THE IMPACT OF CONNECTED AND AUTONOMOUS VEHICLES ON THE SUPERSTREETS

by

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ABSTRACT

SHAOJIE LIU. The impact of connected and autonomous vehicles on the superstreets
(Under the direction of DR. WEI FAN)

Connected and autonomous vehicles (CAVs) are a type of emerging technology that has promising potentials in improving many aspects of the existing transportation infrastructure, including operations, safety, and the environment. With the capability of traveling on the roads with shorter headways and more stable speeds, CAVs can yield a larger road capacity compared to human-driven vehicles (HDVs). Additionally, since the CAVs run on the roads with the guidance of computers or algorithms, accidents caused by errors from human drivers may be prevented, which can greatly reduce significant economic and societal losses. Less speed fluctuations are also beneficial to decrease the emissions and contribute to the environment.

Thanks to the rapid development of computer science and communication technology, CAVs have evolved from theoretical experiments in academic labs to reliable products by commercial companies. Since both academic and industrial professionals have high expectations for CAVs, many studies have been conducted to explore and identify the impacts of CAV technologies on the transportation performances in many scenarios. These scenarios included conventional intersections, highway segments, on/off ramps, and roundabouts. Through extensive investigations on CAVs in different scenarios, it can be concluded that CAVs can perform better overall than HDVs. Nevertheless, it has also been found that the performances of CAVs are affected by many factors such as communication range, acceleration capabilities, and market penetration rates. Improvement in operational performances has been confirmed by existing studies when the market penetration of CAVs reaches a certain rate.

Superstreet is one of the innovative intersection designs and was proposed to alleviate the road congestions especially where unbalanced traffic volumes from main street and minor street exist. Superstreets have been successfully implemented in numerous states. Nevertheless, how CAVs would affect the performances of superstreets has not been explored, even to a minimum extent. This research is designed to investigate how CAVs with different technologies perform in the environment of superstreets. To be specific, the following questions will be answered: (1) at what market penetration rate CAVs would bring benefits towards operational performances; (2) at what extent CAVs would bring benefits towards operational performances of superstreets; (3) how the impact of CAVs on the operational performance would vary across different traffic scales and market penetration rates.

To achieve the research goals, models for CAV platooning, trajectory planning, and signal optimization have been developed, respectively. The effects of these models are tested respectively in a simulation environment where relevant traffic measures are extracted to evaluate the performances. The finding of this research may also be applied to other innovative intersection designs which have similar geometric characteristics and traffic patterns.

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LIST OF ABBREVIATIONS

ACC	adaptive cruise control
AV	autonomous vehicles
CACC	cooperative adaptive cruise control
CAV	connected and autonomous vehicles
FHWA	Federal Highway Administration
GA	genetic algorithm
HDV	human-driven vehicles
IDM	intelligent driver model
MILP	mixed-integer linear programming
MIP	mixed-integer programming
NHTSA	National Highway Traffic Safety Administration
RCUT	Restricted crossing U-turn intersection
SUMO	Simulation of Urban Mobility

CHAPTER 1 INTRODUCTION

1.1 Problem Statement and Motivations

Road congestion has been a critical issue for transportation professionals as it increases travel time, energy use and pollutant emissions. Due to recent technology development of wireless communication and artificial intelligence, connected and autonomous vehicles (CAVs) become a practical approach to increase road capacity and reduce fuel consumption. As many studies have been done to explore the potential of CAVs in various scenarios of transportation environment, such as freeway segments (Liu and Fan 2020, Yu and Fan, 2018), signalized intersections (Han et al., 2020; Feng et al., 2018; Yu et al., 2018), unsignalized intersections (Sharon and Stone, 2017), roundabouts (Anagnostopoulos and Kehagia, 2020) and on/off ramps (Rios-Torres and Malikopoulos, 2016), the operational performance of CAVs on the innovative intersections had received relatively less attention. Innovative intersection designs are often quite different from conventional intersection designs. Most innovative intersection designs create minor intersections and limit the number of movements in each minor intersection. Different impacts of CAVs are expected in the environment of superstreets.

The research gaps exist between CAVs and innovative intersections. This research aims to mitigate the gaps by conducting simulation-based research to explore the impact of CAVs on the operational performances in the environment of superstreets. A popular approach to evaluating the impact of CAVs is to employ a simulation environment and model CAVs and HDVs respectively. The behaviors of CAVs and HDVs are captured by different models or logic so that they can represent real-world situations as accurately as possible. This research follows this approach by identifying and developing proper behavior models for CAVs and HDVs respectively according to their distinguishing characteristics. Particularly, the modeling components of CAVs include car following, platooning, trajectory planning, and signal optimization. Selected and developed models can also be used in other studies on topics of CAVs. Sensitivity analysis is also conducted in some specific scenarios, including market penetration rates and different arm lengths. To fulfill the research purpose, a real-world typical superstreet situated in North Carolina (NC) has been selected and replicated in a professional microscopic traffic simulation software platform known as Simulation of Urban Mobility (SUMO). To make a fair comparison, simulated CAVs traveling through an equivalent conventional intersection with similar geometric features are implemented and investigated in SUMO.

1.2 Study Objectives

The proposed work in this research intends to achieve the following purposes:

1. To select and develop proper behavior models for CAVs and HDVs based on existing studies with a focus on car following, platooning, trajectory planning, and signal optimization.
2. To calibrate an HDV car following model in the simulation environment.
3. To compare the performances of CAVs in the superstreet and at conventional intersections.
4. To evaluate the performances of CAVs with different techniques, including platooning, trajectory planning, and signal optimization.
5. To obtain the performance improvement magnitudes of CAVs at different traffic scales.

6. To understand the traffic performances in a mixed traffic environment where CAVs and HDVs coexist.

1.3 Expected Contributions

This research not only utilizes or develops reliable models for CAV and HDV behaviors but also conducts extensive experiments for various aspects of CAVs and superstreets. By investigating performances of CAVs in superstreets, this research can provide important insights for CAVs in other innovative intersection designs which share similar configurations. This information can be an important reference for policy makers to understand the impacts of CAVs in innovative intersections. In the process of this investigation, the researchers can deliver the following contributions:

1. Ability to select proper scenarios to evaluate the performances of different intersection designs concerning CAVs.
2. Ability to test the CAV performances with different techniques in other innovative intersection designs.
3. Ability to estimate the performances of CAVs on different traffic scales and with different market penetration rates.
4. Ability to understand the CAV performance with different arm lengths in the superstreet environment for adaptive signal controls.

1.4 Dissertation Overview

Chapter 1 presents essential background information about CAVs and superstreets in the problem statement section. This chapter also discusses the research objectives and expected contributions from this research. Towards the end of the section, Chapter 1 describes the overall research structure for this study.

Chapter 2 presents a comprehensive review of the existing literature on the behavior models for CAVs and HDVs as well as superstreets. The behavior models for simulated vehicles can be grouped into four categories, which are intersection management, car following, lane changing, and CAV platooning. For the superstreets, this chapter presents the concept and application of the superstreet design, existing studies on the operational performance of superstreet, and research on the CAVs and superstreets.

Chapter 3 illustrates the methodologies and the overall experiment framework. First, this chapter introduces the behavior models employed in this research, including the Wiedemann 99 (W99) and Intelligent Driver Model (IDM), platooning control, trajectory planning, adaptive signal control, and trajectory planning under adaptive signal controls, followed by the description of the simulation platform. Two sets of platooning control and trajectory planning controls are developed and tested respectively. This research develops and applies different car following models for HDVs and CAVs to distinguish their characteristics. Sensitivity analyses of traffic scales, market penetration, and arm lengths from superstreets are conducted. Chapter 3 also provides information about the selected real-world superstreet and the designed simulation experiments.

Chapter 4 presents the simulation results for the operation performances of CAVs in the environment of the superstreet and the equivalent conventional intersection in terms of traffic delay and fuel consumption. According to the designed scenarios in Chapter 3, the effects of each CAV technique are examined by the corresponding simulation results. This chapter also provides relevant rationales for the different performances with CAV techniques and environments. Traffic delays and fuel consumption are selected as the performance indicators since they can represent transportation efficiency and environmental impacts respectively.

Chapter 5 concludes this research with the presentation of main findings. These findings may provide important references for policymakers or transportation designers. The control strategies devised to obtain these findings can also be utilized for other CAV studies. In addition, this chapter also gives future research directions that are highly related to the current research topic.

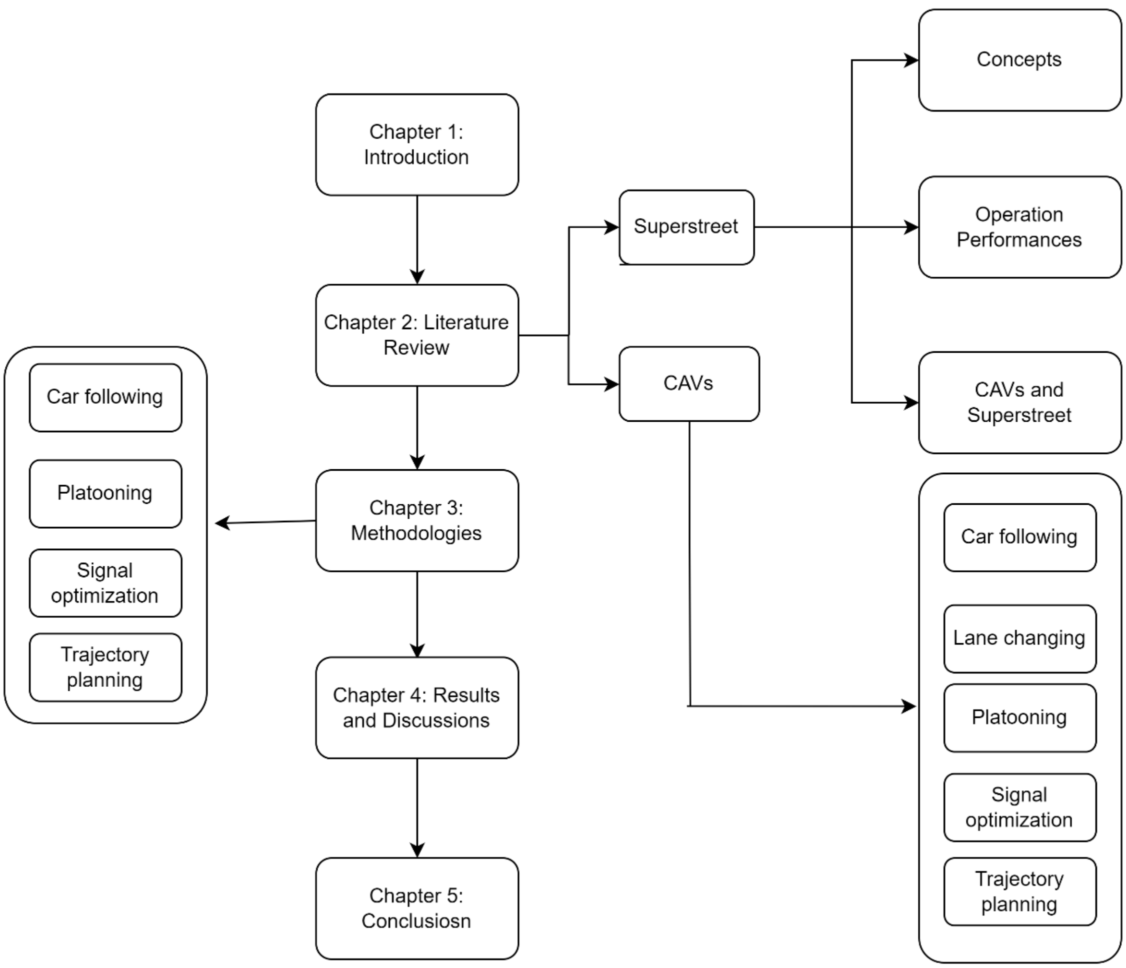


FIGURE 1.1: Dissertation Structure

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

This chapter introduces the existing work on CAVs and the superstreets, respectively. First, background information on CAVs is provided in section 2.2, which covers the definition of CAVs and the impacts of CAVs regarding road capacity, safety, and environment in a generalized sense. Then this dissertation discusses the existing literature on the CAV behavior models in Sections 2.3-2.6. The literature for CAVs can be classified into four categories, including intersection control, car-following models, lane-changing models, and platooning. Although in some literature, the lane-changing model is integrated with the definitions of the car-following model, this research separates the lane-changing model from the car-following model to offer a comprehensive understanding of the mechanism of CAVs' lane changing. Section 2.7 describes the literature on the superstreets. As for the superstreets, many studies have been done on the operational performances compared to the conventional intersections and/or other innovative intersection designs.

