2I systems coordinates the display of both the in-vehicle and roadside messages to drivers. Vehicle-specific messages are meant for drivers and are more cautious than the roadside signs. The former must not conflict with the latter.

As mentioned above the V2I systems are closely related to the V2V communications. Most of the V2I applications rely on the V2V on-board units, so these applications can commonly be called Intelligent Transportation System (ITS) applications. Naturally several applications currently exist are based only on roadside sensors, which typically require only observation (e.g., toll control, and speed measurement).

The safety applications aim to decrease the number of accidents by prediction and notifying the drivers of the information obtained through the communications between the vehicles and sensors installed on the road. The typical safety applications could include the following:

- Warning for hazardous situations (such as congestions, accidents, and obstacles),
- Merging assistance,
- Intersection safety,
- Speed management,
- Rail crossing operations,
- Priority assignment for emergency vehicles.

The efficiency applications can support the better utilization of the roads and intersections. These functions can operate locally at an intersections or on a given road section, or in an optimal case on a large network, such as a busy downtown. It is important to note that the efficiency applications also have a beneficial effect on safety in most cases. The following typical applications can enhance the traffic efficiency:

- Traffic jam notification,
- Prior recognition of potential traffic jams,
- Dynamic traffic light control,
- Dynamic traffic control,
- Connected navigation.

The number plate recognition serves as the base for the payment applications, which is well-tried and reliable camera-based technology. The payment applications could include the following:

- Parking control,
- Congestion charge,
- Highway toll control.

The information services can be typically the conventional variable traffic signs or temporary road signs supplemented with a DSRC beacon.

2.3. Intersection Efficiency Analysis Methods

The recent development of CAV technologies provides the potential for better traffic operations. V2I communications between CAVs and infrastructures allow vehicles and traffic signals be controlled to improve traffic efficiency and benefit the environment. Most studies focused on either vehicle trajectory optimization or signal optimization.

2.3.1. Trajectory Optimization Based Methods

2.3.1.1. Yu et al.'s research work

Yu et al. (2019) proposed a mixed-integer linear programming (MILP) model to cooperatively optimize the trajectories of CAVs along a corridor for system optimality.

The car-following and lane-changing behaviors of each vehicle along the entire path were optimized together. The trajectories of all vehicles along the corridor were coordinated for system optimality in terms of total vehicle delay. All vehicle movements were considered at each intersection. Vehicles were controlled to pass through intersections without traffic signals. Numerical studies validated the advantages of the proposed CAV-based control over the coordinated fixed-time control at different demand levels in terms of vehicle delay and throughput. The average delay under the CAV-based control was from 1.1 to 3.9 seconds while the delay under the fixed-time control was from 27 to 116.9 seconds.

2.3.1.2. Liu et al.'s research work

Liu et al. (2019) proposed a cooperative scheduling mechanism for autonomous vehicles passing through an intersection. The study aimed to ensure safe driving while minimizing delay at an intersection without traffic lights. Firstly, an intersection management system used as an info-collecting-organizing center, assigned reasonable priorities for all present vehicles and hence planned their trajectories. Secondly, a window searching algorithm was performed to find an entering window, which can produce a collision-free trajectory with minimal delay, besides backup windows. Finally, vehicles can arrange their trajectory individually, by applying dynamic programming to compute velocity profile, in order to pass through intersection. MATLAB/Simulink and SUMO based simulations were established among three types of traffic mechanisms with different traffic flows. The results showed that the proposed mechanism significantly reduced the average evacuation time and increased throughput by over 20%. Moreover, intersection delay can be reduced to less than 10% compared to classical light management systems.

2.3.1.3. Mirheli et al.'s research work

Mirheli et al. (2019) developed a distributed cooperative control logic to determine conflict-free trajectories for CAVs at signal-free intersections. The cooperative trajectory planning problem was formulated as vehicle-level mixed-integer non-linear programs (MINLPs) that aimed to minimize travel time of each vehicle and their speed variations, while avoiding near-crash conditions. A coordination scheme was developed between CAVs on conflicting movements. The coordination scheme shared vehicle states over a prediction horizon. Therefore, the CAVs could reach consensus through an iterative process and select conflict-free trajectories that minimize their travel time. The numerical results showed that the proposed distributed coordinated framework converges to near-optimal CAV trajectories with no conflicts in the intersection neighborhood. The proposed control logic reduced travel time by 43.0-70.5%, and increased throughput and average speed respectively by 0.8-115.6% and 59.1-400.0% compared to an optimized actuated signal control.

2.3.1.4. Stebbins et al.'s research work

Stebbins et al. (2017) generalized the advice given to a vehicle, by optimizing for delay over the entire trajectory instead of suggesting an individual speed. The delay was minimized for a vehicle if it followed any trajectory that meets certain requirements. The results demonstrated that there are multiple benefits acquired from using the trajectory advice algorithms that were presented in the paper. Delay was reduced typically by 30-50%. Average stopped time was reduced dramatically. Stopped time was almost eliminated in under-saturated conditions.

2.3.1.5. Yao et al.'s research work

Yao et al. (2018) proposed a trajectory smoothing method based on Individual Variable Speed Limits with Location Optimization (IVSL-LC) in coordination with pre-fixed traffic signals. This method dynamically imposed speed limits on some identified Target Controlled Vehicles (TCVs) with V2I communication ability at two IVSL points along an approaching lane. According to real-time traffic demand and signal timing information, the trajectories of each approaching vehicle were made to run smoothly without any full stop. The result showed that compared with the benchmark, the IVSL-LC method can greatly increase traffic efficiency and reduce fuel consumption.

2.3.1.6. He et al.'s research work

He et al. (2015) proposed a multi-stage optimal control formulation to obtain the optimal vehicle trajectory on signalized arterials, where both vehicle queue and traffic light status were considered. To facilitate the real-time update of the optimal speed trajectory, a constrained optimization model was proposed as an approximation approach. The optimization formulation can be solved more efficiently, which allows optimal speed control strategies to be updated in real time.

2.3.1.7. Wei et al.'s research work

Wei et al. (2017) presented a set of integer programming and dynamic programming models for scheduling longitudinal trajectories aiming to consider both system-wide safety and throughput requirements under support from various communication technologies. Newell's simplified linear car following model was used to characterize interactions and collision avoidance between vehicles, and a control variable of time-dependent platoon-level reaction time was introduced to reflect various degrees of V2V or V2I communication connectivity. By adjusting the lead vehicle's speed and platoon-level reaction time at each time step, the proposed optimization models could effectively control the complete set of trajectories in a platoon, along traffic backward propagation waves.

2.3.1.8. Abbas and Chong's research work

Abbas and Chong (2013) used machine learning approach to modeling car-following trajectory data and compared the results with regression analysis. Neuro-Fuzzy Actor-Critic Reinforcement Learning network was trained using vehicle trajectory data extracted from the Naturalistic Car Driving Study databases provided by the Virginia Tech Transportation Institute. The results showed that both the machine learning and regression analysis could predict the upcoming acceleration value. However, only the machine learning approach could reproduce the vehicle trajectory, while the regression analysis would ultimately lead to an erroneous model.

2.3.1.9. Ilgin Guler et al.'s research work

Ilgin Guler et al. (2014) proposed an algorithm for two one-way-streets to optimize traffic operations at an intersection. The algorithm enumerated different sequences of cars discharging from the intersection to minimize the objective function. The results showed that a minimum green time increases the delay only under the low and balanced demand scenarios. Therefore, the value of using cars with autonomous vehicle control can only be seen at intersections with this kind of demand patterns, and could result in up to 7% decrease in delay. Using information from connected vehicles to better adapt the traffic signal can significantly reduce the average delay by up to 60%.

2.3.1.10. Yang et al.'s research work

Yang et al. (2016) incorporated trajectory design for automated vehicles by providing the optimal departure sequence to minimize the total delay based on position information. The optimal departure sequence and trajectories were obtained by a branch and bound method, which shows the potential of generalizing this algorithm to a complex intersection. The simulation results showed an evident decrease in the total number of stops and delay when using the connected vehicle algorithm for the tested scenarios at information level of as low as 50%.

2.3.1.11. Lazar et al.'s research work

Lazar et al. (2018) used the cooperative adaptive cruise control (CACC) of vehicle platoons waiting at a red traffic signal which enables vehicles begin accelerating in a coordinated manner once the traffic signal turns green. The simulation results showed that the vehicle platoon with coordinated start generates shorter following gaps ensuring the arterial intersection improvement by increasing the urban arterial capacity.

In summary, trajectory optimization methods are capable of increasing intersection mobility, reducing vehicle emissions, and reducing traffic delay. A variety of trajectory optimization based intersection mobility analysis studies considering CAV technologies have been done to achieve this goal. **Error! Reference source not found.** exhibits a summary of the trajectory optimization based intersection analysis studies reviewed in this section.

Table 2-1 Summary of Existing Trajectory Optimization Based Intersection Analysis Studies

No.	Author, Year	Model	Object	Findings
1	Yu et al., 2019	Mixed-integer linear programming	Optimize car-following and lane-changing behaviors	Average delay under the CAV-based control is from 1.1 to 3.9 seconds
2	Liu et al., 2019	Cooperative scheduling mechanism	Minimize traffic delay	Increases throughput by over 20%
3	Mirheli et al., 2019	Distributed cooperative control logic	Minimize travel time	Reduced travel time by 43.0–70.5%
4	Stebbins et al., 2017	-	Optimize delay	Delay was reduced typically by 30–50%
5	Yao et al., 2018	Trajectory smoothing method	-	Increase traffic efficiency and reduce fuel consumption
6	He et al., 2015	Multi-stage optimal control formulation	Obtain optimal vehicle trajectory	Optimal speed control strategies updated in real time
7	Wei et al., 2017	Integer programming and dynamic programming models	Scheduling longitudinal trajectories	Effectively control the complete set of trajectories in a platoon
8	Abbas and Chong, 2013	Machine learning approach	-	Machine learning approach could reproduce vehicle trajectory
9	Ilgin Guler et al., 2014	-	Optimize cars discharging from intersection	Reduce average delay by up to 60%
10	Yang et al., 2016	Branch and bound method	Minimize total delay	Decrease in the total number of stops and delay
11	Lazar et al., 2018	Cooperative adaptive cruise control	-	Generates shorter following gaps

2.3.2. Signal Optimization Based Methods

Traffic signal optimization remains a hot topic in the field of transportation. The ideal traffic signal control is to optimally allocate green time to serve traffic from different approaches to achieve the best system performance (e.g., minimum delay and maximum throughput). Several representative studies of signal optimization based methods are reviewed.