2.2 Background of CAVs

2.2.1 Definition of CAVs

The connected and autonomous vehicles, as the name implies, represent the vehicles that are both connected and autonomous. Connected vehicles refer to the vehicles that can exchange information with other vehicles on the roads such as their speed, acceleration rates, and position. In addition, connected vehicles are also expected to be capable of communicating with transportation infrastructure to obtain information on traffic volumes and traffic signal status. Autonomous vehicles refer to the vehicles that can complete the driving tasks without human intervention completely or partially. It is commonly accepted that autonomous vehicles would experience several stages before fully autonomous vehicles can run on the roads. Defined by the National Highway Traffic Safety Administration (Thorn, 2018), autonomous vehicles conceptually have six levels of automation as shown in Table 2.1.

TABLE 2.1: Automation Levels and Corresponding Descriptions

Level of automation	**Descriptions**
0	The human driver does all the driving
1	An advanced driver assistance system (ADAS) on the vehicle can sometimes assist the human driver with either steering or braking/accelerating, but not both simultaneously.
2	An advanced driver assistance system (ADAS) on the vehicle can itself control both steering and braking/accelerating simultaneously under some circumstances. The human driver must continue to pay full attention (“monitor the driving environment”) at all times and perform the rest of the driving task.
3	An automated driving system (ADS) on the vehicle can itself perform all aspects of the driving task under some circumstances. In those circumstances, the human driver must be ready to take back control at any time when the ADS requests the human driver to do so. In all other circumstances, the human driver performs the driving task.
4	An automated driving system (ADS) on the vehicle can itself perform all driving tasks and monitor the driving environment – essentially, do all the driving – in certain circumstances. The human does not need to pay attention in those circumstances.
5	An automated driving system (ADS) on the vehicle can do all the driving in all circumstances. The human occupants are just passengers and need never be involved in driving.

2.2.2 Impacts of CAVs on capacity, safety, traffic delay, and environment

2.2.2.1 Road capacity

Due to short headways, prompt reaction, and accuracy of maneuvering, CAVs can increase the road capacity theoretically. Existing studies have employed two approaches in evaluating the impacts of CAVs on-road capacity, which include theoretical framework and simulation of CAVs. Chen et al. (2017) developed a theoretical framework for estimating the capacity of a single lane considering the market penetration rate, headway, and platoon size. Conclusions were made that the segregation of automated vehicles and HDVs can reduce road capacity and mixed-use of CAVs and HDVs would result in a higher capacity.

In addition to the theoretical approach, many simulation-based studies had been conducted to evaluate the impact of CAVs at different market penetration rates. In the simulation-based studies, it had been found that the improvement of road capacity is highly correlated to the market penetration rate of CAVs (Levin and Boyles 2016; Yoon et al., 2016; Shladover et al., 2012; Liu and Fan, 2020). A summarized finding is presented in Table 2.2.

TABLE 2.2: Potential Improvement of Road Capacity Identified by Existing Studies

Authors, year	**Findings**	**Environments**
Liu et al., 2017	54% improvement in road capacity when the market penetration rate increases from 0 to 100 percent.	Freeway
Talebpour et al., 2017	With dedicated lane for automated vehicles, the	Freeway

	penetration rate should be at least 50% for two-lane freeway and 30% for a four-lane freeway	
Mena-Oreja et al., 2018	39% improvement when market penetrate rate is 100%	Freeway
Olia et al., 2018	Capacity improvement was found very little for automated vehicles while CAVs were found to improve the capacity as much as around threefold.	Freeway

2.2.2.2 Safety

According to the estimation of the Insurance Institute for Highway Safety (IIHS, 2010), if all vehicles had installed forward collision and lane departure warning, side view assists, and adaptive headlights, both the crash and fatality rate could be reduced by around a third. These functions are generally supported in AVs with Automation Level 0 and Level 1. Nevertheless, though some functions are fulfilled in automation Level 0 and Level 1, drivers' errors are not eliminated. When the automation level advances to Level 3, the vehicle can stay in one lane with a safe distance to the leading vehicle automatically, partially reducing the crashes caused by drivers' errors. In Level 5, the crashes caused by drivers' errors can be fully eliminated when the vehicles can handle all circumstances. Research had also found that CAVs and autonomous vehicles can improve the string stability of traffic flow.

Li and Wagner (2019) conducted a simulation-based study on the impact of the automated vehicle on mobility, safety, emissions, and fuel consumption on the simulation platform of Simulation of Urban MObility (SUMO). A freeway segment of Auckland Motorway SH16 in New Zealand was selected for the case study. Scenarios were developed under different market penetration rates and traffic volumes. Time to collision (TTC) was used to measure the safety performance of automated vehicles. The number of TTC<5s was obtained from the simulation and the result showed that automated vehicles could reduce the TTC from 42 to 1 when the market penetration rate increased from 0% to 100%.

Li et al. (2017) evaluated the safety impacts of different market penetration rates of ACC vehicles on the roadway segments. The safety performances were measured through Time Exposed Time-to-collision (TET) and Time Integrated Time-to-collision (TIT). TET is a summation of all moments when the TTC value is below a certain threshold. TIT measures the entity of vehicles whose TTC is lower than the threshold. ACC vehicles were modeled using IDM and it was found that the safety performance of the ACC system was largely influenced by the parameter selection. The results showed that if the ACC system was properly designed, it would exert a positive effect on the safety conditions in congested traffic flow conditions. Also, equipped with a variable speed limit (VSL) control, the ACC system could bring a more significant improvement in safety performance.

Rahman et al. (2018) investigated the highway safety benefits of different approaches of connected vehicles in reduced visibility conditions. In this research, the human driver behaviors in foggy conditions were modeled with the default car following model from PTV VISSIM while the CAVs were modeled with IDM. It was also found that the market penetration rate of connected vehicles had to reach up to 30% for the benefit to appear. Rahman and Abdel-Aty (2018) further tested safety benefits for CAVs in the managed-lane scenarios and found that managed-lane CV platoons outperformed all-lanes CV platoons with same market penetration rate.

2.2.2.3 Traffic delay

On freeways, CAVs follow preceding vehicles with shorter headways and thus can reduce traffic delays compared to HDVs. While in intersections, CAVs communicate with other vehicles or signal controllers to obtain the information for calculating the optimal trajectories. The optimal trajectory can be easily defined as the minimal traffic delay trajectory. There are many studies that have tested the impact of CAVs on the traffic delay in different environments, such as conventional intersections (Feng et al., 2018; Yu et al., 2018; Wu et al., 2012), freeway ways (Guo and Ma 2020), roundabouts (Mohebifard and Hajbabaie, 2020; Mohebifard and Hajbabaie, 2021).

Feng et al. (2018) developed a trajectory planning and signal optimization model for CAVs in the conventional intersection environment with the goals of minimizing traffic delay and fuel consumption. The numerical experiments showed that the traffic delay can be reduced by about 13% in high traffic volume scenarios. Mohebifard and Haibabaie (2021) designed the optimal trajectory for CAVs entering the roundabout. The designed optimal trajectory scheme can successfully reduce the average traffic delay at different market penetration rates of CAVs. The highest traffic delay improvement can be more than 90% in all defined traffic volume scenarios.

Guo and Ma (2020) evaluated the performance of CAVs in the environment of freeways through simulation experiments. The CAVs were enabled with speed harmonization, CACC, and cooperative merging. It was found that CAVs can reduce the traffic delay and increase the throughput on freeways. Moreover, CACC was identified as the most effective CAV feature that improves operational performance.

2.2.2.4 Environment

Because CAVs can travel on the roads with shorter headways and less travel time, CAVs often consume less fuel and thus fewer emissions. Morrow et al. (2014) pinpointed a list of factors in automated vehicles (AVs)' implementation that could have impacts on the environment, and they included vehicle weight, performance, and size. The authors estimated that AVs were expected to have a positive influence on the emission. This is because AV was supposed to reduce the accidents and hence, the vehicles could remove unnecessary equipment to decrease the vehicle weights. Regarding vehicle performance, Taiebat et al. (2018) concluded that four factors regarding vehicle's performances influence the emission and fuel consumption, including vehicle operation, electrification, vehicle design, and platooning. For vehicle operation, eco-driving is important and an encouraged driving pattern could reduce fuel consumption by 2-45%. Detailed information is summarized in Table 2.3. Autonomous vehicles had advantages in following the eco-driving pattern when the control strategy was coded into the system.

TABLE 2.3: Eco-Driving Impact on the Reduction of Fuel Consumption

Researchers	**Reduction of fuel consumption**	**Environments**
Barth and Boriboonsomsin, 2008	10-20%	Freeway
Boriboonsomsin et al., 2012	13%	Network
Gonder et al., 2012	15-20%	Network

Brown et al., 2013	20%	Network
National Research Council, 2013	4 -10%	Network
Chen et al., 2017	30-45%	Freeway
Lu et al., 2019	2%	Freeway

2.3 Intersection Control in the Environment of CAVs

The control strategies for CAVs traversing the intersections are one of the most heightened interests to transportation professionals. The intersection can be simply classified into two types of intersection, i.e., unsignalized intersection and signalized intersection. CAVs require different control strategies when they travel through the signalized intersection and unsignalized intersections. This section reviews the existing literature on the CAV control strategies respectively.

2.3.1 Unsignalized intersection

The control strategies can be generally classified into two categories, one is reservation-based and the other is trajectory planning-based. Reservation-based strategies divide the intersection as space-time slots for upcoming vehicles to occupy, which is often a centralized approach.

2.3.1.1 Reservation based strategies for CAVs traversing the intersection

Dresner and Stone (2004) proposed a time and space reservation-based system that uses square patches as parts of the road space to reserve. This method was also known as autonomous intersection management (AIM). In this reservation-based system, before entering the intersection, CAVs would send a message to the supervising agent installed at the intersection to request a time-space reservation for passing the intersection. If the trajectory is not intersected with other existing time-space reservations from previous vehicles, then the supervising agent would send back the message of approval. Otherwise, the reservation request would be rejected, and the vehicle would have to decelerate. They demonstrated the reservation-based framework could be extended to incorporate existing intersection control strategies, i.e., stop signs and traffic lights. Besides, it was also found that though there was no necessity of preserving the turning lane in the reservation-based scenario, the result showed relaxing the restriction of the turning lane worsened the performance of the intersection. In addition, the smaller the square patches were, the more vehicles could pass the crossroads in a given period. This is because, with smaller patches, it is possible to reserve and free the needed space in the intersection more precisely, thus letting unneeded space be available to other vehicles. However, this approach was quite demanding for the computation capability of the supervising agent at the intersection as the patch decreases its size.

Later, Dresner and Stone (2008) improved the time and space reservation-based system by incorporating the reservation-based approach with traffic signals, stop signs, and emergency vehicles, which made the system more robust. With a traffic signal or a stop sign in place combined with reservation-based for autonomous vehicles, the traffic mixed with both human-driven vehicles and autonomous vehicles became possible. When a traffic light is in place, the autonomous vehicles would receive the message from the intersection controller that informs the autonomous vehicles of the next green time. Autonomous vehicles could adjust their trajectories to achieve the best performance based on traffic light information. In the study, consideration for the stop sign was also included, though might not be practical in the real world due to the fact that a stop sign is usually used in very light traffic conditions. For a reservation-based system combined with a stop sign, the intersection controller would only accept the messages from the vehicles which have stopped at the intersection. Vehicles that are approaching the intersection would receive a rejection for passing the intersection. Besides, by adding priority to a certain type of vehicle, the intersection controller can allow emergency vehicles to pass through the intersection. An experimental result was presented which shows that the proposed framework could produce better performance compared to traditional human-driven vehicles.