2.3.2.1. He et al.'s research work

He et al. (2012) used a unified platoon-based mathematical formulation to perform arterial traffic signal control while considering multiple travel modes in a V2I communications environment. First, a headway-based platoon recognition algorithm was developed to identify pseudo-platoons given probe vehicles' online information. It was assumed that passenger vehicles constitute a significant majority of the vehicles in the network. This algorithm identified existing queues and significant platoons approaching each intersection. Second, a mixed-integer linear program (MILP) was solved to determine future optimal signal plans based on the current traffic controller status, online platoon data and priority requests from special vehicles. Microscopic simulation using VISSIM showed that the proposed algorithm can significantly reduce delays under both non-saturated and oversaturated traffic conditions.

2.3.2.2. Priemer and Friedrich's research work

Priemer and Friedrich (2009) proposed a novel concept for a decentralized adaptive traffic signal control in urban networks using V2I communication data. The phase-based strategy took advantage of the improved detection data and optimized the phase sequence at each time interval of five seconds in order to reduce the total queue length within a forecast horizon of twenty seconds. For optimization, the methods of dynamic programming and complete enumeration were used. The methods were embedded in the simulation environment of the microscopic traffic simulator AIMSUN NG. Various market penetration levels were modeled since they are the critical factor that impacts the quality of the new signal control. The results showed that the average delay can be reduced by up to 24%. And the mean speed was increased by 5% which is significantly higher than in the reference scenario.

2.3.2.3. Feng et al.'s research work

Feng et al. (2015) presented a real-time adaptive signal phase allocation algorithm using connected vehicle data. The proposed algorithm optimized the phase sequence and duration by solving a two-level optimization problem. Two objective functions were considered: minimization of total vehicle delay and minimization of queue length. Due to the low penetration rate of the connected vehicles, an algorithm that estimates the states of unequipped vehicle based on connected vehicle data was developed to construct a complete arrival table for the phase allocation algorithm. A real-world intersection was modeled in VISSIM to validate the algorithms. Results with a variety of connected vehicle market penetration rates and demand levels were compared to well-tuned fully actuated control. The results showed that the proposed control algorithm outperforms actuated control by reducing total delay by as much as 16.33%.

2.3.2.4. Datesh et al.'s research work

Datesh et al. (2011) presented an innovative traffic signal control algorithm, the IntelliGreen Algorithm (IGA), which utilizes IntelliDrive technologies to improve the efficacy of traffic signals. The IGA was fully decentralized and took a novel approach to traffic signal control using k-means clustering. A VISSIM model of a real-world arterial was used to evaluate the IGA and its performance was compared to that of an actuated timing plan. The IGA was found to consistently improve traffic mobility, and sustainability as volumes increased, even at lower IntelliDrive market penetration levels. The results demonstrated the power of IntelliDrive data and that decentralized traffic signal control can achieve system-wide benefits at lower computational costs.

2.3.2.5. Qi and Hu's research work

Qi and Hu (2019) proposed a Monte Carlo Tree Search-based model to solve the intersection optimization problem (named MCTS-IO) with explicit modeling of channelized section spillover (CSS) dynamic evolution. The model worked in a rolling horizon way. At each decision point, MCTS-IO simulated the intersection by selecting a sequence of phases, and progressively updated the relative preferences of the phases. The method was tested against Synchro results with both stable and variable demand, which demonstrated the proposed model is always able to find a solution better than Synchro.

2.3.2.6. Li and Sun's research work

Li and Sun (2019) presented a multi-objective optimization method on signal setting for improving traffic performance at intersections. Vehicle conflicts and pedestrian interference were considered in the microscopic simulation of the traffic system. The signal timing and lane assignment were optimized for different traffic flows. The multi-objective optimization problem was solved with the cell mapping method. It was observed that the proposed optimization method is effective in controlling the traffic at the intersection.

2.3.2.7. Chow et al.'s research work

Chow et al. (2019) developed and analyzed the centralized and decentralized solution procedures for urban network traffic management through an optimal signal control framework. The optimal control was formulated based upon the Hamilton-Jacobi formulation of kinematic wave model. The use of semi-analytical performance was derivative when developing the decentralized solution algorithm. The proposed control strategies were applied to a set of test scenarios constructed from a real road network in Central London in the UK. The results showed that the network-wide delay under high demand scenarios can be improved by up to 59.6 veh-h.

In summary, signal optimization based methods are capable of improving the intersection mobility considering the impacts of CAV technologies. A variety of signalized optimization based intersection analysis studies have been conducted to achieve this goal. **Error! Reference source not found.** exhibits a summary of the signal optimization based intersection analysis studies reviewed in this section.

Table 2-2 Summary of Signal Optimization Based Intersection Analysis Studies

No.	Author, Year	Model	Object	Findings
1	He et al., 2012	Platoon-based mathematical formulation	Optimal signal plans	Reduce delay under both non-saturated and oversaturated traffic conditions
2	Priemer and Friedrich, 2009	Dynamic programming and complete enumeration	Decentralized adaptive traffic signal control	Reduce average delay by up to 24 %
3	Feng et al., 2015	Real-time adaptive signal phase allocation algorithm	Optimize phase sequence and duration	Reduce total delay by as much as 16.33%
4	Datesh et al., 2011	IntelliGreen Algorithm	Improve efficacy of traffic signals	Achieve system-wide benefits at lower computational costs
5	Qi and Hu, 2019	Monte Carlo Tree Search-based model	Intersection optimization	Better than Synchro
6	Li and Sun, 2019	Multi-objective optimization method	Optimal signal setting	Effective in controlling the traffic at the intersection
7	Chow et al., 2019	Hamilton-Jacobi formulation of kinematic wave model	Optimal signal control framework	Improve the network-wide delay by up to 59.6 veh-h

2.3.3. Integrated Optimization Methods

2.3.3.1. Guo et al.'s research work

Guo et al. (2019) proposed an efficient DP-SH (dynamic programming with shooting heuristic as a subroutine) algorithm for the integrated optimization problem that can simultaneously optimize the trajectories of CAVs and intersection controllers (i.e., signal timing and phasing of traffic signals), and developed a two-step approach (DP-SH and trajectory optimization) to effectively obtain near-optimal intersection and trajectory control plans. Also, the proposed DP-SH algorithm can also consider mixed traffic stream scenarios with different levels of CAV market penetration. Numerical experiments were conducted, and the results proved the efficiency and sound performance of the proposed optimization framework. The proposed DP-SH algorithm, compared to the adaptive signal control, can reduce the average travel time by up to 35.72% and save the consumption by up to 31.5%. In mixed traffic scenarios, system performance improved with increasing market penetration rates. Even with low levels of penetration, there were significant benefits in fuel consumption savings. The computational efficiency, as evidenced in the case studies, indicated the applicability of DP-SH for real-time implementation.

2.3.3.2. Yu et al.'s research work

Yu et al. (2018) presented a mixed integer linear programming (MILP) model to optimize vehicle trajectories and traffic signals in a unified framework at isolated signalized intersections in a CAV environment. A new planning horizon strategy was applied to conduct the optimization. All vehicle movements such as left-turning, right-turning and through were considered. Phase sequences, green start and duration of each phase, and cycle lengths were optimized together with vehicle lane-changing behaviors and vehicle arrival times for delay minimization. Vehicles were split into platoons and were guaranteed to pass through the intersection at desired speeds and avoid stops at stop bars. Exact vehicle trajectories were determined based on optimized vehicle arrival times. For the trajectory planning of platoon leading vehicles, an optimal control model was implemented to minimize fuel consumption/emission. For following vehicles in a platoon, Newell's car-following model was applied. Simulation results validated the advantages of the proposed control method over vehicle-actuated control in terms of intersection capacity, vehicle delays, and CO_2 emissions. Vehicle trajectories were optimized so that all vehicles can pass through the intersection at high desired speeds without stops. Thus, no vehicle queues were generated at stop bars, either. As a result, the green start-up lost time was eliminated and more vehicles can pass the intersection during the same green interval compared with actuated control.

2.3.3.3. Feng et al.'s research work

Feng et al. (2018) investigated a joint control framework for isolated intersections. The control framework was modeled as a two-stage optimization problem with signal optimization at the first stage and vehicle trajectory control at the second stage. The signal optimization was modeled as a dynamic programming (DP) problem with the objective to minimize vehicle delay. Optimal control theory was applied to the vehicle trajectory control problem with the objective to minimize fuel consumption and emissions. A simplified objective function was adopted to get analytical solutions to the optimal control problem so that the two-stage model was solved efficiently. Simulation results showed that the proposed joint control framework was able to reduce both vehicle delay and emissions under a variety of demand levels compared to fixed-time and adaptive signal control when vehicle trajectories were not optimized. The reduced vehicle delay and CO_2 emissions can be as much as 24.0% and 13.8%, respectively for a simple two-phase intersection.

2.3.3.4. Li et al.'s research work

Li et al. (2014) developed a signal control algorithm that allows for vehicle paths and signal control to be jointly optimized based on advanced communication technology between approaching vehicles and signal controller. The algorithm assumed that vehicle trajectories can be fully optimized, i.e., vehicles will follow the optimized paths specified by the signal controller. An optimization algorithm was developed assuming a simple intersection with two single-lane through approaches. A rolling horizon scheme was developed to implement the algorithm and to continually process newly arriving vehicles. The algorithm was coded in MATLAB and results were compared against traditional actuated signal control under a variety of demand scenarios. It was concluded that the proposed signal control optimization algorithm could reduce the Average Travel Time Delay (ATTD) by 16.2-36.9% and increase throughput by 2.7-20.2%, depending on the demand scenario. However, no mathematical proofs were given regarding the optimal number of trajectory segments in terms of fuel consumption or emissions under different situations, which were specifically addressed in this paper. The signal control algorithm enumerated all possible timing plans, which cannot be extended to complex phase structures.

In summary, with the rapid development of CAV technologies, vehicles equipped with DSRC can communicate not only with other CAVs but also with infrastructure. Joint control of vehicle trajectories and traffic signals becomes feasible and may achieve greater benefits regarding system efficiency and environmental sustainability. Traffic control framework is expected to be extended from one dimension (either spatial or temporal) to two dimensions (spatiotemporal). **Error! Reference source not found.** exhibits a summary of the integrated optimization based intersection analysis studies that were reviewed in this section.

Table 2-3 Summary of Integrated Optimization Method Based Intersection Studies

No.	Author, Year	Model	Object	Findings
1	Guo et al., 2019	Dynamic programming with shooting heuristic	Near-optimal intersection and trajectory control	Reduce the average travel time by up to 35.72%
2	Yu et al., 2018	Mixed integer linear programming	Optimize vehicle trajectories and traffic signals	Decrease of vehicle delays by up to 80%
3	Feng et al., 2018	Dynamic programming	Minimize vehicle delay	Reduce about 10% vehicle delay
4	Li et al., 2014	Rolling horizon scheme	Optimize vehicle paths and signal control	Increase throughput by 2.7–20.2%

2.4. Intersection Modeling Scenarios and Parameters

Boski et al. (2019) presented traffic simulation and emission modeling approach for a signalized intersection using VISSIM which is a microscopic traffic simulation tool widely used to model real traffic conditions. Wiedemann 74 car following model of VISSIM consists of driving behavior parameters that are used to create real traffic characteristics in the road network. Model input parameters include vehicle composition, desired speed distributions, desired acceleration distribution, traffic flow and signal control. VISSIM can generate output results in terms of traffic volume of an individual approach of the road network. The simulated intersection was four-legged signalized intersection facing heavy traffic congestion almost every day during a peak hour period. The intersection was controlled in a four phase signal system having a signal cycle length of 120 s. It carried traffic volume of 8659 vehicles per hour.

Le Vine et al. (2015) investigated the implications for intersection capacity and level-of-service of providing occupants of automated and autonomously-operating cars. The study employed VISSIM, a traffic microsimulation technique, to assess the hypothesized relationship between intersection capacity and the occupants' ride experience with autonomous cars. The authors designed a road network consisting of a single four-way 90° signalized intersection with identical single-lane approaches on all four legs. Signal timing in all scenarios was based on a 90-s cycle length in two-phase operation with permissive left turns. All simulation parameters were the default values in VISSIM, such as passenger cars' longitudinal acceleration and deceleration values. All simulations included a 15-min 'warm-up' increment followed by a 60-min analysis period. To accommodate the stochastic nature of traffic microsimulation, 100 runs under each scenario were performed each with a unique 'seed' value.

Makarem et al. (2012) used AIMSUN to simulate decentralized control of autonomous vehicles at intersections. The intersection consisted of one junction, eight sections that correspond to four two-way streets. The length of each street was 200 m, which makes an isolated intersection at the junction point. The maximum speed was 50 km/h. The decentralized navigation of autonomous vehicles was compared with control by actuated traffic lights. The proposed method showed a significant reduction in travel time and number of stops.

Mathew and Radhakrishnan (2010) proposed a methodology for representing nonlane-based driving behavior and calibrating a microsimulation model for highly heterogeneous traffic at signalized intersections. A four-legged fixed-time signalized intersection having significant turning movements was simulated in VISSIM, a car-following based microsimulation tool. Simulation parameters, such as length, width, desired speed, acceleration rate, and deceleration rate, were preset for different types of vehicles. The Wiedemann 74 model has three car-following parameters including the average standstill distance, the additive safety distance, and the multiplicative safety distance. All three parameters were calibrated using GA based optimization. In addition to the car-following parameters, lateral clearance, look-ahead distance, and waiting time before diffusion were also considered in the calibration.

Lioris et al. (2017) assessed the potential mobility benefits of platoons of connected vehicles. A simulation study of a road network near Los Angeles was conducted using a mesoscopic simulator PointQ. The input links had exogenous demands modeled as stationary Poisson streams and intersections were regulated by fixed time controls and offsets. PointQ is a discrete event simulation that accurately models vehicle arrivals, departures and signal actuation. A standard four-legged intersection was simulated. The results showed that the intersection capacity can double if vehicles can cross the intersection in platoons with 0.75-s headways at 45 mph. For urban mobility, the network travel demand could increase with the increase of saturation flow rate, without any increase in queuing delay or travel time or changing signal control.

Past research has sought better understanding of how intersections are simulated. Based on the literature review as presented above, Table 2-4 exhibits a summary of the existing intersection modeling scenarios using simulation methods.

Table 2-4 Summary of Freeway Modeling Scenarios

No.	Author, Year	Tool	Scenarios
1	Boski et al., 2019	VISSIM	Four-legged signalized intersection facing heavy traffic congestion
2	Le Vine et al., 2015	VISSIM	Single four-way signalized intersection with identical single-lane approaches on all four legs
3	Makarem et al., 2012	AIMSUN	Signalized intersection with four-legged two-way streets
4	Mathew and Radhakrishnan, 2010	VISSIM	Four-legged fixed-time signalized intersection having significant turning movements
5	Lioris et al., 2017	PointQ	Standard four-legged intersection

2.5. Summary

A comprehensive review and synthesis of the current state-of-the-art and state-of-the-practice of historical researches related to CAV technology, intersection mobility analysis methods, simulation scenarios, and parameters have been discussed and presented in the preceding sections. This is intended to provide a solid reference and assistance in formulating intersection mobility analysis methods and developing effective simulation strategies for future tasks.

Chapter 3. Identify Potential Signalized Intersection

3.1. Introduction

As discussed in the literature review conducted in Chapter 2, this chapter will identify potential signalized intersection and collect necessary data related to the selected intersection. The case study is conducted in Charlotte, North Carolina. The information on potential signalized intersection including traffic volume and signal plan are provided by the City of Charlotte.

The following sections are organized as follows. Section 3.2 presents information on the selected signalized intersection. Section 3.3 presents the signal plan related to the selected intersection. Finally, section 3.4 concludes this chapter with a summary.

3.2. The Potential Signalized Intersection

3.2.1. Layout of the Potential Signalized Intersection

To better investigate the impact of CAV technologies on the operation of signalized intersection, the potential intersection should have existing congestion problem with regular vehicles. Based on this criterion, the selected signalized intersection is located in the north of Charlotte. It is a four-leg signalized intersection with two-way road in each direction. The westbound has three through lanes and two left turn lanes. The eastbound has three through lanes and two left turn lanes. The southbound has two through lanes, two left turn lanes, and one right turn lane. The northbound has two through lanes, two left turn lanes, and one right turn lane. The map of the selected signalized intersection is shown in Figure 3.1.

Figure 3.1 The map of the selected signalized intersection

3.2.2. Taffic Volumes of the Selected Intersection

The study period spans 1 hour of the midday peak, from 12:30p.m. to 1:30p.m. on April 3rd, 2018. The detail traffic volume information during the study period is shown in Table 3-1.

Table 3-1 Traffic Volume of Selected Signalized Intersection

Leg Direction	N. Tryon St Southbound					Harris Blvd Westbound					N. Tryon St Northbound					Harris Blvd Eastbound					
Time	R	T	L	U	All	R	T	L	U	All	R	T	L	U	All	R	T	L	U	All	Total
12:30 PM	66	80	94	0	240	65	328	49	11	453	48	83	84	15	230	51	276	27	1	355	1278
12:45 PM	47	60	69	0	176	65	307	61	14	447	71	98	96	12	277	39	261	46	1	347	1247
1:00 PM	54	84	92	0	230	59	277	60	10	406	76	107	82	11	276	40	234	36	6	316	1228
1:15 PM	49	69	98	0	216	50	317	42	10	419	56	109	85	19	269	39	279	49	2	369	1273
Total	216	293	353	0	862	239	1229	212	45	1725	251	397	347	57	1052	169	1050	158	10	1387	5026
% Approach	25.1	34.0	41.0	0	-	13.9	71.2	12.3	2.6	-	23.9	37.7	33.0	5.4	-	12.2	75.7	11.4	0.7	-	-
% Total	4.3	5.8	7.0	0	17.2	4.8	24.5	4.2	0.9	34.3	5.0	7.9	6.9	1.1	20.9	3.4	20.9	3.1	0.2	27.6	-

3.2.3. Signal Plan

The cycle length of the selected intersection is 140s and there are eight movements in one cycle. Detailed time split for each movement can be seen in Table 3-2. The signal phasing is shown in Figure 3.2.

Table 3-2 Time Split for Each Movement

Movement	1	2	3	4	5	6	7	8	Total
Split (s)	28	46	20	46	24	50	18	48	140

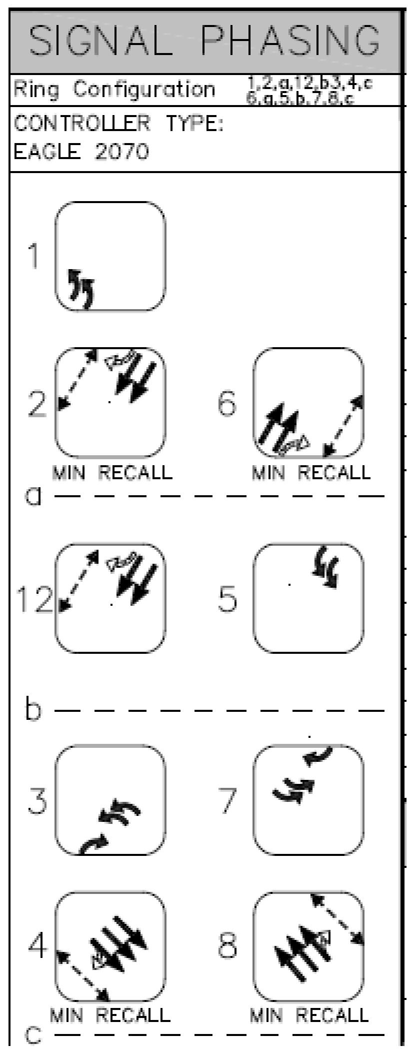

Figure 3.2 Signal phasing

3.3. Summary

To better investigate the impact of CAVs at signalized intersections. A signalized intersection with existing congestion problem is selected in the north of Charlotte, North

Carolina. This is a four-leg signalized intersection with a length of 300m for each leg. The cycle length of the selected intersection is 140s. The basic information on the selected signalized intersection is discussed. Traffic volume of the study period and signal plan are shown. This is a basic preparation for simulating signalized intersection with CAV technologies in the future tasks.

Chapter 4. Microscopic Traffic Simulation Model

4.1. Introduction

Microscopic simulation models are widely employed in transportation planning and operation analysis. Compared to field testing, simulation provides a safer, faster, and costless environment for researchers. The simulation in this study is conducted in VISSIM, a microscopic traffic simulation software. VISSIM uses the Component Object Model (COM) interface to give access to data and functions contained in other programs. VISSIM contains numerous default parameters to describe traffic flow characteristics and driver behavior. But it also allows users to input other values for the parameters. This chapter presents the speed advisory strategy for CAVs as well as the parameters preset for AVs and CAVs.

This chapter is organized as follows. Section 4.2 presents the speed advisory strategy for CAVs in the simulation. Section 4.3 describes the vehicle driving behavior for regular vehicles, AVs, and CAVs. Finally, in section 4.4, a summary concludes this chapter.

4.2. Speed Advisory Strategy

In this study, three types of vehicles are considered in the network, which are regular vehicles, AVs, and CAVs. Only CAVs can receive the signal information and adjust their speed accordingly. The speed advisory strategy is developed and aims to help CAVs arrive at a green traffic light without stopping. The detail of the strategy is explained in the following section.