Sharon and Stone (2017) further developed a time and space reservation-based method by proposing a protocol named Hybrid Autonomous Intersection Management (Hybrid-AIM), which was designed for mixed autonomous vehicles and human-driven vehicles allowing different turning movements in the intersection. The model was established and developed by combining the reservation-based algorithm with traffic signals as proposed by Dresner and Stone (2008). This study introduced new intersection management by considering the traffic pattern that comprised most human-driven vehicles. The Hybrid-AIM differs from AIM in denying the requested trajectories that conflict with the active green trajectories while AIM denies the request trajectories that conflict with all green trajectories. In addition, this study also discussed in greater detail the safety and efficiency associated with different turning policies compared with previous studies. The simulation results suggested that at the early stage of autonomous vehicle adoption, the turning policy should be set as restrictive. Hybrid-AIM was not superior to AIM until more than a 10% CAV technology penetration level was reached.

Mehani and Fortelle (2007) also developed a time and space reservation-based method, proving the efficiency of the reservation algorithm in X-junction. The reservation algorithm was validated through their ad hoc simulator written in Python. The reservation algorithm framework did not take full account of every patch in the intersection but only the critical point where the vehicle trajectories intersected. Three scenarios were developed: 1) The first named None, in which vehicles traveled through the intersection at their full speed without concern of collision; the second named Poll, in which vehicles treated the intersection as the single atomic resource and travel through the intersection one by one; 3) and the last one being the proposed reserved scenario. The None scenario had full attention to the throughput capacity of the intersection and the results similar to the one from the None scenario can be considered as a good one and is preferred. The Poll scenario had full attention to safety while compromising significantly to the throughput capacity of the intersection. The results showed that the proposed reserved scenario generates a greater throughput capacity with zero collision. The Poll scenario, though also had zero collision, had compromised over half of the through capacity. The research had its limitations on many assumptions, for example, constant speed, and only a one-time request from a vehicle.

2.3.1.2 Trajectory planning based for CAVs traversing the intersection

The time and space reservation-based method schedules the time and space resources for the upcoming vehicles. Because these spaces are usually connected, another method, which focuses on planning the trajectories for the CAVs, also received considerable attention.

Kamal et al. (2013) developed a coordination scheme for automated vehicles at an unsignalized intersection. The model consisted of three parts, discrete-time state equations, risk function, and predictive control model. Discrete-time state equations described how the position of the vehicle in the intersection varies based on three variables, time, acceleration, and the initial speed. The risk function was defined to quantitatively indicate whether the vehicle pair poses a potential risk of collision at a cross collision point at a given time. Then the predictive model was formulated as an objective function which minimizes velocity deviation from the desired speed, acceleration, and the risk of collision. The simulation results showed that the proposed scheme could reduce acceleration and almost eliminate stop delay. This model could also be used for turning traffic but with the compromise of intersection capacity.

The game theory-based approach considers the global optimal operation for the intersection, in which the intersection agent would assign a choice to each vehicle to achieve the minimum conflicts, traffic delay, or travel time. Elhenawy et al. (2015) developed a game theory-based model for automated vehicles traveling through the intersection. In this model, each vehicle would have three choices when they are traveling through the intersection, i.e., acceleration, remaining constant speed, and deceleration. For each decision made by vehicles, a global occupancy time on the conflict zone could be calculated and the objective of the developed model was to obtain the minimum global occupancy time and traffic delay. The developed model was demonstrated through the Monte Carlo simulation of 1000 times. The results were compared to the base scenario, a four-way intersection that was stop sign controlled. The simulation results showed the proposed scheme produces a significantly lower delay of 35 seconds.

Yan et al. (2009) studied the trajectory planning problem for CAVs in the context of a four-way intersection. The vehicles entering the intersection were first partitioned into different classes according to their arrival time and passing time. One class of vehicles consisted of those that could travel through other vehicles without collision. Then the optimal sequences of going through the intersection were decided by the technique of dynamic programming. The procedures of transferring the minimum unit from car to group could significantly reduce the recursions in dynamic programming algorithms.

However, the methods mentioned above still have a drawback, which is that the computation demand would rise significantly when the number of lanes increases. To solve this problem, Wu et al. (2012) proposed an ant colony system to solve the control problem for a large number of vehicles and lanes. The ant colony system is a heuristic algorithm that could provide an acceptable result since an optimal result through an exhaustive search is often not feasible because of the large number of vehicles and lanes. Finding the optimal sequence problem is found to be the analogy to Travelling Salesman Problem (TSP), when each vehicle is considered as a city to be visited once and only once, the headway of each pair of vehicles would be the distance between two adjacent cities, and the shortest path would be the optimal sequence of vehicles with the minimal exit time. This proposed system was proved to outperform the intersection controlled by an adaptive controller. Table 2.4 provides a review of existing studies on the two methods mentioned above.

TABLE 2.4: Existing Studies on CAVs in the Environment of Intersections

Authors	**Year**	**Models**	**Model features**
Dresner and Stone	2004	Space and time reservation-based	Assuming 100% CAVs in the intersection
Dresner and Stone	2006	Space and time reservation-based	Improving previous AIM by accommodating traditional human-operated vehicles. Priority vehicles can also be served such as ambulances, police cars, and fire trucks
Schepperle et al.	2007	Space and time reservation-based	Introducing a third exchange agent at the intersection, in case people might want to pay for the right of traveling through the intersection
Mehani and Fortelle	2007	Space and time reservation-based	Improving the reservation-based algorithm by defining the active conflict point only
Yan et al.	2009	Trajectory planning-based	A dynamic programming algorithm was developed for solving the trajectory planning problem
Azimi et al.	2012	Space and time reservation-based	Vehicles require a token for a certain tile in the intersection. The token could be prioritized.
Bento et al.	2012	Space and time reservation-based	Developing a simulator to test reservation-based CAVs in the intersection
Wu et al.	2012	Trajectory planning-based	Propose an ant colony system to solve the scenario where a large number of lanes are observed
Ghaffarian et al.	2012	Trajectory planning-based	Integer linear programming optimizes the traffic trajectories
Lee and Park	2012	Trajectory planning-based	Non-linear constrained optimization was derived to minimize the overlapping of time and space of two conflicting vehicles

Colombo et al.	2012	Trajectory planning-based	Proving that for a general model of vehicle dynamics at an intersection, the problem of checking membership in the maximal controlled invariant set is NP-hard and introduce a solution that can approximately solve it
Kamal et al.	2013	Space and time reservation-based	The positions of vehicles are determined by DTS, Risk function return the collision results and predictive control model attempt to obtain the desired speeds for the vehicles
Choi et al.	2013	Space and time reservation-based	An optimization problem of finding the best sequence of vehicle’s entrances is formulated
Gregoire et al.	2014	Trajectory planning-based	Derive an efficient and trajectory and incorporate priority motion planning to account for unexpected event
Qian et al.	2014	Trajectory planning-based	A priority-based coordination system with provable collision-free and deadlock-free features has been presented.
Elhenawy, et al.	2015	Space and time reservation-based	Each vehicle has three choices during traveling the intersection: acceleration, remaining constant speed, and deceleration. A global occupancy time on the conflict zone is minimized
Zhu et al.	2015	Trajectory planning-based	Developing a novel non-linear programming formulation for autonomous intersection control accounting for traffic dynamics
Sharon and Stone	2017	Space and time reservation-based	Considering traffic mixed with both HDVs and CAVs

Li et al.	2019	Trajectory planning-baed	Developing a Discrete Forward-Rolling Optimization Control algorithm, which is proved to perform better than the First Come First Serve (FCFS) Policy

Though many studies have been performed on formulating autonomous intersection management strategies for CAVs, HDVs and CAVs are expected to coexist for a considerable period of time. As such, traffic control devices are still indispensable to regulate HDV traffic to avoid collisions. Nevertheless, CAVs are advantageous compared to HDVs in that CAVs can receive the signal phasing and timing information and react promptly to achieve certain objectives such as minimal travel time or fuel consumption.

2.3.2 Signal controlled intersections with CAVs

When vehicles are equipped with CAV technologies, it is convenient to assume the communication between CAV and signalized intersections. While signalized intersections optimize its phase duration and sequence, CAV can adjust trajectories based on its updated signal timing to improve the performance indicators. Currently, there are different methodology trends in terms of optimizing the signal timing. According to Qadri et al. (2020), these methods can be grouped into five categories, including artificial intelligence models, metaheuristics-based approaches, multi-objective-based approaches, dynamic/mixed-integer programming (MIP) based approaches, and miscellaneous approaches. Each of these approaches can further grow its branches. For example, artificial intelligence approaches could have neural network models and deep learning models. This dissertation intends to employ an MIP-based approach to develop a signal optimization model, and hence a review of existing studies for MIP-based signal optimization is summarized in Table 2.5. According to Table 2.5, it can be observed that the cell transmission model, Space-Phase-Time Hypernetwork based model, and green start/duration mixed-integer programming models are three popular approaches when modeling signal optimization problems.

TABLE 2.5: Recent Studies on Signal Optimization Approaches

Title	**Important assumption**	**Authors**	**Year**
An enhanced 0–1 mixed-integer LP formulation for traffic signal control	Cell Transmission Model	Lin et al.	2004
Distributed optimization and coordination algorithms for dynamic speed optimization of connected and autonomous vehicles in urban street networks	Cell Transmission Model	Tajalli, and Hajbabaie	2018
A novel traffic signal control formulation	Cell Transmission Model	Hong K. Lo	1999
A cell-based traffic control formulation: strategies and benefits of dynamic timing plans	Cell Transmission Model	Hong K. Lo	2001
Recasting and optimizing intersection automation as a connected-and-automated-vehicle (CAV) scheduling problem: A sequential branch-and-bound search approach in phase-time-traffic hypernetwork	Space-Phase-Time Hypernetwork	Li and Zhou	2017
Solving simultaneous route guidance and traffic signal optimization problem using space-phase-time hypernetwork	Space-Phase-Time Hypernetwork	Li et al.	2015
A mixed integer programming formulation and scalable solution algorithms for traffic control coordination across multiple intersections based on vehicle space-time trajectories	Space-Phase-Time Hypernetwork	Wang et al.	2020
Collaborative control of traffic signal and variable guiding lane for isolated intersection under connected and automated vehicle environment	Green start and duration MIP	Ding et al	2021
A platoon-based adaptive signal control method with connected vehicle technology	Green start and duration MIP	LI, et al.	2020

2.3.2.1 Cell transmission model

The cell transmission model was derived from Lighthill, Whitham, and Richards (LWR) model, which describes the dynamic relationship among traffic flow, density with respect to space, and time variables. Later, Daganzo (1994, 1995) proposed a simplified solution by assuming the traffic flow equals the minimum of three norms, i.e., the product of free speed and current density, inflow capacity, and the product of backward shock wave speed, and the difference between jam density and current density. Based on this formulation, the traffic delay is represented by the differences in the number of vehicles that have been left in the current cell between two successive time steps. The flow at the next time step can be equal to the saturated flow rate when the signal is green, and zero when the signal is red.

Through the equations introduced above, researchers can easily construct a mixed-integer linear programming problem for the signal optimization problem (Lo, 1999; Lo, 2001; Lin and Wang, 2004). However, this approach becomes unsuitable when it comes to the microscopic operation level, as it often involves a relatively larger simulation resolution (i.e., simulation step of 10s).

2.3.2.2 Space-Phase-Time hypernetwork model

Li et al. (2015) established a new approach in optimizing the traffic signals on network levels. In this signal optimization, each link in the network was expanded from one dimension to two dimensions considering both position and time step for each vehicle in the planning horizon. Each link was associated with a calculated cost which is largely determined by the travel time with free speed at the current time step within the horizon. Similar assumptions were also made for signal phases. All possible signal phases were expanded in the given planning horizon and represented by nodes. These graphical representations for the links and phases enable researchers to establish the signal optimization model that is convenient for Lagrange relaxation. The derived formulations from Lagrange relaxation can be solved by either branch and bound algorithm or dynamic programming (Li and Zhou, 2017; Li et al., 2015).