Since fixed signal timing plan is used in this study, it is assumed that the total cycle length is T seconds, green starts at T_{GS} second, and green ends at T_{GE} second. As such, T_{GS} and T_{GE} should satisfy

$$0 \le T_{GS} < T_{GE} \le T \tag{1}$$

CAVs will receive the current cycle second t_c through V2I/I2V communication, and t_c should be within the cycle length that satisfies

$$0 \le t_c \le T \tag{2}$$

Therefore, CAVs' travel time until next green start t_{GS} can be calculated as follows:

$$t_{GS} = \begin{cases} T_{GS} - t_c, \ 0 \leq t_c < T_{GS} \\ T + T_{GS} - t_c, \ T_{GS} \leq t_c \leq T \end{cases} \tag{3}$$

CAVs' travel time until next green end t_{GE} can be calculated as follows:

$$t_{GE} = \begin{cases} T_{GE} - t_c, \ 0 \leq t_c \leq T_{GE} \\ T + T_{GE} - t_c, \ T_{GE} < t_c \leq T \end{cases} \tag{4}$$

Since CAVs can also receive information about distance to intersection D through V2I/I2V communication, the maximum speed for CAVs arriving after next green start v_{max} can be calculated as follows:

$$v_{max} = \frac{D}{t_{GS}} \tag{5}$$

This speed ensures that CAVs arrive at the intersection right at the start of green (i.e., green start). If vehicle's speed is higher than v_{max}, the vehicle will arrive early and have to wait until next green light starts. If vehicle's speed is less than v_{max}, the vehicle will arrive after green starts, which will waste some green time and reduce the efficiency of the intersection.

The minimum speed for CAVs arriving before next green end v_{min} can be calculated as follows:

$$v_{min} = \frac{D}{t_{GE}} \tag{6}$$

This speed makes CAVs arrive at the intersection right at the end of green (i.e., green end). CAVs should travel no less than v_{min} in order to arrive at a green traffic light.

Then, CAVs will determine the optimal speed to arrive at a green traffic light without stopping according to the signal status. Note that CAVs' speeds will not exceed the speed limit v_{SL} of the roadway segment.

If the signal display is green, optimal speed v_{os} is calculated by

$$v_{os} = \begin{cases} \min(v_{max}, v_{SL}), & v_{min} > v_{SL} \\ v_{SL}, & v_{min} \leq v_{SL} \end{cases} \tag{7}$$

CAVs will first try to arrive before green end of current cycle with a speed higher than v_{min}. So, if the speed limit is higher than v_{min}, CAVs will drive at a speed that is equal to the speed limit. However, if the speed limit is less than v_{min}, it means that CAVs cannot arrive before next green ends, because CAVs cannot drive at a speed which is higher than the speed limit. Then CAVs will adjust their speed in order to arrive when a green traffic light starts in the next cycle. Then the optimal speed is calculated the same way as that in the situation when signal is red.

If the signal is red, optimal speed v_{os} is calculated by

$$v_{os} = \min(v_{max}, v_{SL}) \tag{8}$$

CAVs will try to arrive at next green starting with v_{max}, but still, they cannot exceed the speed limit. So CAVs will choose the smaller one as their optimal speeds.

4.3. Vehicle Driving Behavior

VISSIM uses the Component Object Model (COM) interface to give access to data and functions contained in other programs. The speed advisory strategy for CAVs is written in Python. During each simulation time step, VISSIM calls the Python script to determine the optimal speed of the vehicle by passing the current state of the vehicle and signal information to the script and retrieving the updated state calculated by the script.

CAVs and AVs behave more deterministically than regular vehicles without stochastic value spreads. For acceleration and deceleration functions, the maximum and minimum values are identical to the median value of regular vehicles. Speed limit is defined as 50 km/h on all intersection legs. VISSIM's default values for regular vehicles are stochastic and speed-dependent. The maximum and desired acceleration is uniformly distributed between 0.9 m/s2 and 3.3 m/s^2 with a median value of 2.0 m/s^2 at 50 km/h. The desired deceleration is distributed uniformly between -2.5m/s^2 and -3.0 m/s^2 with a median value of -2.8 m/s^2 at 50 km/h. The maximum deceleration is distributed uniformly between -6.0 m/s^2 and -8.0 m/s^2 with a median value of -7.0 m/s^2 at 50 km/h. The average headway is 0.5s for CAVs and AVs and 0.9s for regular vehicles.

The simulation includes a 15-min warm-up time followed by a 60-min analysis time. Fifteen scenarios are analyzed with different market penetration rates of the three vehicle types. For each scenario, 10 runs are performed with different random seeds and the average of the results is calculated as the final outputs of the simulation.

4.4. Summary

This chapter presents the speed advisory strategy for simulating CAVs. The speed advisory strategy is developed and aims to help CAVs arrive at a green traffic light without stopping. Through V2I and I2V technologies, CAVs can receive real time signal timing of the signalized intersection ahead. Based on the distance to the intersection and the signal timing, the optimal speed for CAVs can be provided. Also, VISSIM contains default parameters to describe traffic flow characteristics and driver behavior for regular vehicles. These parameters need to be adjusted to model driving behavior of AVs and CAVs in the microscopic simulation model.

Chapter 5. Numerical Results

5.1. Introduction

This chapter presents the numerical results of the simulation. A speed advisory strategy is employed to simulate the CAVs' maneuver. The simulation is conducted in a mixed traffic environment including regular vehicles, AVs, and CAVs. The impact of CAVs on the signalized intersection is evaluated under different penetration level of CAVs. The chapter is organized as follows. Section 5.2 describes the numerical results of the simulation in terms of intersection performance and vehicle emissions. Finally, in section 5.3, a summary concludes this chapter.

5.2. Numerical Results

Based on the selected signalized intersection identified from Chapter 3, the simulation is conducted in VISSIM under a mixed traffic environment. The speed advisory strategy is provided to adjust CAVs' speeds approaching the intersection. The impact of CAVs on intersection efficiency and environment is examined under different CAV penetration levels. The numerical results are discussed in detail in the following sections.

5.2.1. Performance of the Strategy

The performance of the proposed strategy is evaluated by comparing the vehicle trajectories, speeds, and acceleration rates of CAVs, AVs, and regular vehicles. The comparison is conducted in one signal cycle and there are six vehicles passing the intersection during this cycle.

The trajectory of regular vehicles is shown in Figure 5.1. According to the slope of the trajectory, one can see that regular vehicles keep a relative constant speed while approaching the intersection without any deceleration. If the signal is red, regular vehicles have to decelerate with a high rate when they are close to the stop line. As a result, queue will gradually form at the intersection. The speed of regular vehicles is shown in Figure 5.2. It can be seen that the speed decrease from free flow speed to zero in a short time. The acceleration rate of regular vehicles is shown in Figure 5.3. One can see that regular vehicles have unstable acceleration rate while approaching to the intersection ranging from -3 to 3 m/s^2.

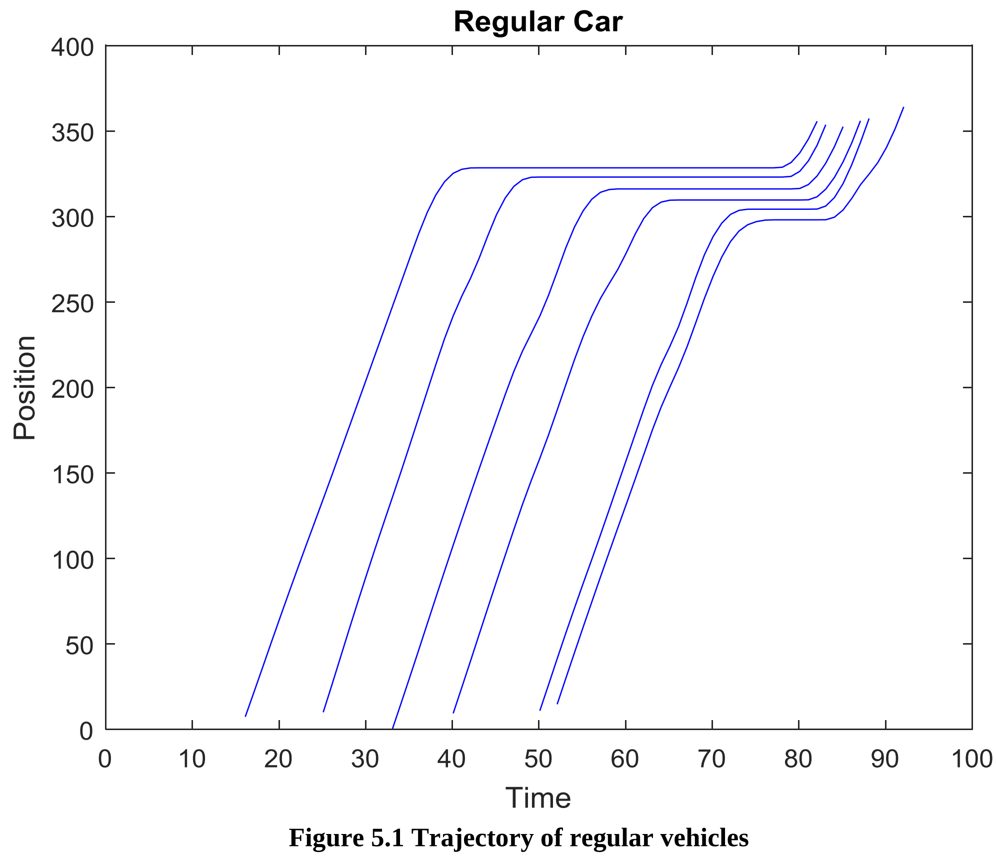

Figure 5.1 Trajectory of regular vehicles

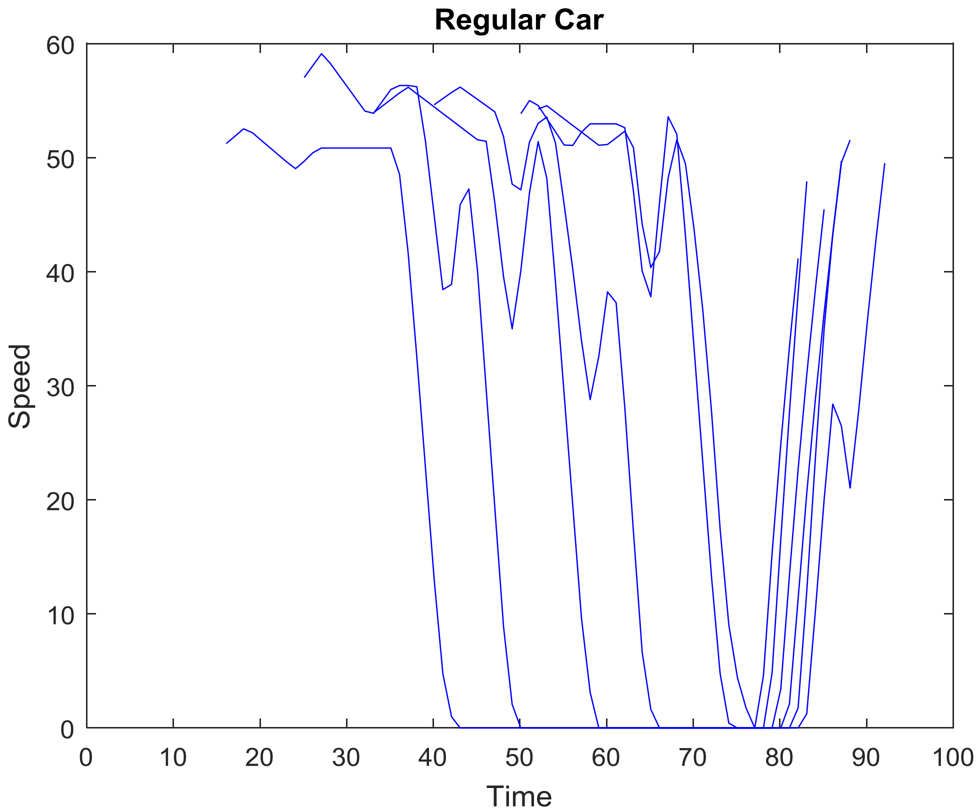

Figure 5.2 Speed of regular vehicles

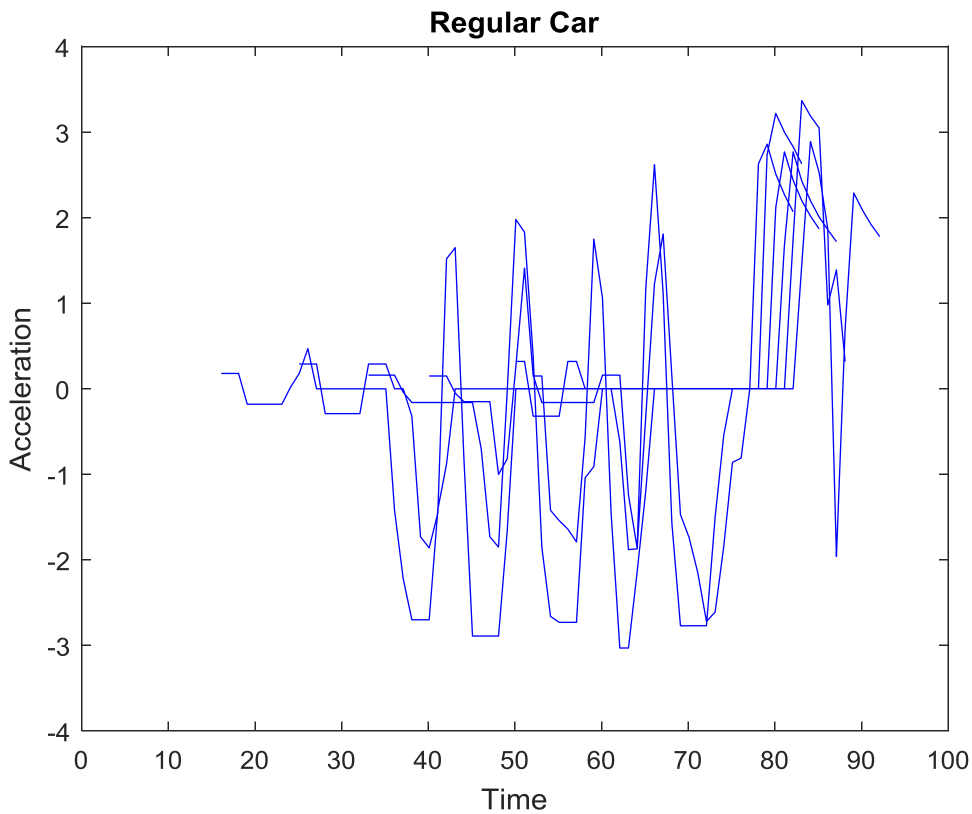

Figure 5.3 Acceleration rate of regular vehicles

The trajectory of AVs is shown in Figure 5.4. The trajectory of AVs is similar to regular vehicles but more smooth, which means that AVs keep a relatively constant speed and acceleration rate. This can be verified from Figure 5.5 and Figure 5.6, which are the speed and acceleration rate of AVs, respectively. It can be seen from Figure 5.6 that AVs have more stable acceleration rate while approaching to the intersection ranging from -3 to 0.5 m/s^2.