2.3.2.3 Green start and green duration-based MIP

Another popular approach for signal optimization is to optimize signal timing by taking the green start and green duration as the decision variable for each phase in an MLP model. In a connected environment, signal controllers are assumed to receive the arrival information, and hence the traffic delay can be easily estimated by calculating the difference between the green start time and vehicle arrival time.

Li et al (2020) constructed a signal optimization for the NEMA phase with a dual-ring structure. The phase boundaries and sequences were modeled as constraints in the MILP model and the objective was to minimize the traffic delay. One of the highlights in this research is that the researchers considered the arrival times of platoons instead of individual vehicles. However, the signal optimization model still yielded a signal timing plan with a fixed number of phases and phase sequence, which may limit the signal timing performance.

Similarly, Ding et al. (2021) also developed a signal timing optimization model in the connected environment with green start time and green duration being the decision variables. Particularly, this research selected the wasted green time as the objective to be minimized. The wasted green time was defined as the time difference between vehicle arrival time and green start, as described below. One of the merits of the model developed by Ding et al. (2021) is that the phase sequence is flexible because of the introduction of the auxiliary binary variable indicating which phase is first between conflicting phases.

2.3.2.4 Trajectory planning under signalized intersection

To further enhance the potentiality of CAVs, researchers have developed models that control both signal timing and trajectory planning simultaneously, such as Yu et al. (2018), Guo et al. (2019), Soleimaniamiri et al. (2020), and Li et al. (2014). Signalized intersection provides CAVs proper setting for trajectory optimization application. Other studies developed trajectory planning strategies in other environments with various goals. For example, Mu et al. (2021) proposed an event-triggered rolling horizon-based trajectory planning method to smooth trajectories and reduce emissions in a freeway environment. Popular trajectory planning methods include shooting methods (Ma et al., 2017), mathematical program methods (Han et al., 2020), dynamic programming (Yao et al., 2020), and the Pontryagin Minimum Principle approach (Wang et al., 2012; Wang et al., 2014; Feng et al., 2018; Yu et al., 2018).

Shooting approach

Ma et al. (2017) proposed a parsimonious shooting heuristic method for the trajectory planning problem of CAVs approaching the signalized intersections. This shooting heuristic algorithm can construct a feasible trajectory considering realistic constraints including vehicle kinematic limits, traffic arrival patterns, safety, and signal control logic. The target goals of the trajectory were to improve mobility, environment, and safety. An innovative solution approach was proposed to solve the problem and the numerical study demonstrated the proposed model could outperform all human drivers at all measures.

Mathematical program approach

Pourmehrab et al. (2019) employed a stage-wise trajectory control of the CAVs approaching the signalized intersection in which vehicles cruise at a constant speed at the middle segment and constant acceleration/deceleration rate at the first and the third segment. A mathematical program formulation was constructed to solve the transition points between stages considering the road speed limit and vehicle acceleration capacity. The proposed control strategies applied different controls for the lead vehicle, follower vehicle, and traffic signals assuming two-way communication technologies between vehicles and infrastructure. The speed trajectories and signal phase were optimized simultaneously to achieve the minimum travel delay. Compared with a fully actuated signal control, the proposed algorithm is found to reduce the average travel time by 38%-52%.

Zhao et al. (2021) developed a bi-level programming method where the arrival speed was maximized at the lower level and the travel time was optimized in the upper level. Both levels of formulation had forms of linear mathematical programs. The bi-level optimization problem introduced by Zhao et al. (2020) was difficult to solve and thus a heuristic algorithm was proposed to obtain a viable solution. This proposed control strategy was tested with different demands, intersection lengths, communication ranges, and traffic compositions.

Pontryagin Minimum Principle approach

Feng et al. (2018) utilized the Potryagin Minimum Principle to prove the efficiency of the three-segment trajectory. This method can reduce traffic delay while preventing an increase in fuel consumption. This work also applied dynamic programming to solve the signal optimization problem, in which signal phasing and duration were optimized for every rolling horizon length. By applying this combined optimization strategy, fuel consumption and traffic delay were both reduced significantly. Later Yu et al. (2018) and Ding et al. (2021) utilized the three-segment trajectory concept and then developed a mixed integer programming method to optimize the signal timing of CAVs.

Jiang et al. (2017) developed speed planning strategies for CAVs approaching the signalized intersection to optimize mobility and fuel efficiency. The optimal control problem was solved through Pontryagin's Minimum Principle. Undersaturated scenarios and oversaturated scenarios were both developed for comparison. The benefits were found to be greater in the oversaturated scenarios. The simulation results showed that fuel consumption can be reduced by as much as 58.01% under oversaturated conditions. The emission benefits were as much as 33.26%. The proposed control strategy outperformed the state-of-the-art eco-drive system, GlidePath, which was developed by the Federal Highway Administration (FHWA).

2.3.3 CAVs in other transportation environments

Except for the studies on the performances of CAVs in conventional intersections, freeways and roundabouts are also two popular transportation scenarios for researchers. Investigations on CAVs on freeways were focused on the car following, platooning, cooperative merging, and diverging behaviors (Milanés et al., 2010; Milanés and Shladover, 2014). For CAVs traveling through roundabouts, researchers mainly focused on the trajectory designs and merging sequences. Table 2.6 provides a brief review of recent studies in these two environments.

TABLE 2.6: Recent Studies on CAVs in the Environments of Freeways and Roundabouts

Transportation Environments	Authors	Year	CAV Features
Freeway	Adebisi et al.	2020	CACC models
	Liu and Fan	2020	CAVs with revised intelligent Driver Model
	Chityala et al.	2020	CAVs with shorter headways
	Hu and Sun	2019	Cooperative Lane Changing Control, Cooperative Merging Control
Roundabout	Mohebifard and Hajbabaie	2020	CAVs with optimized trajectory
	Mohebifard and Hajbabaie	2021	Trajectory control in a roundabout with a mixed fleet of automated and human-driven vehicles
	Martin-Gasulla and Elefteriadou	2021	Roundabout management algorithm for trajectory planning of CAVs
	Chalaki et al.	2020	Trajectory planning control framework for roundabout

2.4 Longitudinal Behavior Models of CAVs

2.4.1 Overview of car-following models

Car following model are a cornerstone for microscopic traffic simulation, which helps traffic engineers to evaluate the operational performance of the proposed traffic regulating strategies. The history of car-following models can be dated back to the 1960s-1980s (Aghabayk et al., 2015). The attributes of the subject vehicles can be described by the state vector (x_n, v_n, a_n, t_n), where x_n denotes the position of the subject vehicle on the road, v_n represents the subject vehicle's speed, a_n denotes the acceleration rate of the vehicle and t_n means the current time step. In the development of the car-following model, two different kinds of car-following models were identified, classic methods and artificial intelligence methods. The classic methods formulate analytical equations to describe the relationships among the four variables often with assumptions that the state of the subject vehicle is related to the behaviors of the leading vehicle. Based on the assumption of these models, the classic car following models include stimulus-response, safe-distance, desired headway, and psychophysical models. Though classic methods may suffer insufficiency in failing to consider unobserved factors that may also have an impact on the following behavior of the vehicle, they are usually easier to understand and analyze compared with artificial intelligence models. Many simulation platforms have utilized this type of car-following model such VISSIM, AIMSUN, CORISM and PARAMICS. The classic methods can be further split into four categories, which are the stimulus-response model, safety distance model, desired headway models, and psychophysical models. The artificial intelligence model is rule-based and relies on computer programming for prediction, including fuzzy logic and neural networks.

2.4.2 Classic car following models

2.4.2.1 Stimulus-response model

The stimulus-response models capture the driver's behaviors according to the leading vehicle's 'stimulus', which could be relative speed or the spacing between two vehicles. The response is the acceleration or deceleration of the subject vehicles, which is delayed by an overall reaction time, T.

Gazis-Herman Rothery (GHR) model

The GHR model was first introduced by Chandler et al. (1958) at General Motors research laboratories and Kometani and Sasaki (1958) in Japan. The model yields the desired acceleration rate based on current speed, relative speed difference to the preceding vehicle, the distance to the preceding vehicle, current headway, and desired headway. Two calibration parameters were added to the norm of current speed and position difference. The parameters in the GHR model have been continuously calibrated by many researchers. Chandler et al., (1958) suggested that two calibration parameters be zero according to speed profiles from 8 vehicles in the real world. Herman and Potts (1959) obtained a better fit when l was set as 1. Later, many more following investigations on the parameter's calibration were conducted using different datasets (Aron, 1988; Hoefs, 1972; Ceder and May, 1976; Heyes and Ashworth, 1972). The stimulus-response model has no limitation on acceleration and deceleration rates, which is inconsistent with the mechanic features of vehicles in the real world. Thus, unrealistic acceleration and deceleration behaviors might be observed during the simulation.

Linear (Helly) model

Helly (1959) developed the Linear (Helly) model by adding the consideration of the leading vehicle braking and preferred distance based on the GHR model. Two calibration parameters were added to relative speed difference and distance difference. The preferred distance was a function of current speed, acceleration, the difference between desired headway and current headway with three calibration parameters.

Later this model was calibrated on the urban freeway under congested and uncongested traffic conditions (Hanken and Rockwell, 1967; Rockwell et al., 1968). Bekey et al. (1977) demonstrated the efficiency in replicating the trajectories of 125 vehicles in a period of 4 minutes. However, it was also pointed out that the linear (Helly) model could produce unrealistically large headways when the variation of acceleration increases (Aghabayk et al., 2015).

Optimal velocity model (OVM)

The optimal velocity model holds the assumption that the acceleration rate of the subject vehicle is largely dependent on the difference between the current velocity and the optimal velocity, which is a function of headway between two successive vehicles. However, this model may generate large acceleration rates according to Nagel et al. (2003). As such, the applicability was limited and had not been broadly used.

IDM

IDM was originally developed for human-driven vehicles in the single lane without consideration of lane changing (Treiber et al, 2000). IDM can be classified as one of OVM. The acceleration assumed in the IDM is a continuous function of the velocity, the gap, and the velocity difference to the preceding vehicle. This model has several advantages: 1) it is collision-free due to the dependence on the relative velocity; 2) its model parameters are intuitively measurable and easy to interpret; 3) The model allows for a fast-numerical simulation. Kesting and Treiber (2008) later calibrated their IDM model through genetic algorithm optimization to obtain a set of calibrated parameters. In many studies that investigated the impact of CAVs on the existing transportation system, the IDM model has been popularly employed to simulate the car following characteristics of autonomous vehicles (Kesting et al., 2008, Kesting et al., 2010, Zhou et al., 2016; Liu and Fan, 2020).

Full velocity difference model

Another notable popular car following model is the full velocity difference model (FVDM). The FVDM was firstly proposed by Jiang et al. (2001), which was developed by combining OVM and generalized forced model (GFM). The original OVM is biased in the respect of too high acceleration rate and unrealistic deceleration compared with observations on the field. Based on OVM, GFM was proposed, and the results showed that GFM's output was more consistent with field data. However, GFM failed to consider the case when the velocity difference between the preceding vehicle and the following vehicle is positive, which means preceding cars are much faster than the following vehicle. This insufficiency results in the poor delay time of car motion and kinematic wave speed at jam density. To include this consideration in the car-following model, FVDM was proposed and both negative and positive velocity differences were considered. Later, this model was further developed by Zhao and Gao (2005) with modifications to account for the urgent brake condition of the following vehicles. Table 2.7 provides a brief review of the literature on the OVM, FVDM, and IDM.

TABLE 2.7: Summary for the literature reviewed on OVM, IDM, and FVDM

Authors	**Year**	**Model**	**Model features**
Bando et al.	1995	OVM	Assuming the vehicle has an optimal velocity which depends on the distance to the preceding vehicle

Treiber et al.	2000	IDM	Developed from optimal velocity model. Measurable parameter and collision-free
Jiang et al.	2001	FVDM	Combining optimal velocity model and general forced model
Zhao and Gao	2005	FVDM	Improving full velocity difference model by accounting for the urgent brake condition of following vehicles
Kesting et al.	2008	IDM	Applying the genetic algorithm to optimize the parameters in IDM using trajectory data
Derbel et al.	2013	IDM	Improving intelligent Driver Model by guaranteeing traffic safety and reducing the overly high deceleration
Malinauskas	2014	IDM	Examining the intelligent Driver Model in the vector-valued time-autonomous ODE system
Treiber et al.	2017	IDM	Adding external noise and action points to the Intelligent Driver Model
Xin et al.	2018	IDM	Improving Intelligent Driver Model by accounting for eco-driving while the vehicles are approaching a signalized intersection
Xiong et al.	2019	IDM	Improving the intelligent driver model by reducing the overly high deceleration

2.4.2.2 Safe-distance model

The safe-distance model identifies a sufficient gap size which would allow the following vehicle to avoid unexpected collisions when the leading vehicle behaves unpredictably. Gipps model was selected as a representative of such type of model for illustration (Gipps, 1981). The Gipps model was developed based on the work of Kometani and Sasaki (1959). The model introduced a safety margin by considering an additional delay before reacting to the vehicle ahead. The delay was assumed to be equal to half of the drivers' reaction time for all drivers.

2.4.2.3 Desired headway models and psychophysical models

Desired headway models have the assumption that the following vehicle has a fixed desired headway to its leading vehicle. Bullen (1982) proposed a car-following model which could be put into this category. However, in addition to the common drawbacks shared by the other stimulus-response model, this model cannot be calibrated and failed to capture realistic drivers' reactions to the small changes of the headway.

Michaels (1963) proposed a car-following model based on the assumption that drivers can estimate the speed of the leading vehicle based on the visual angle of the leading vehicle. This model is one of the psychophysical models. This type of model could potentially capture the difference between passenger vehicles and heavy vehicles as they usually have distinguished characteristics in terms of vehicle width.

This model inspired many researchers to develop perception-based studies (Evans and Rothery, 1973; Burnham and Bekey, 1976; Lee, 1976; Wiedemann, 1974; Wiedemann and Reiter, 1992). Among these studies, the Wiedemann model is one of the most popular models that have been applied in the microscopic simulation platform, such as Widemann 1974 in PTV VISSIM (Lownes and Machemehl, 2006).

2.4.3 Artificial intelligence car following models

Differing from the classic methods which formulate an equation for the vehicle states, artificial intelligence car-following models predict the behaviors of the following vehicle by learning the underlying patterns from large training datasets. Existing popular approaches are fuzzy logic-based models and artificial neural network (ANN) learning-based models. A brief review of the literature on the artificial intelligence model with ANN is presented in Table 2.8.

TABLE 2.8: A Brief Review of the Artificial Intelligence Car-following Model

Authors	**Model**	**Data**	**Required Input**	**Results**
Hongfei et al.,2003	ANN	Trajectory data from two test vehicle driven by human	Relative distance, relative speed, desired speed, speed of the following vehicle,	ANN model can feasibly replicate the speed profile of the test vehicles.
Panwai and Dia,2007	ANN	Stop and go traffic during afternoon peak hour	Relative speed and distance, speed of the leading and following vehicle	The proposed ANN techniques in the car-following model outperform the Gipps model in terms of error metric on distance (EM) and root-mean-square
Zhou et al., 2009	ANN and RNN	Trajectory data retrieved from NGSIM, FHWA (2008)	Velocity and acceleration	RNN model was proved to have a stronger performance in predicting the

				trajectories compared with ANN
Khodayari, et al. 2012	ANN	Trajectory data retrieved from NGSIM, FHWA (2008)	Relative distance, speed of the following vehicle, reaction delay, acceleration of the following vehicle	The discrepancy between the observed and simulated trajectory was reduced to a satisfactory level.
Chong et al., 2013	Agent-based Back-propagation ANN	Trajectory data from a real-world driver	Speed, longitudinal and lateral accelerations, yaw angle, heading, and turn signal indications.	The proposed neural agent model was proved to outperform the GHR model in predicting the drivers' behavior

Fuzzy logic models

In the architecture of the fuzzy logit system, the acceleration or deceleration of the subject vehicle is coded into numerous categorical values, as well as important inputs such as relative speed and/or spacing between two vehicles. A simple fuzzy logic example is that if the following vehicle is "close" and "closing" to the leading vehicle, then "decelerate". Here, "close", "closing" is the fuzzy inputs, and "decelerate" is the fuzzy output. The fuzzy logic models are valid in that the perception of drivers is not accurate and they often make decisions based on their experience and logic. Therefore, this type of model is more consistent with drivers' behaviors. One notable difficulty in implementing a fuzzy logic model is defining a proper set of fuzzy rules which can correctly replicate the drivers' behaviors. Kikuchi and Charkroborty (1992) applied the fuzzy logit model to the car following model and since then, many efforts were made in developing the car-following model with the same model structure (Das et al., 1999; Gao et al., 2008; Gonzalez-Rojo et al., 2002; Zheng and McDonald, 2005).

Neural network models

The neural network is one of the typical machine learning methods which rely on computation capability and large datasets. Neural networks mimic the way that the human brain processes information. In the initial layer, the observed values of variables were put in the neurons where a coefficient would be assigned to each variable. Then the obtained results from the first layer were passed to the neurons in the second layer where the same operation is conducted for the neurons. A greater number of layers usually can produce a better fit. Khodayari et al. (2012) applied a modified neural network model to the field trajectory data and proved that the proposed model outperforms other types of car-following models in terms of various evaluation criteria.

2.4.4 Car following models for CAVs

IDM is one of the popular car-following models assumed for CAVs. In addition to the IDM, ACC, CACC, Newell car following models have also been widely utilized in describing the possible behaviors of CAVs.

ACC is a terminology that describes the longitudinal control strategy for autonomous vehicles that have radar, Lidar, and camera installed. Many of these longitudinal control strategies were distance regulation oriented (Shladover, 1995; Xiao et al., 2011). According to He et al. (2019), the ACC models can be classified as proportional-integral-derivative (PID) feedback/feedforward control, model predictive control (MPC), and fuzzy logic control (FLC). PID control is a commonly accepted and tested strategy for ACC and a representative is a model proposed by Shladover et al (2012), in which the acceleration rate of the following vehicle was expressed as a function of the distance error and the relative speed. Geiger et al. (2012) developed a CACC system (which covers the functions of ACC) based on the MDC. By assuming the preceding vehicle drive at constant yaw rate and acceleration in the defined time horizon, the optimal acceleration rate was obtained by minimizing the cost function which contains the terms of distance error, relative speed difference, and the current acceleration rate. FLC resolves the ACC problem by calculating the safe distance depending on whether a preceding vehicle is present or not. As in Tsai et al. (2010), when the preceding vehicle is detected, predefined rules were applied where the inputs of a predefined matrix which contains distance error and relative speed were connected with the output of a corresponding desired speed.

CACC improves ACC by adding communication between vehicles. For ACC vehicles, the information on the preceding vehicle is retrieved by on-board sensors like radar or Lidar. CACC vehicles can share the speed, position, and acceleration rate with shorter communication latencies. CACC and ACC share a similar model structure in Xiao et al. (2017), but CACC has a shorter reaction time and spacing margins.

Newell's car-following model is appealing in modeling CAVs for its simplicity and consistency with the triangular fundamental diagram, by giving the exact numerical solution for the kinematic wave model (Chen et al., 2012). Numerous researchers have applied Newell's car following model in their trajectory optimization or platooning models (Gong and Du et al., 2018; Wei et al., 2017)

2.5 Lane Changing Models

2.5.1 Classification on lane-changing model

Based on different approaches used in modeling lane-changing behavior, existing lane-changing models could be classified into four categories including rule-based models, discrete choice-based models, artificial intelligence models, and incentive-based models (Rahman et al., 2013). The rule-based models include the Gipps model (Gipps 1986), CORSIM model (Halati et al.. 1997), ARTEMiS model (Hidas 2005), Cellular Automata model (Rickert et al. 1996), and game theory model (Kita et al., 1999). Discrete-choice-based models include Ahmed's model (Ahmed et al. 1996) and Toledo et al.'s (2007) model. Artificial intelligence models include fuzzy-logic-based models (Ma, 2004) and ANN models (Yang et al., 1992). Incentive-based models include MOBIL (Kesting et al., 2007) and Lane-changing Model with Relaxation and Synchronization (LMRS, Schakel et al., 2012). The following sections present existing studies utilizing these models.

2.5.2 Discrete choice model

Toledo et al. (2003) developed a lane-changing model that consists of two parts. The first part was to determine whether the vehicle is willing to change lanes or not. This step was modeled using a utility function, which would output three alternative results, maintaining the current lane, lane changing to left, and lane changing to the right. This step assumed that the vehicle would make the lane change decision which results in the maximum utilization that considers the individual driver characteristics and other explanatory variables (including the immediate neighborhood in each lane, leader speed in each lane, presence of heavy vehicles, and tailgating), path plan considerations (e.g., the distance to a point where the driver must be in a specific lane and the number of lane changes needed to be in that lane), and knowledge of the system (e.g., avoiding the left lane before permissive left turns or avoiding on-ramp merging lanes). The second part was to evaluate whether the gap in the target is sufficient for the lane changing for the driver. The model resulting from the second part assumed that the critical gaps follow a lognormal distribution. The parameters in the model were obtained through the maximum likelihood method by collecting travel trajectory data of drivers.

2.5.3 Incentive-based models

Kesting et al. (2007) proposed lane-changing rules that were dependent on the acceleration of the vehicle. By doing so, the car following models contains the parameters required by the lane changing model. The model essentially evaluated the differences of new acceleration rates after a prospective lane change and current acceleration rates. A greater acceleration rate means a higher speed that the vehicle can travel. In addition, acceleration rate differences of two immediate neighbors were also considered to evaluate the impact of lane change on the current lane. When this model result was greater than a specified threshold, the driver was determined to execute a lane change. The safety criteria, which evaluate whether the lane changing is safe or not, were also modeled as a function of acceleration. If the vehicle had to make significant deceleration for a lane change, then it may not be safe for the vehicle to change lanes. Thus, the expected acceleration rate was smaller than a certain threshold, and the vehicle was not able to make the lane change either.

2.5.4 Rule-based models

Yang et al. (2019) established a lane-changing behavior model in both traditional and connected environments based on game theory. In this model, researchers mainly considered two players, the merging vehicle, and the following vehicle in the target lane. The payoff was set as the acceleration for different choices. The merging vehicle has two choices, merging and waiting, which would require two different acceleration rates. For the following vehicle in the target lane, it has four choices including forced merging, courtesy yielding, doing nothing, and changing lane, which would also generate four acceleration rates. Bi-level programming optimization was utilized to estimate the parameters for the prediction model. The upper-level objective function was to minimize the discrepancy between observed lane changing decision and predicted lane changing decision, while the lower-level objective function was to obtain the Nash Equilibrium. Compared to other existing game theory-based lane-changing models, the proposed model considered more choices that might fall into consideration of following vehicles. The proposed model was also found to have a high accuracy in predicting lane-changing action. Table 2.9 provides a brief review of the literature mentioned above.

TABLE 2.9: Summary for Literature on Lane-Changing Model

Authors	**Year**	**Required Input**	**Model Characteristics**
Salvucci et al.	2007	steering wheel angle; accelerator depression, lateral position, etc.	Mapping observation actions to intention; model is like intelligent tutoring systems
Toledo et al.	2003	individual characteristics and environmental characteristics	Lane changing decision-based on utility; evaluation of the sufficiency of the gap based assumed lognormal critical gap distribution
Kesting et al	2007	speed, gap, acceleration rate	Incorporated into intelligent driver model, which describes the longitudinal movement of vehicles
Letter and Elefteriadou	2017	vehicle's position, speed, and acceleration	Maximization of the average travel speed in the communication zone

Wei et al.	2019	position, initial speed, and acceleration rate	Lane changing path is planned first in 2d cartesian coordinates. A nonlinear mathematical programming model is used to generate the velocity profiles
Ma et al.	2019	surrounding vehicles' spacing	Based on energy field theory, the lane-changing model is developed for the B-type weaving section
Yang et al.	2019	Lane changing trajectory	Game theory-based lane-changing model, considering more choices for the following vehicle in the target lane

2.5.5 Artificial intelligence models

Salvucci et al. (2007) developed a model-tracing methodology to map a person's observable actions to his/her intention. The observable actions included steering wheel angle, accelerator depression, lateral position, longitudinal distance and time headway to a lead vehicle, longitudinal distance, front and back, to vehicles in adjacent lanes; and the presence or absence of a lane to the left and right of the current travel lane. A validation model was also proposed to evaluate the model performance. This framework was most similar to intelligent tutoring systems, which had utilized predictive cognitive models to infer student's intentions. To validate the proposed lane changing predictive model, lane changing data were collected by recruiting drivers driving in the designated simulator. The prediction results achieved an accuracy of 95%.