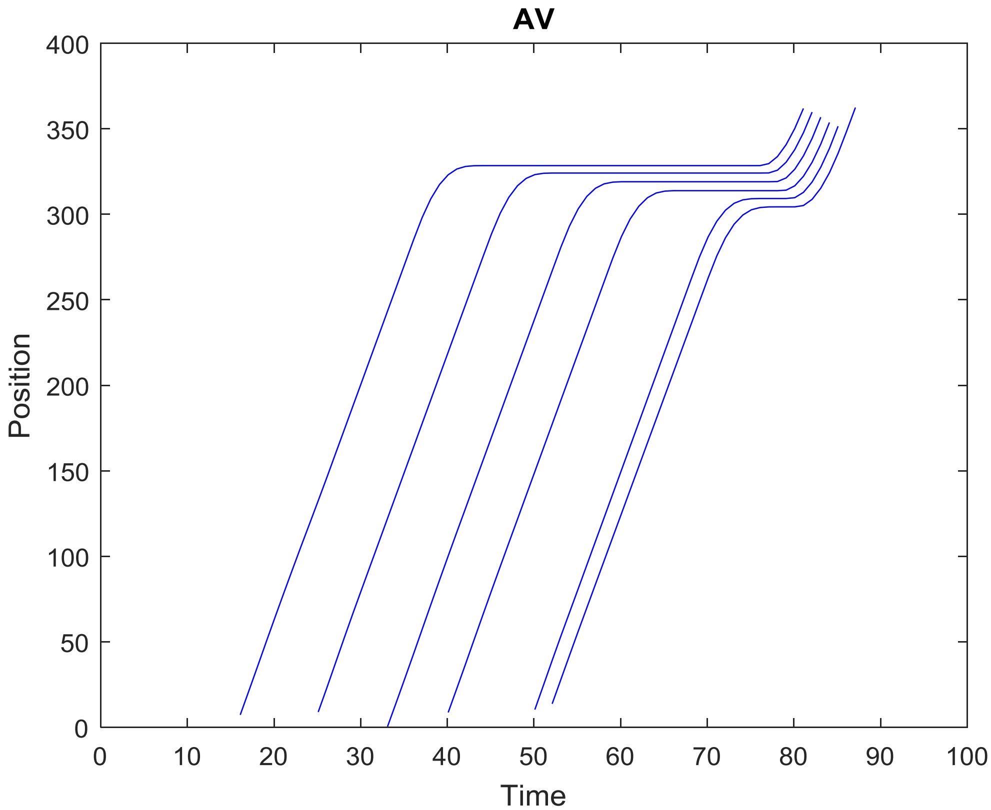

Figure 5.4 Trajectory of AVs

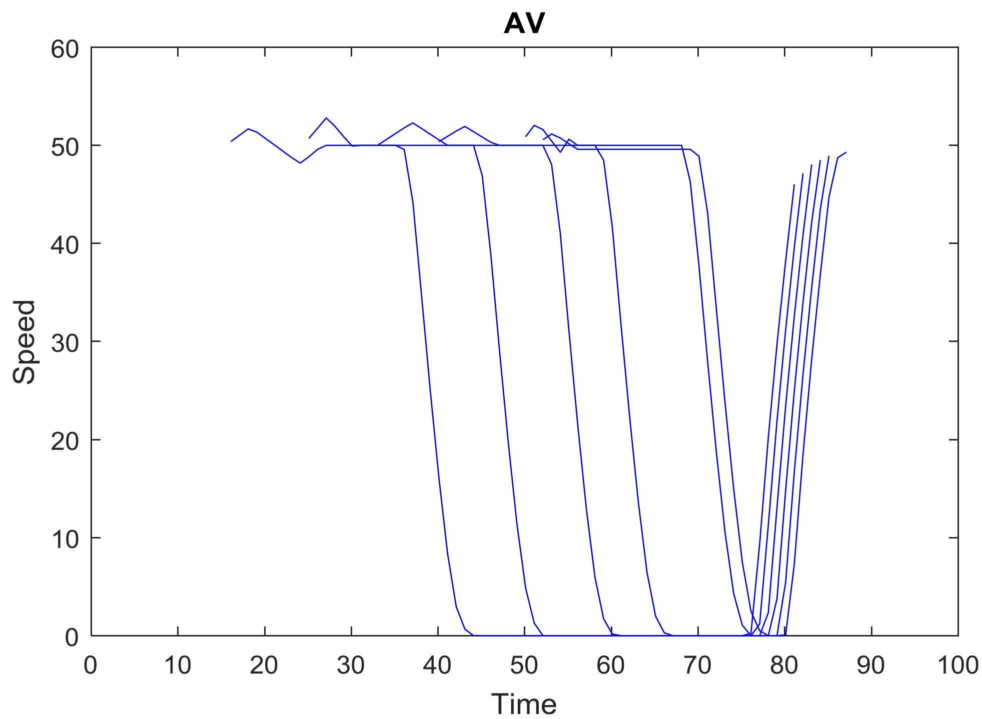

Figure 5.5 Speed of AVs

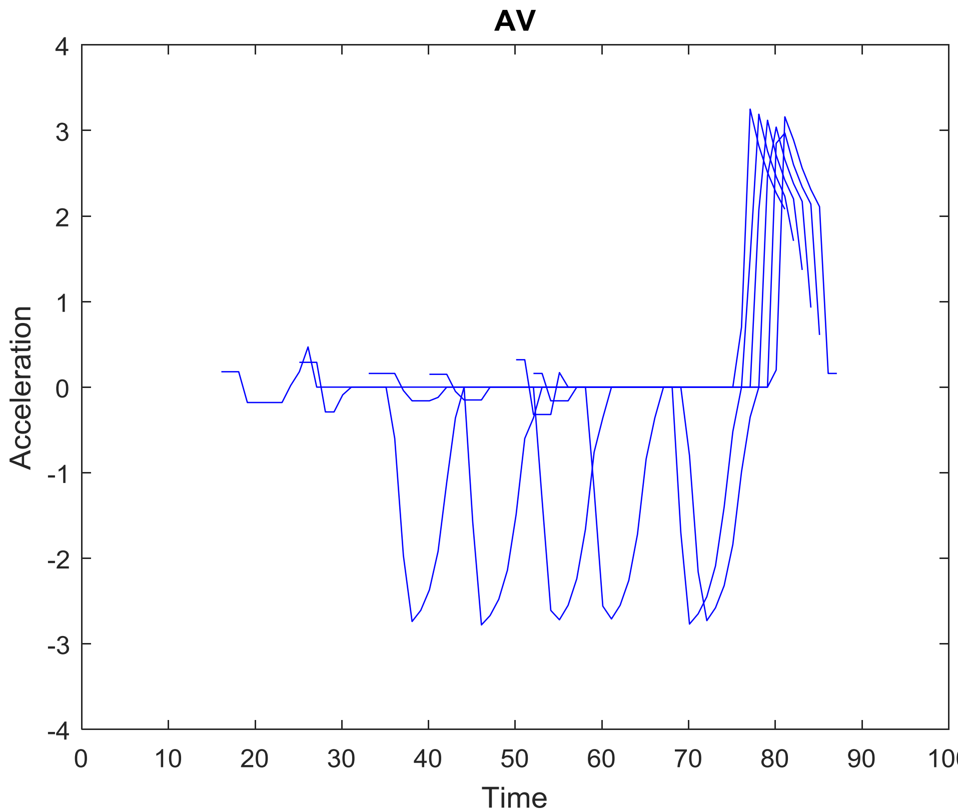

Figure 5.6 Acceleration rate of AVs

The trajectory of CAVs is shown in Figure 5.7. According to the slope of the trajectory, one can see that CAVs can adjust their speeds in advance while approaching the intersection. As a result, all CAVs can pass the intersection at green without stopping. The speed of CAVs is shown in Figure 5.8. It can be seen that CAVs start to decrease their speed earlier than other two types of vehicles. And the minimum speed is around 10 m/s, which means that CAVs can pass the intersection without idling. The acceleration rate of CAVs is shown in Figure 5.9. One can see that CAVs have the most stable acceleration rates compared to AVs and regular vehicles while approaching to the intersection ranging from -1.5 to 1 m/s^2.

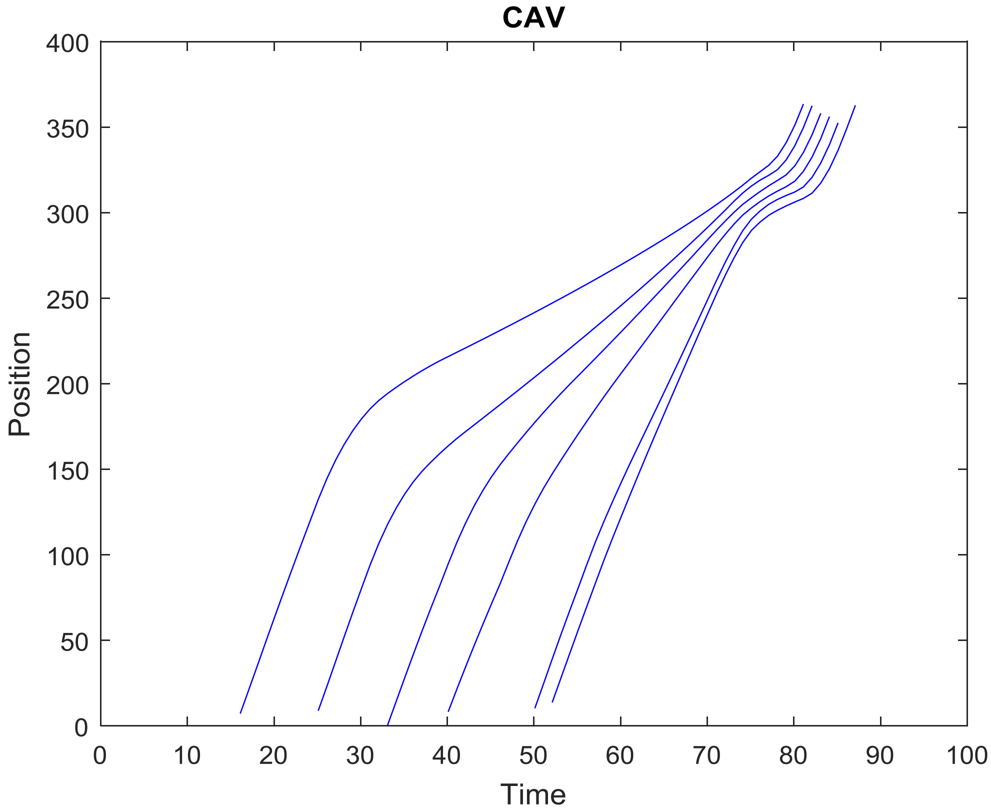

Figure 5.7 Trajectory of CAVs

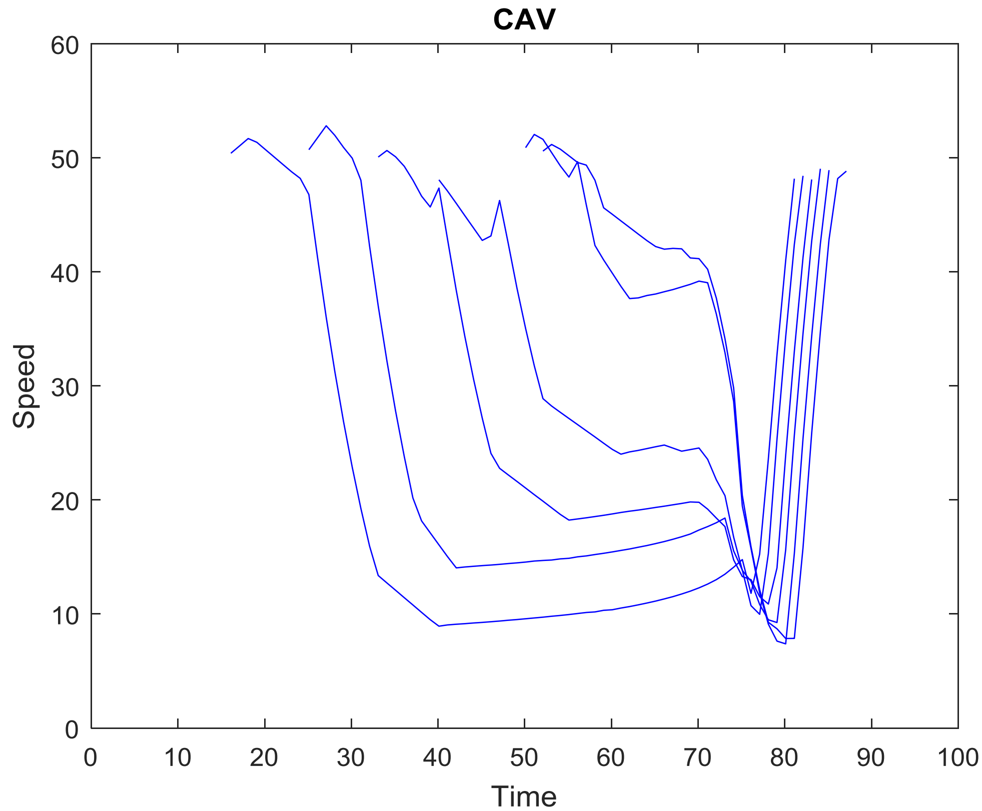

Figure 5.8 Speed of CAVs

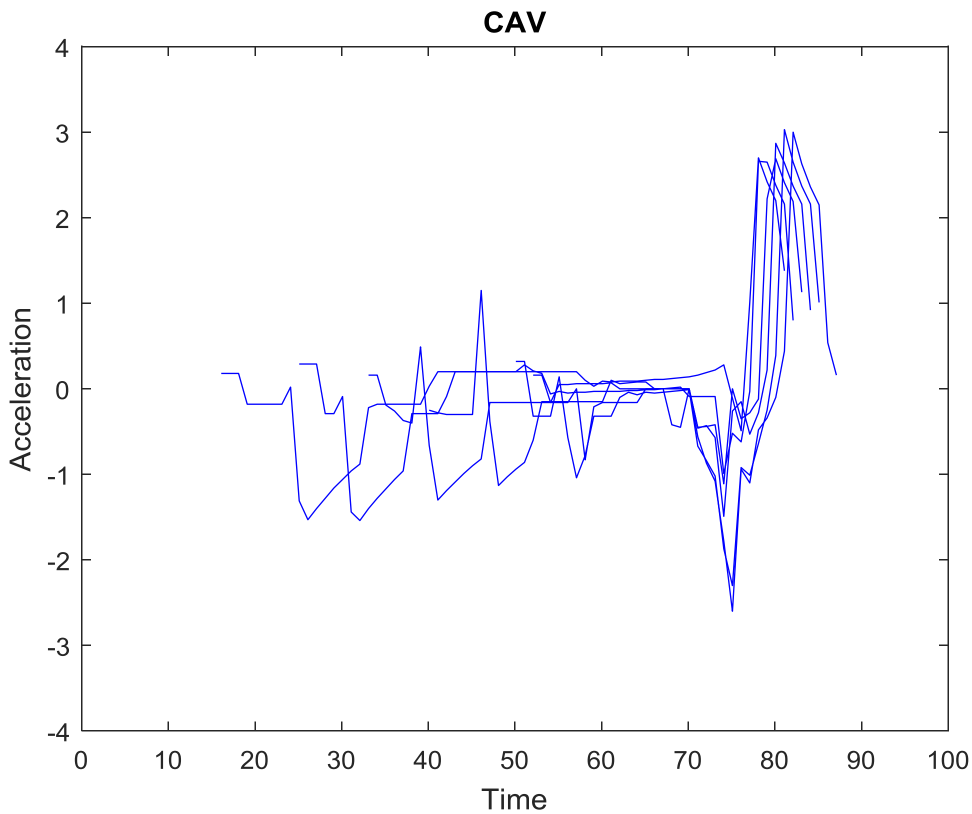

Figure 5.9 Acceleration rate of CAVs

By comparing the vehicle trajectories, it can be found that CAVs can be decelerated in advance to avoid stops at the intersection. All CAVs can pass the intersection smoothly without idling so that the traffic efficiency is improved. Through the comparison of speed trajectories, it can be seen that the minimum speed for CAVs is around 10 m/s and 0 m/s for AVs and regular vehicles. It means that CAVs can arrive at a green traffic light due to the speed advisory strategy while AVs and regular vehicles have to wait for the green light. By comparing vehicle acceleration trajectories, one can see that CAVs maintain a small range of acceleration/deceleration rate. This indicates that CAVs travel with relatively stable speeds, which is consistent with the results of speed trajectories. From the comparison among CAVs, AVs, and regular vehicles, it can be concluded that the proposed strategy can effectively reduce vehicle delay at signalized intersections and thus improve traffic efficiency.