2.6 CAV Platooning

2.6.1 Virtual platoon

Some studies conveniently defined the platoon as a group of vehicles that travel through the intersections together or share a close headway.

Feng et al. (2018) and Yu et al. (2018) developed a signal optimization scheme and trajectory planning scheme for CAVs in the conventional intersections. They defined the vehicle platoons as a group of vehicles that can travel through the intersections. In this way, the vehicles that can pass the intersections entered the trajectory planning module together.

Ye et al. (2019) identified the vehicle platoons by their inter-distance and speeds. When the vehicles are close to each other and share a similar speed, they are then grouped into a platoon for trajectory optimization whose aim was to minimize fuel consumption. With such a module, the computation burden was reduced since a group of vehicles can be regarded as a single unity for the trajectory optimization process.

2.6.2 Optimization-based platooning

Platooning is a unique behavior feature of connected vehicles that can communicate with surrounding vehicles. Different from the automated vehicles that detect the gap and velocity of preceding vehicles, connected vehicles proactively share the velocity and acceleration rate with the surrounding vehicles. With such communication capability, CAVs can have shorter reaction times and headways which can further reduce fuel consumption (Xiao et al., 2018).

Wang et al. (2020) established an MPC approach to model the platooning behaviors of CAVs. In this research, two solutions were proposed to obtain the optimal trajectories for vehicles inside platoons and the solutions were applicable in real-world tests. Such a method can significantly reduce the computation time and improve the control efficiency according to the simulation results. In the case study, the CAV platoon whose leading vehicle's trajectory was obtained from field data. The results demonstrated that the proposed model framework can dampen traffic oscillations efficiently and smooth the deceleration and acceleration behaviors for all following vehicles inside the platoon.

Xiao et al (2018) proposed a real-time traffic signal optimization algorithm in the CAV environments. The proposed algorithm identified naturally occurring platoons that may include both connected vehicles and non-connected vehicles. Then the proposed signal timing algorithm optimized the sequence at which these platoons are allowed to enter the intersection to obtain the minimal total vehicle delay. The proposed signal timing plan incorporating the platooning control can save the computation time by more than 85%.

Utilizing the distributed algorithm for multi-users proposed by Koshal et al. (2011), Gong et al. (2016) analyzed and obtained the solution to the optimization problem of CAV platooning control. The distributed algorithm could be applied in real world to obtain the solution to the control problem. Then the usefulness of this control strategy was demonstrated through extensive numerical simulations. It was shown via stability analysis that the linear closed-loop system is asymptotically stable.

Later, Gong and Du (2018) proposed a cooperative platoon control strategy for the mixed traffic flow where CAV and HDV coexist. The movement of CAVs was controlled by One- or P- step model predictive control (MPC) models while the HDVs were modeled by the well-accepted Newell car-following models (Newell, 1993; Newell, 2002). Gong and Du (2018) also developed an online curve matching algorithm to anticipate the aggregate response delay of the HDVs. The MPC problem was solved by a distributed algorithm proposed by the authors. The numerical studies proved that the proposed algorithm can solve the One-step and P-step MPCs problem quickly. Finally, the authors demonstrated that this cooperative platoon control strategy is superior to the non-cooperative control strategy and latest CACC strategy.

2.6.3 Model-based platooning

Another category of platooning models can be classified as rule-based models, which define different car following modes according to the distances between the subject vehicles, preceding vehicles, and the lead vehicle in the platoon.

Xiao et al. (2017) developed the CACC model to describe the car following behaviors of CAVs that can communicate with each other. The CACC model was developed from the ACC model that could maintain a desired distance towards the leading vehicle. However, the CACC model forms only loosen platoons. Differing from this approach, several researchers developed car following models for vehicles inside platoons specifically.

Bang and Ahn (2017) developed platooning schemes based on the spring-mass-damper system. The acceleration rate was a function of the velocity of the preceding vehicle and the leading vehicle, and the positions in the platoons. The differences were weighted by the spring constant and damping coefficient respectively. The valid domains of control parameters were derived based on vehicles’ physical properties. This research also tested the different relationships between the control parameters and traffic flow, including maximum, quadratic, and cubic spring constants. The results showed that the maximum spring constant and flow with critical damping has the most efficient platooning.

A cubic spring constant was desirable in light traffic conditions to allow proper lane changing.

Rajamani et al. (2012) proposed a vehicle platooning controller that has been well accepted (Bian et al., 2019; Darbha et al., 2017; Darbha et al., 2018; Paden et al., 2016). With the same platooning control structure, Darbha et al. (2017, 2018) verified the minimum headway requirements at different connection levels (how much predecessor information can be received and whether the acceleration information is available). Bian et al. (2019) further proved that a platoon can be asymptotically and string stable when the time headway is lower bounded, and this boundary can be reduced when more predecessors' information is available. Overall, the popular safety assumption was that the minimum headway should be two times the communication delay and CAV platooning can yield benefits when the minimum headway is less than 1s (Darbha et al., 2018).

Platooning also plays a critical role in trajectory planning. When the trajectory planning system is implemented on the platoons, only the trajectory of the platoon leader is controlled and optimized and the rest of the vehicles in the platoon can follow the platoon leaders' trajectory. The operation can reduce the computation burden of trajectory planning, especially when large-scale microscopic simulation is involved.

2.7 Existing Studies on Superstreets

2.7.1 Concepts, benefit, and application of superstreet

Superstreet, also known as restricted crossing U-turn intersection, J-turn, reduced conflict intersection, or synchronized street intersection, is one of the innovative intersection designs which relieve traffic congestion, especially when unbalanced traffic is present in the intersection. By sending through and left-turn movement from cross street to a one-way median opening (crossover intersection) in hundreds of feet away from the two-way median opening (main intersection), both through movement and left-turn movement from the cross street would have to make a right turn and U-turn first. Then no more movement is required for left-turn movement while through movement needs to make a right turn again at the two-way median opening. Superstreet is also a variation of median U-turn intersection which prohibits left-turn vehicles from both the main and minor streets. However, median U-turn intersection allows through movement from minor intersection to travel through the main intersection directly without making the detour to the median opening. Figure 2.1 presents the traffic flow from the main street in median U-turn and superstreet respectively.

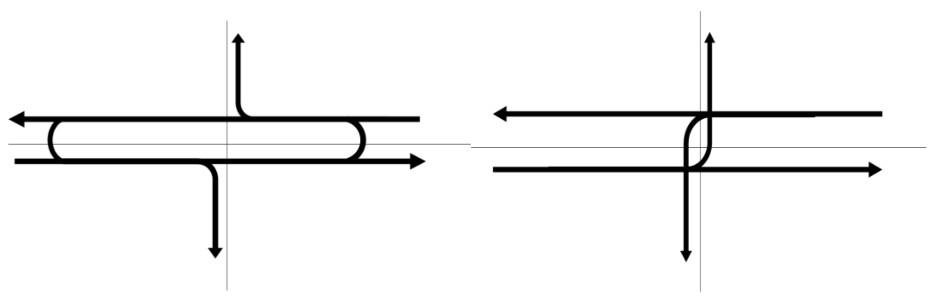


FIGURE 2.1: Traffic flow from the main street in median U-turn (left) and superstreet (right)

According to different control strategies, there are three types of superstreets essentially, including signalized, stop-controlled, and merge- or yield-controlled superstreets. Figure 2.2 presents a typical design of a superstreet according to FHWA (Hummer et al., 2014).

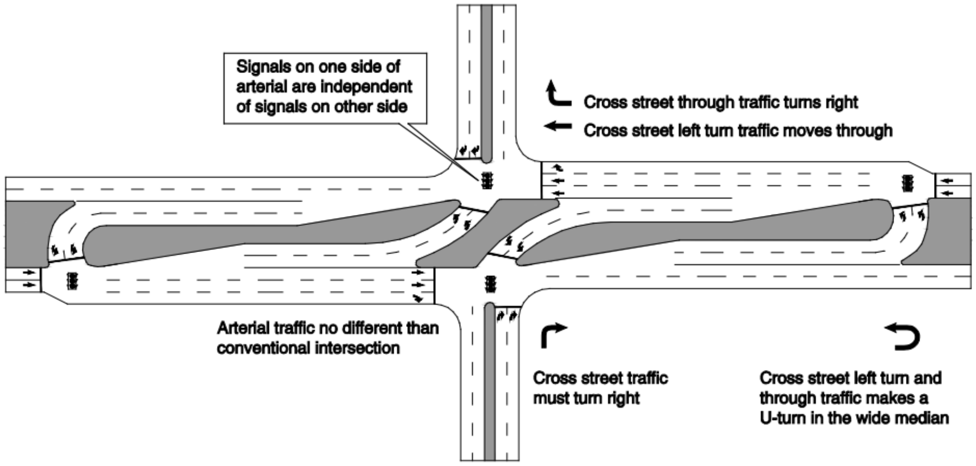


FIGURE 2.2: Example of signalized intersection (source Hummer et al., 2014)

Coming along with the substantial benefits from superstreet, the construction cost for a superstreet is inevitably expensive because of its larger footprint. In addition, there are additional signal controllers that may need to be installed. Table 2.10 shows some construction costs in Hummer et al. (2014).

TABLE 2.10: Construction Cost for Some Superstreets (Hummer et al., 2014)

Road	**Year**	**Cost**	**State**	**Mileages**
US 15/501 (adding 2 lanes, relocated frontage road)	2006	5 million	North Carolina	0.4 mile
US 17 (3 signalized Superstreet)	2006	2 million	North Carolina	0.6 mile
US 301	2005	0.618 million	Maryland	1400 feet between crossover intersection and main intersection

2.7.2 Signal timing and geometric design of superstreet

Xu et al. developed a two-stage control model for optimizing traffic signal control plans of signalized superstreets (2019). The first stage was to select the optimal cycle length for all sub-intersections in the superstreet while the second stage was to determine the offsets to achieve the signal progression and to minimize the waiting time of drivers from the minor road. The goal of the first stage was to maximize the throughput of the superstreet and the second stage was to maximize the signal progression. During the second stage, the proposed model can maximize the weighted bandwidth with consideration of minimal waiting time on the minor road. This was achieved by optimization of waiting time for over long cycle length of signal timing, and bandwidth for traffic flow progressions. The contribution of this study was combining the core notions of the existing bandwidth optimization method, MAXBAND, with traffic delay optimization. Through the demonstration of a numerical example, the proposed model was proved to be capable of producing shorter cycle lengths and queues in the superstreets.

Xu et al. (2017) developed a model to determine the minimal U-turn offset of a superstreet with consideration of three-segment, namely acceleration and merging, lane changing, and deceleration, and initial queue. The acceleration and lane changing was determined by both the acceleration capacity of vehicles and the probability of vehicle finding an acceptable gap in the traffic flow on the main road. Then the length of the lane-changing segment was overlapped with acceleration and merging segments. The last segment, deceleration, and initial queue length could be determined by queueing theory with headway distribution being assumed to follow a shifted negative exponential distribution. To demonstrate the model, the Surrogate safety assessment model (SSAM) was utilized to evaluate the designed scenarios. The numerical results of crash difference brought by different lengths of offset proved the efficiency of the model.