5.2.2. Performance of the Intersection

The intersection performance and vehicle emissions are recorded during the 60-min simulation with different combinations of CAVs, AVs, and regular vehicles. The travel delay for each penetration level of three vehicle type is shown in Table 5-1. The vehicle delay is the total delay of all vehicles passing the intersection during the simulation. It can be seen that with only CAVs, AVs, or regular vehicles on road, the vehicle delay is 41.23s, 49.30s, and 76.43s, respectively. With 100% penetration rate of CAVs vehicle delay can be reduced by 46.06% compared to regular vehicles only. AVs can reduce vehicle delay by as much as 35.50%

compared to regular vehicles only. So with V2I/I2V communications, CAVs can effectively improve the efficiency of signalized intersections.

Table 5-1 Traffic Delay under Different CAV Penetration Rates

Vehicle Delay (s)		CAV				
		0%	25%	50%	75%	100%
AV	0%	76.43	56.79	51.61	45.66	41.23
	25%	55.55	53.46	47.39	44.44	
	50%	51.98	49.98	46.22		
	75%	50.70	48.86			
	100%	49.30				

The vehicle stop for each penetration level of three vehicle type is shown in Table 5-2. The vehicle stop is the number of vehicle stops per vehicle during the simulation. It can be seen that with only CAVs, AVs, or regular vehicles on road, the vehicle stop is 0.56, 0.75, and 1.36, respectively. With 100% penetration rate of CAVs, vehicle stop can be reduced by 58.82% compared to regular vehicles only. AVs can reduce vehicle stop by as much as 44.85% compared to regular vehicles only.

Table 5-2 Vehicle Stops under Different CAV Penetration Rates

Stops		CAV				
		0%	25%	50%	75%	100%
AV	0%	1.36	1.26	1.09	0.75	0.56
	25%	0.85	1.08	0.85	0.65	
	50%	0.80	0.94	0.77		
	75%	0.78	0.86			
	100%	0.75				

The stopped delay for each penetration level of three vehicle type is shown in Table 5-3. The stopped delay is the stopped delay per vehicle during the simulation. It can be seen that with only CAVs, AVs, or regular vehicles on road, the stopped delay is 23.04s, 40.74s, and 63.02s, respectively. With 100% penetration rate of CAVs, stopped delay can be reduced by 63.44% compared to regular vehicles only. AVs can reduce stopped delay by as much as 35.35% compared to regular vehicles only.

Table 5-3 Stopped Delay under Different CAV Penetration Rates

Stopped Delay (s)		CAV				
		0%	25%	50%	75%	100%
AV	0%	63.02	38.25	29.81	25.61	23.04
	25%	44.41	36.20	27.49	25.03	
	50%	41.69	33.20	26.69		
	75%	40.74	32.33			
	100%	39.73				

The queue length for each penetration level of three vehicle type is shown in Table 5-4. In each time step, the current queue length is measured and the arithmetic mean is thus calculated per time interval. It can be seen that with only CAVs, AVs, or regular vehicles on road, the queue length is 10.45m, 10.02m, and 23.88m, respectively. With 100% penetration rate of CAVs, the queue length can be reduced by 56.24% compared to regular vehicles only.

Table 5-4 Average Queue Length under Different CAV Penetration Rates

Queue Length (m)		**CAV**				
		0%	25%	50%	75%	100%
AV	0%	23.88	17.27	15.64	12.58	10.45
	25%	14.08	14.89	12.27	11.02	
	50%	12.14	12.55	10.85		
	75%	11.12	11.11			
	100%	10.02				

The maximum queue length for each penetration level of three vehicle type is shown in Table 5-5. In each time step, the current queue length is measured and the maximum is thus calculated per time interval. It can be seen that with only CAVs, AVs, or regular vehicles on road, the maximum queue length is 186.76m, 138.90m, and 272.96m, respectively. With 100% penetration rate of CAVs, the maximum queue length can be reduced by 31.58% compared to regular vehicles only.

Table 5-5 Maximum Queue Length under Different CAV Penetration Rates

Qlen Max (m)		**CAV**				
		0%	25%	50%	75%	100%
AV	0%	272.96	208.04	207.22	199.71	186.76
	25%	226.50	185.29	175.48	183.85	
	50%	177.82	192.79	184.19		
	75%	155.20	158.49			
	100%	138.90				

The CO emissions under all scenarios are shown in Table 5-6. The numbers reflect the quantity of carbon monoxide emitted by all vehicles passing the intersection during the simulation. As one can see from Table 5-6, with only CAVs, AVs, or regular vehicles on road, the CO emissions are 6594.78g, 7431.42g, and 9912.17g, respectively. CAVs can reduce CO emissions by as much as 33.47% compared to regular vehicles and 11.26% compared to AVs. As a result, CAVs can benefit the environment through V2I/I2V communications.

Table 5-6 CO Emissions under Different CAV Penetration Rates

CO Emissions (grams)		**CAV**				
		0%	25%	50%	75%	100%
AV	0%	9912.17	8725.95	8126.39	7187.46	6594.78
	25%	7928.60	8224.88	7465.15	6936.46	
	50%	7667.01	7794.19	7260.71		

	75%	7543.33	7589.18			
	100%	7431.42				

The NO_x emissions under all scenarios are shown in Table 5-7. The numbers reflect the quantity of nitrogen oxides emitted by all vehicles passing the intersection during the simulation. As one can see from Table 5-7, with only CAVs, AVs, or regular vehicles on road, the NO_x emissions are 1283.10g, 1445.89g, and 1928.55g, respectively.

Table 5-7 NO_x Emissions under Different CAV Penetration Rates

NO_x Emissions (grams)		**CAV**				
		0%	25%	50%	75%	100%
AV	0%	1928.55	1697.75	1581.10	1398.42	1283.10
	25%	1542.62	1600.26	1452.45	1349.58	
	50%	1491.72	1516.47	1412.67		
	75%	1467.66	1476.58			
	100%	1445.89				

The VOC emissions under all scenarios are shown in Table 5-8. The numbers reflect the quantity of volatile organic compounds emitted by all vehicles passing the intersection during the simulation. As one can see from Table 5-8, with only CAVs, AVs, or regular vehicles on road, the VOC emissions are 1528.40g, 1722.30g, and 2297.24g, respectively.

Table 5-8 VOC Emissions under Different CAV Penetration Rates

VOC Emissions (grams)		**CAV**				
		0%	25%	50%	75%	100%
AV	0%	2297.24	2022.32	1883.37	1665.76	1528.40
	25%	1837.53	1906.20	1730.12	1607.59	
	50%	1776.90	1806.38	1682.74		
	75%	1748.24	1758.87			
	100%	1722.30				

The fuel consumptions under all scenarios are shown in Table 5-9. The numbers reflect the fuel consumptions by all vehicles passing the intersection during the simulation. As one can see from Table 5-9, with only CAVs, AVs, or regular vehicles on road, the fuel consumptions are 94.35 gallons, 106.32 gallons, and 141.80 gallons, respectively.

Table 5-9 Fuel Consumption under Different CAV Penetration Rates

FC (gallon)		CAV				
		0%	25%	50%	75%	100%
AV	0%	141.80	124.83	116.26	102.82	94.35
	25%	113.43	117.67	106.80	99.23	
	50%	109.69	111.50	103.87		
	75%	107.92	108.57			
	100%	106.32				

5.3. Summary

This chapter focuses on describing the case study results using VISSIM. The detailed information (e.g., vehicle trajectory, speed, acceleration rate, and vehicle emissions) on the case studies is presented. From the comparison among CAVs, AVs, and regular vehicles, it can be concluded that the proposed strategy can effectively reduce vehicle delay at signalized intersections and thus improve traffic efficiency. Also, CAVs can benefit the environment through V2I/I2V communications.

Chapter 6. Summary and Conclusions

6.1. Introduction

CAV technologies are known as an effective way to improve safety and mobility of the transportation system. As a combination technology of connected vehicle and autonomous vehicle, CAVs share real time traffic data with each other, such as position, speed, and acceleration. Also, CAVs enable the communication between vehicles and transportation infrastructures. The coordinated operations among CAVs and the communication between CAVs and traffic signals will improve the throughput at signalized intersections and lead to a higher intersection capacity. The coordinated through or turning maneuvers of CAVs may reduce crashes and minimize the total delay at an isolated signalized intersection. Traffic signals play an important role in urban traffic management. On the other hand, traffic signals increase travel time, gas emissions and fuel consumption of vehicles. Moreover, stop-and-go traffic increases the possibility of vehicle collisions and leads to economic cost in result. As the increasing travel demand in recent years, traditional signalized intersections have been generating more delays as well as gas emissions. There is an urgent need to improve intersection efficiency and the throughput mobility using the emerging CAV technologies.

This research develops guidelines and recommendations for estimating and predicting intersection efficiency in the presence of CAVs, and therefore will lead to a better understanding of how CAVs will improve mobility at signalized intersections. To better understand the impact of CAVs on the operation of signalized intersections, autonomous vehicles (AVs) are also involved in this study, so that a mixed traffic environment can be investigated including regular vehicles, AVs, and CAVs. A case study is conducted with a signalized intersection in Charlotte, North Carolina. The selected signalized intersection is simulated in VISSIM, a traffic microsimulation tool, to explore the impact of CAVs on the intersection. To obtain valid results, various driving behavior parameters such as standstill distance and minimum headway between vehicles are adjusted for AVs and CAVs. Simulation results are discussed in details. Overall, the results of this study can help traffic engineers and stakeholders better understand how different market penetration levels of CAVs influence traffic operation of signalized intersections and improve efficiency of signalized intersections.

The following sections are organized as follows. In section 6.2, the principal features of the CAV technologies are reviewed and a summary of conclusions for the numerical results derived from simulation is discussed. Section 6.3 presents a brief discussion of the limitations of the current approaches and possible directions for further research are also given.

6.2. Summary and Conclusions

With the rapid development of CAV technologies, CAVs equipped with DSRC can communicate with both other CAVs and infrastructures. Traffic signal control framework becomes feasible and can achieve greater benefits regarding transportation system efficiency. Microscopic simulation models have been widely employed in transportation planning and operation analysis. Compared to field testing, simulation provides a safer, faster, and costless environment for researchers. The simulation in this study is conducted in VISSIM, a microscopic traffic simulation software. VISSIM uses the Component Object Model (COM) interface to give access to data and functions contained in other programs. VISSIM contains numerous default parameters to describe traffic flow characteristics and driver behavior, and it also allows users to input other values for the parameters.

In this study, three types of vehicles are considered in the network, which are regular vehicles, AVs, and CAVs. Only CAVs can receive the signal information and adjust their speed accordingly. The speed advisory strategy is developed and aims to help CAVs arrive at a green traffic light without stopping. The speed advisory strategy for CAVs is written in Python. During each simulation time step, VISSIM calls the Python script to determine the optimal speed of the vehicle by passing the current state of the vehicle and signal information to the script and retrieving the updated state calculated by the script.

CAVs and AVs behave more deterministically than regular vehicles without stochastic value spreads. For acceleration and deceleration functions, the maximum and minimum values are identical to the median value of regular vehicles. Speed limit is defined as 50 km/h on all intersection legs. VISSIM's default values for regular vehicles are stochastic and speed-dependent. The maximum and desired acceleration is uniformly distributed between 0.9 m/s2 and 3.3 m/s^2 with a median value of 2.0 m/s^2 at 50 km/h. The desired deceleration is distributed uniformly between -2.5m/s^2 and -3.0 m/s^2 with a median value of -2.8 m/s^2 at 50 km/h. The maximum deceleration is distributed uniformly between -6.0 m/s^2 and -8.0 m/s^2 with a median value of -7.0 m/s^2 at 50 km/h. The average headway is 0.5s for CAVs and AVs and 0.9s for regular vehicles.

The simulation includes a 15-min warm-up time followed by a 60-min analysis time. Fifteen scenarios are analyzed with different market penetration rates of the three vehicle types. For each scenario, 10 runs are performed with different random seeds and the average of the results is calculated as the final outputs of the simulation.

The intersection performance and vehicle emissions are recorded with different combinations of CAVs, AVs, and regular vehicles. For example, with 100% penetration rate of CAVs, vehicle delay can be reduced by 46.06% compared to regular vehicles only. AVs can reduce vehicle delay by as much as 35.50% compared to regular vehicles only. So with V2I/I2V communications, CAVs can effectively improve the efficiency of signalized intersections. The vehicle emissions under all scenarios are also generated. CAVs can reduce vehicle emissions by as much as 33.47% compared to regular vehicles and 11.26% compared to AVs. As a result, CAVs can benefit the environment through V2I/I2V communications.

6.3. Directions for Future Research

In this section, some of the limitations of the developed speed advisory strategy in this study are presented and directions for further research are also discussed.

Typically, the speed advisory strategy aims to adjust CAVs' speed approaching signalized intersections. In the future, the acceleration rate can be considered in the strategy. Also, the speed advisory strategy is based on the V2I and I2V technologies. In the future, the

V2V technologies can also be considered, which means CAVs' speed and acceleration rate can be adjusted according to the status of surrounding vehicles.

In this study, the simulation is only conducted on an isolated signalized intersection. In the future, more complicated intersections can be examined. Also, the impact of CAVs on urban and rural arterials will be studied in the future.

References

1. Abbas, M. M., and Chong, L. (2013). *Car-Following Trajectory Modeling with Machine Learning: Showcase for Merits of Artificial Intelligence* (No. 13-4712).
2. Chauhan, B. P., Joshi, G. J., and Parida, P. (2019). Car following model for urban signalised intersection to estimate speed based vehicle exhaust emissions. *Urban Climate, 29*, 100480.
3. Chow, A. H., Sha, R., and Li, S. (2019). Centralised and decentralised signal timing optimisation approaches for network traffic control. *Transportation Research Part C: Emerging Technologies*.
4. Datesh, J., Scherer, W. T., and Smith, B. L. (2011, June). Using k-means clustering to improve traffic signal efficacy in an IntelliDrive SM environment. *In 2011 IEEE Forum on Integrated and Sustainable Transportation Systems* (pp. 122-127). IEEE.
5. Feng, Y., Head, K. L., Khoshmagham, S., and Zamanipour, M. (2015). A real-time adaptive signal control in a connected vehicle environment. *Transportation Research Part C: Emerging Technologies, 55*, 460-473.
6. Feng, Y., Yu, C., and Liu, H. X. (2018). Spatiotemporal intersection control in a connected and automated vehicle environment. *Transportation Research Part C: Emerging Technologies, 89*, 364-383.
7. Guler, S. I., Menendez, M., and Meier, L. (2014). Using connected vehicle technology to improve the efficiency of intersections. *Transportation Research Part C: Emerging Technologies*, *46*, 121-131.
8. Guo, Y., Ma, J., Xiong, C., Li, X., Zhou, F., and Hao, W. (2019). Joint optimization of vehicle trajectories and intersection controllers with connected automated vehicles: Combined dynamic programming and shooting heuristic approach. *Transportation research part C: Emerging Technologies*, *98*, 54-72.
9. Hashimoto, Y., Gu, Y., Hsu, L. T., Iryo-Asano, M., and Kamijo, S. (2016). A probabilistic model of pedestrian crossing behavior at signalized intersections for connected vehicles. *Transportation research part C: Emerging Technologies, 71*, 164-181.
10. He, Q., Head, K. L., and Ding, J. (2012). PAMSCOD: Platoon-based arterial multi-modal signal control with online data. *Transportation Research Part C: Emerging Technologies, 20*(1), 164-184.
11. He, X., Liu, H. X., and Liu, X. (2015). Optimal vehicle speed trajectory on a signalized arterial with consideration of queue. *Transportation Research Part C: Emerging Technologies*, *61*, 106-120.
12. Jiang, H., Hu, J., An, S., Wang, M., and Park, B. B. (2017). Eco approaching at an isolated signalized intersection under partially connected and automated vehicles environment. *Transportation Research Part C: Emerging Technologies, 79*, 290-307.
13. Lazar, C., Tiganasu, A., and Caruntu, C. F. (2018). Arterial intersection improvement by using vehicle platooning and coordinated start. *IFAC-PapersOnLine, 51*(9), 136-141.

14. Le Vine, S., Zolfaghari, A., and Polak, J. (2015). Autonomous cars: The tension between occupant experience and intersection capacity. *Transportation Research Part C: Emerging Technologies, 52*, 1-14.
15. Li, X., and Sun, J. Q. (2019). Intersection multi-objective optimization on signal setting and lane assignment. *Physica A: Statistical Mechanics and its Applications, 525*, 1233-1246.
16. Li, Z., Elefteriadou, L., and Ranka, S. (2014). Signal control optimization for automated vehicles at isolated signalized intersections. *Transportation Research Part C: Emerging Technologies, 49*, 1-18.
17. Lioris, J., Pedarsani, R., Tascikaraoglu, F. Y., and Varaiya, P. (2017). Platoons of connected vehicles can double throughput in urban roads. *Transportation Research Part C: Emerging Technologies, 77*, 292-305.
18. Liu, B., Shi, Q., Song, Z., and El Kamel, A. (2019). Trajectory planning for autonomous intersection management of connected vehicles. *Simulation Modelling Practice and Theory, 90*, 16-30.
19. Makarem, L., Pham, M. H., Dumont, A. G., and Gillet, D. (2012). Microsimulation modeling of coordination of automated guided vehicles at intersections. *Transportation Research Record, 2324*(1), 119-124.
20. Mathew, T. V., and Radhakrishnan, P. (2010). Calibration of microsimulation models for nonlane-based heterogeneous traffic at signalized intersections. *Journal of Urban Planning and Development, 136*(1), 59-66.
21. Mirheli, A., Hajibabai, L., and Hajbabaie, A. (2018). Development of a signal-head-free intersection control logic in a fully connected and autonomous vehicle environment. *Transportation Research Part C: Emerging Technologies, 92*, 412-425.
22. Mirheli, A., Tajalli, M., Hajibabai, L., and Hajbabaie, A. (2019). A consensus-based distributed trajectory control in a signal-free intersection. *Transportation research part C: Emerging Technologies, 100*, 161-176.
23. Priemer, C., and Friedrich, B. (2009, October). A decentralized adaptive traffic signal control using V2I communication data. *In 2009 12th International IEEE Conference on Intelligent Transportation Systems* (pp. 1-6). IEEE.
24. Qi, H., and Hu, X. (2019). Monte Carlo Tree Search-based intersection signal optimization model with channelized section spillover. *Transportation Research Part C: Emerging Technologies, 106*, 281-302.
25. Stebbins, S., Hickman, M., Kim, J., and Vu, H. L. (2017). Characterising green light optimal speed advisory trajectories for platoon-based optimisation. *Transportation Research Part C: Emerging Technologies, 82*, 43-62.
26. Sun, W., Zheng, J., and Liu, H. X. (2017). A capacity maximization scheme for intersection management with automated vehicles. *Transportation research procedia, 23*, 121-136.

27. Ubiergo, G. A., and Jin, W. L. (2016). Mobility and environment improvement of signalized networks through Vehicle-to-Infrastructure (V2I) communications. *Transportation Research Part C: Emerging Technologies, 68*, 70-82.
28. Wei, Y., Avcı, C., Liu, J., Belezamo, B., Aydın, N., Li, P. T., and Zhou, X. (2017). Dynamic programming-based multi-vehicle longitudinal trajectory optimization with simplified car following models. *Transportation research part B: Methodological, 106*, 102-129.
29. Xie, X. F., and Wang, Z. J. (2018). SIV-DSS: Smart In-Vehicle Decision Support System for driving at signalized intersections with V2I communication. *Transportation Research Part C: Emerging Technologies, 90*, 181-197.
30. Xu, B., Li, S. E., Bian, Y., Li, S., Ban, X. J., Wang, J., and Li, K. (2018). Distributed conflict-free cooperation for multiple connected vehicles at unsignalized intersections. *Transportation Research Part C: Emerging Technologies*, *93*, 322-334.
31. Yang, K., Guler, S. I., and Menendez, M. (2016). Isolated intersection control for various levels of vehicle technology: Conventional, connected, and automated vehicles. *Transportation Research Part C: Emerging Technologies, 72*, 109-129.
32. Yao, H., Cui, J., Li, X., Wang, Y., and An, S. (2018). A trajectory smoothing method at signalized intersection based on individualized variable speed limits with location optimization. *Transportation Research Part D: Transport and Environment, 62*, 456-473.
33. Yu, C., Feng, Y., Liu, H. X., Ma, W., and Yang, X. (2018). Integrated optimization of traffic signals and vehicle trajectories at isolated urban intersections. *Transportation Research Part B: Methodological, 112*, 89-112.
34. Yu, C., Feng, Y., Liu, H. X., Ma, W., and Yang, X. (2019). Corridor level cooperative trajectory optimization with connected and automated vehicles. *Transportation Research Part C: Emerging Technologies, 105*, 405-421.
35. Zheng, J., and Liu, H. X. (2017). Estimating traffic volumes for signalized intersections using connected vehicle data. *Transportation Research Part C: Emerging Technologies, 79*, 347-362.
36. Zhu, F., and Ukkusuri, S. V. (2015). A linear programming formulation for autonomous intersection control within a dynamic traffic assignment and connected vehicle environment. *Transportation Research Part C: Emerging Technologies, 55*, 363-378.