Holzem et al. (2015) studied pedestrian and bicyclist accommodation strategies in the context of superstreet. For pedestrians, the options included the diagonal cross, median cross, two-state Barnes Dance, and midblock cross. For bicyclists, the options included the bicycle U-turn, bicycle use of the vehicle U-turn, bicycle direct cross, and midblock cross. These strategies were evaluated through simulation based on average stopped delay, the average number of stops, and average travel time per route. The Level of Service (LOS) calculated based on 2010 HCM was presented for these strategies as well as travel time generated from PTV VISSIM simulation. The results demonstrated that the two-stage Barnes Dance is the optimal pedestrian crossing configuration as it can produce the lowest simulated average stopped delay per route, lowest average total stops per route, and lowest average travel time per route. As for bicyclists, the bicycle direct cross had the lowest average number of stops per route and the lowest travel time based on the HCM analysis. The study also showed that shorter cycle length could also benefit the accommodation of bicyclists.

2.7.3 Superstreet performances

The performances of superstreet have been tested by many researchers in different aspects, including safety and efficiency. Table 2.11 provides a summary of existing studies on the performance of superstreet. Most of these studies employed a simulation-based approach.

TABLE 2.11: Summary of Existing Studies on the Operational Performance of Superstreet

Authors	**Year**	**Alternative Intersections**	**Methods**	**Results**

Hummer et al.	2010	conventional intersection, Signalized superstreet, unsignalized superstreet	VISSIM, Empirical Bayes	Superstreet can have more capacity and lower travel time,
Naghawi et al.	2018	signalized convention intersection	VISSIM	Improvement of LOS from F to C
Naghawi & Idewu	2014	conventional intersection	CORSIM	Higher delay and queue were found in the conventional intersection
Reid and Hummer	2001	quadrant roadway intersection, median-U-turn superstreet median, bowtie, jughandle, split intersection, continuous flow intersection	CORSIM	Superstreet is used to replace at the intersection with two-lane cross streets
Haley et al.	2011	Conventional intersection	VISSIM	Decrease the travel time on the major road and increase and travel time on the minor road
Ott et al.	2015	none	Survey	Superstreet has both positive and negative impacts on the local business. Superstreet is safer to travel through
Ott et al	2012	Conventional intersection	Accident report review	Reduction of the accident has been observed in total, angle, right-turn,

				and left-turn collision
Click et al.	2010	diamond with reversing lanes, roundabout, diverging interchange, median U-Turn, superstreet	SILS, VISSIM and Econolite	Superstreet has a reasonable performance during the mid-term traffic volumes forecast

2.7.3.1 Operational performance analysis for superstreet

Naghawi and Idewu (2014) evaluated the operational performances of superstreet considering different approaching volumes and turning percentages on the major/minor road, resulting in a total number of 72 scenarios including conventional intersection as the base scenario. The signal timing for each scenario employed the optimal cycle length that was calculated using the methods provided from HCM 2000. Based on the simulation results of CORSIM, superstreet consistently outperformed the equivalent conventional intersection in terms of average traffic delay and queue length.

Similarly, Haley et al. (2011) analyzed the operational performances of three signalized superstreets in North Carolina using PTV VISSIM. Calibration of the simulation was conducted to minimize the difference between observed and simulated travel time. The observed travel time data was collected by the researchers who drove through the targeted superstreets for as long as the time that the video camera lasted. Two sets of data were collected, one for calibration and the other for validation. The results showed that superstreets increase the travel time for the vehicles on minor streets while decreasing that of vehicles on major streets. However, overall speaking, the superstreet outperformed the conventional design due to the large traffic volume present on the major streets. Besides, this research also found that the superstreets could reduce the travel time variations caused by off-peak and peak hours.

Ott et al. (2015) evaluated residents, commuters, and business owners' opinions on the superstreets across North Carolina. The researchers selected ten sites from a comprehensive list of superstreets. Ten sites were selected according to two criteria, the first one of which was that the superstreets must be constructed within five years. This is because drivers might not remember what the driving situation is if the superstreets have been there for more than five years. The second criterion was that there must exist road construction before the superstreet was present. This is important because drivers surveyed must have something to compare. The researchers identified four key questions in the survey, which represent navigation, safety, travel time, and the number of stopped vehicles, respectively. About the navigation, the responses indicated a mixed attitude towards superstreet because the same amounts of people found navigating through superstreet easier and more difficult compared with the conventional intersection. However, more than half of the respondents reported that they found superstreets are safer to travel through. For people who lived in a neighborhood of superstreet, they thought the superstreets had increased their travel time. This might be due to that superstreet improves the traffic flow on a major road with a compromise of traffic flow in the minor road. People, who live in the neighborhood, were likely to experience longer travel time while they used the minor road. As for the commuters, superstreets were difficult to navigate for half of them according to the response received. The percentage of people who found superstreets safer was greater than the percentage of people who found the otherwise by 8 percent. 12% of commuters believed that superstreets take more travel time and approximately 50% of commuters perceived no change in safety or travel time. This study also investigated the impact of superstreet on the business. Business owners or managers close to the superstreet were interviewed or questioned through mails. According to the results of the survey, the superstreet had a neutral or negative impact on the local business because of additional restrictions resulting from the superstreets.

Reid and Hummer (2001) evaluated travel times in seven different unconventional arterial intersection designs, including the quadrant roadway intersection, median U-turn, superstreet median, bowtie, jug-handle, split intersection, and continuous flow intersection designs. Seven sites in the real world were identified and modeled in CORSIM along with their equivalent unconventional intersection designs. Five of them were put in CORSIM with seven intersections designed at three volume levels. Note that these five intersections had four through lanes on each of the cross streets. Two of them were put in CORSIM with six intersection designs at three volume levels. These two intersections had a through lane on the cross streets. The conclusions were made that conventional design never produced the lowest average total time but often produced the lowest percent stops. The superstreet median and bowtie designs were competitive with the conventional design at intersections with two-lane cross streets.

Hummer et al. (2010) evaluated the operational, safety, and perceived effects of superstreets through VISSIM simulation. The simulation results were compared to those of the equivalent conventional intersection. It showed that travel time per vehicle had been reduced. This means the superstreets could provide more capacity and lower travel time. Though signalized superstreet did not provide significant crash reduction, the unsignalized superstreet can bring a significant reduction in crash accidents. In addition, the researchers also implemented a survey investigating the reactions towards superstreets from road users. The results did not indicate a clear preference in superstreets over a conventional one, but an agreement was reached in that superstreets provide a safer trajectory through the intersection. However, business managers felt that the superstreet harms the business growth and operation due to access and confusion incurred in the superstreet.

2.7.3.2 Replacement of conventional intersections

Numerous studies had been done to evaluate the feasibility and improvement of replacing existing conventional intersections with superstreets. Since constructing a superstreet in the real world is a massive undertaking, the popular approach is to replicate the superstreet in the simulation platform. Most of the results identified from the existing literature were positive.

Naghawi et al. (2014) assessed the possibility of implementing the superstreet in Amman, Jordan. The signal timing of the existing intersection was optimized before obtaining the results of the operational performance of the intersection. Then an equivalent superstreet was designed in VISSIM to obtain simulated operational performance. The results showed that the superstreet outperforms the existing intersection design by improving the level of service from F to C. Furthermore, with a forecast of the increased traffic demand in five years, the operational performance of superstreet was not significantly superior compared with a signalized intersection.

Moon et al. (2011) evaluated the feasibility of replacing the existing conventional intersection situated in National Highway 38, Gyeonggi-do, South Korea, which consisted of three signalized intersections. PTV VISSIM was employed to replicate the geometric designs of both conventional intersections and superstreets. The operational performances in terms of total travel time, the number of arrived vehicles, the average delay time per vehicle, average speed, and average stopped delay per vehicle were discussed. Also, vehicle trajectories were all output to Surrogate Safety Assessment Model (SSAM) for safety evaluation. The results showed that the superstreet had the fewest stops and lowest delays due to the effective traffic progression. Collisions were also reduced according to the SSAM analysis.

2.7.3.3 Safety performance of superstreet

The number of conflict points is a commonly accepted measure for evaluating the safety performance of transportation infrastructure. Figure 2.3 and Figure 2.4 show the pedestrian-vehicle conflict points in the conventional intersection and superstreet, respectively. Based on these two figures, it can be observed that the pedestrian-vehicle conflict points are reduced substantially in the superstreet compared to the conventional intersection. As superstreet often provides a designed channel for pedestrians and pedestrians to be guided to conduct “Z” crossing, the number of conflict points is reduced from 24 to 8 compared to the conventional intersection. However, pedestrians who attempt to come across the main street may need to travel a longer distance.

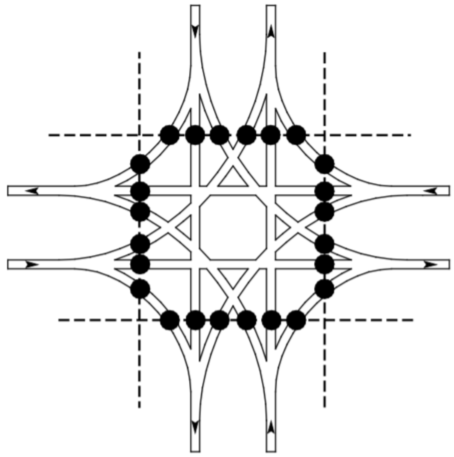


FIGURE 2.3: Pedestrian-vehicle conflict points in a conventional intersection (Hummer et al., 2014)

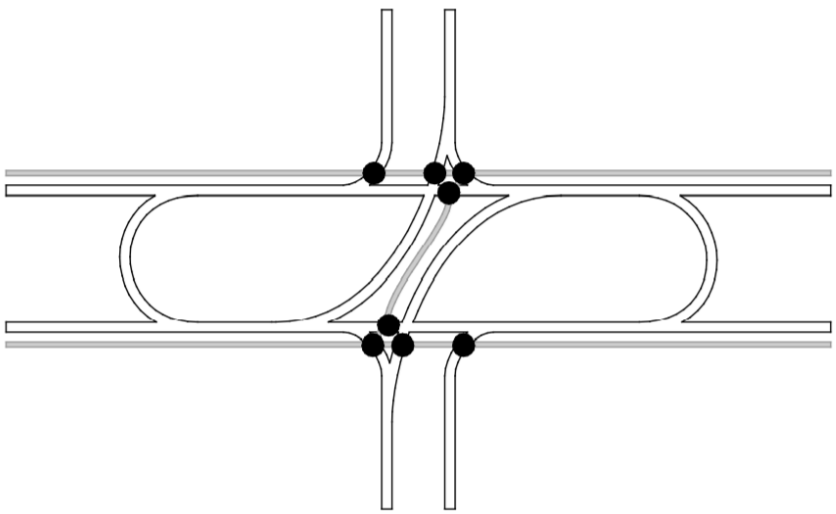


FIGURE 2.4: Pedestrian-vehicle conflict points in superstreet (Hummer et al., 2014)

As for the vehicle-to-vehicle conflict points, superstreet still outperforms the convention intersections. For three-leg intersection, the conventional intersection has 9 conflict points while the superstreet (RCUT referred to in the table) has 7. For a four-leg intersection, the conventional intersection has 32 conflicts while the superstreet has 14 conflict points, as shown in Table 2.12.

TABLE 2.12: Vehicle Conflict Points Comparison in Conventional Intersections and Superstreets (Hummer et al., 2014)

	Conflict Points	
Number of Intersection Legs	Conventional Intersection	Superstreet
3	9	7
4	32	14

2.7.4 The impact of CAVs on the innovative intersection

Few research efforts have been made in exploring the impacts of CAVs in the environment of superstreet. Zhong et al. (2019) investigated the operational performance of CAVs in the environments of diverging diamond intersections and restricted crossing U-turn intersections (i.e., superstreets). In this research, a standard and hypothetical superstreet network was established with assumed traffic volumes based on the PTV VISSIM simulation platform. HDV traffic and CAV traffic were modeled by the Wiedemann model and enhanced IDM, respectively. The results showed that the throughput of superstreet overall increases as the market penetration increases. However, the hypothetical network with assumed traffic volumes may not reflect accurately the impact of CAVs at the superstreet, which leaves a research gap to be fulfilled.

CHAPTER 3 METHODOLOGY

3.1 Introduction

Based on the literature review, it can be seen that the behaviors of CAVs require specific models to describe. This dissertation attempts to model the car following, platooning, trajectory planning, and adaptive signal control. The following subsections provide more details about these models.

3.2 Car-following Models

3.2.1 IDM

IDM was developed by Treiber et al. (2000). It is a collision-free model with intuitively measurable parameters. Due to these advantages, the IDM has been popularly used in modeling CAVs (Do et al., 2019; Liu and Fan, 2020; Yi et al., 2020). The acceleration rate in IDM is a function of the velocity of the subject vehicle, the gap to the preceding vehicle, and the velocity difference to the preceding vehicle, as indicated in Equation 3.2.1.1 and Equation 3.2.1.2 shown below:

$$a(s, v, \Delta v) = a_m \left(1 - \left(\frac{v}{v_d}\right)^{\propto} - \left(\frac{s^*(v, \Delta v)}{s}\right)^2\right) \tag{3.2.1.1}$$

$$s^*(v, \Delta v) = s_0 + vT + \frac{v \times \Delta v}{2\sqrt{a_m b}} \tag{3.2.1.2}$$

where a indicates the acceleration rate; a_m is the maximum acceleration rate; v denotes the current speed; v_d indicates the desired speed (assumed equal to the speed limit in this research); Δv represents the speed difference between the subject vehicle and its preceding vehicle; $\propto$ means the acceleration exponent, which is set as 4 in this research; s is the current headway between the subject vehicle and its preceding vehicle; $s^*(v, \Delta v)$

represents the minimum desired headway; s_0 denotes the standing distance (2.5m); T represents the desired headway (1s); and b is the desired deceleration rate.

3.2.2 W99 model

W99 is a psychophysical model that has ten parameters available for calibration in micro-simulations. These ten parameters are intuitively consistent with human driver behaviors with certain randomness (Durrani et al., 2016). To ensure that the W99 can represent the local traffic accurately, the ten parameters were calibrated to ensure that the average speeds on each approach in the simulation are matched with the ones that were collected from the field survey according to Hummer (2010).

Considering the data availability, this research selects the minimal difference between simulated average speeds and observed average speed for each approach as the objective function used in the calibration process. An overall difference within 15% is regarded as acceptable performance.

$$\frac{\left(\sum_{i}^{N} \frac{|v_{o,i} * - v_{s,i}|}{v_{o,i}}\right)}{N} \tag{3.2.2.1}$$

where $v_{o,i}$ and $v_{s,i}$ are the observed and simulated average speed for approach i respectively, and N indicates the total number of approaches.

A genetic algorithm is utilized to minimize the difference between the observed average speeds and simulated average speeds for each approach. GA is a popular and efficient approach in calibrating the car-following model parameters. For brevity, this research skips the introduction of GA, and readers may refer to existing studies of GA calibration for more details (Ma and Abdulhai, 2002). The population size and the maximum number of generations are set as 10 and 20, respectively. This research implements simulation experiments and the final difference became stable at 11%. This is recognized as an acceptable difference (Manjunatha et al., 2013). The obtained parameter values from GA are presented in Table 3.1. The lane changing movement is controlled by the default car-following model in SUMO, i.e., LC2013 (Erdmann, 2015).

TABLE 3.1: GA Calibrated W99 Parameter Values

Parameters	Interpretation	Default Values	Calibrated Values	Value Range
CC0	average standstill distance (meter)	1.4	1.287251	[0.1, 10.0]
CC1	headway (seconds)	1.2	1.569918	[0.1, 5.0]
CC2	longitudinal oscillation (meters)	8	1.28187	[0.1, 15.0]
CC3	start of deceleration process (seconds)	-12	-12.3849	[-27.0, -5.0]
CC4	negative following threshold Δv (m/s)	-1.5	-2.398	[-5.0, 0.0]
CC5	positive following threshold Δv (m/s)	2.1	0.324976	[0.0, 5.0]
CC6	speed dependency of oscillation (10^{-4} rad/s)	6	4.047425	[0.1, 11.0]
CC7	oscillation acceleration - m/s^2	0.25	0.29111	[0.0, 7.0]
CC8	acceleration rate when starting (m/s^2)	2	4.582238	[0.1, 7.0]
CC9	acceleration behavior at 80 km/h / 49.7 mph (m/s^2)	1.5	4.261776	[0.1, 8.0]

3.3 Platooning Control

Vehicle platooning is one of the advanced features of CAVs. It can only be achieved with CAVs that have communication capabilities with other vehicles. Two assumptions are often made with CAVs platooning. One is shorter headways for vehicles inside a defined platoon, and the other is homogenous speeds. With shorter headways and homogenous speeds, the vehicles inside the same platoon can be regarded as a single unity to travel on the roads, which can increase the capacity of the roads and also reduce the computational complexity when trajectory planning is involved. This research has also adopted these concepts to fully release the potentials of CAVs. Two sets of platooning controls are defined in this research, namely platooning control I and platooning control II. The essential difference between platooning control I and platooning control II lies in that Platooning control II allows CAVs to dynamically adjust their distances to the preceding vehicles.

3.3.1 Platoon formulation and splitting

The platoon control system in this research iterates all active vehicles in the simulation environment and checks whether the neighboring vehicles meet the requirements for the platoon formulation. The requirements are that the vehicles:

1) are in the same lane;
2) stay within the range of a certain distance; and
3) share the same path.

If the requirements above are met, then the system can define such a group of vehicles as a platoon and thus share the same speed with the leading vehicle. However, if any of the vehicles inside the platoon fails to meet these requirements, then the platoon splits up and switches back to the default car-following model.

There is one more condition guaranteeing platoon splitting. When the platoon is approaching an intersection, the remaining green time g_p may not be sufficient for all vehicles in a platoon to pass the intersection together, especially when the platoon size is large. Thus, to make the platoon system practical, the vehicles with platooning are assumed to have the knowledge of remaining green time. With the information on the remaining green time g_p, the platooning system checks whether all vehicles inside a platoon can pass the intersection or not through Equation (3.2.1.1),

$$g_p^w \geq \frac{D_t^i}{v_t^i}, i \in \boldsymbol{P} \tag{3.3.1.1}$$

where g_p^w denotes the remaining green time for the platoon $\boldsymbol{P}$, D_t^i and v_t^i indicate the remaining distance towards the intersection and speed of the i^{th} vehicle inside the platoon $\boldsymbol{P}$ at the time step t. In the platoon $\boldsymbol{P}$, when the i^{th} the vehicle cannot pass the intersection and the vehicle directly ahead of the i^{th} vehicle, i.e., $i-1^{th}$, can pass the intersection, then the platoon $\boldsymbol{P}$ disbands from the $i-1^{th}$ vehicle. The vehicles after the $i-1^{th}$ vehicle in the platoon $\boldsymbol{P}$ would reform a new platoon to decelerate together. When the platoons are approaching the intersection, the platooning system checks Equation (3.3.1.1) for each vehicle in the platoons at every time step. In this manner, the platoon system can avoid the situations where the platoon runs a red light because of its large platoon size.

3.3.2 Platooning control I

The vehicles inside a platoon share the same speed and keep a constant close distance in between. The platoon speed is naturally determined by the leading vehicle's speed. The platoon attempts to set the following vehicles' speeds the same as that of the leading vehicle within acceleration capacity in every time step. If the speed difference between the leading vehicle and the following vehicle exceeds the acceleration/deceleration capacity, the speeds of the following vehicles will execute the boundary speeds to match the leading vehicle speed as close as possible, as shown in Equation 3.3.2.1.

$$v_t^{following} = \begin{cases} \max\left(v_{t-1}^{following} - a_L, v_{t-1}^{leading}\right), if\ v_{leading} \leq v_{following} \\ \min\left(v_{t-1}^{following} + a_U, v_{t-1}^{leading}\right), if\ v_{leading} > v_{following} \end{cases} \quad (3.3.2.1)$$

where $v_t^{following}$ and $v_{t-1}^{following}$ indicate the speed of the following vehicle at the time step t and time step $t-1$ respectively, and $v_{t-1}^{leading}$ denotes the speed of the leading vehicle at the time step $t-1$.

Indeed, in this system, the distance that guarantees a platoon formulation may have an important influence on the performance of the platooning system. Hence, this research also conducts a sensitivity analysis of this parameter. The selection of distance boundaries ranges from $5m$ to $31m$ with an increment of $4m$. Each distance boundary has 5 simulation runs and each simulation lasts for $900s$ (15 minutes). This research obtains the traffic delay and fuel consumption to determine the optimal searching distance. Figure 3.1 provides the average traffic delay and fuel consumption results for each distance boundary. According to Figure 3.1, it can be observed that both traffic delay and fuel consumption reach the minimum at the distance of $21m$, and thus this research selects $21m$ as the distance boundary for further analyses.

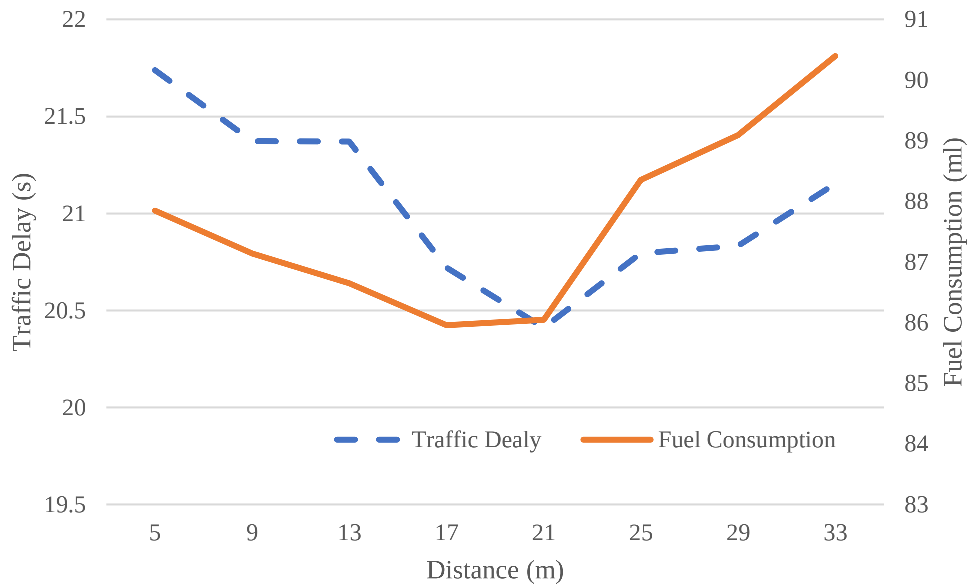


FIGURE 3.1: Performances of platooning with different values of distance boundaries

3.3.3 Platooning control II

Beside the platooning control introduced in Section 3.3.2, the model developed by Rajamani (2011) has been further incorporated in this research. Based on the literature review, the platooning model developed by Rajamani (2011) is one of the most acknowledged platooning models because of tunable parameters and stable performance (Darbha et al., 2017; Darbha et al., 2018; Bian et al., 2019;). Therefore, this research employed such an approach to evaluating the impact of CAV platooning technology in the environment of superstreets. The full form of vehicle platooning model is presented below:

$$\ddot{x}_d = w_1 * \ddot{x}_{i-1} + w_2 * \ddot{x}_0 + w_3 * \dot{\varepsilon} + w_4 * (\dot{x}_i - \dot{x}_0) + w_5 * \varepsilon_i \tag{3.3.3.1}$$

$$\varepsilon_i = x_i - x_{i-1} + L_{i-1} + g_d \tag{3.3.3.2}$$

$$\dot{\varepsilon}_i = \dot{x}_i - \dot{x}_{i-1} \tag{3.3.3.3}$$

where $\ddot{x}_d$ represents the control input for the subject vehicle in terms of acceleration rates. $\ddot{x}_{i-1}$ and $\ddot{x}_0$ denote the acceleration rate for the preceding vehicle and the lead vehicle of the platoon, respectively. w_1, w_2, w_3, w_4, and w_5 are the control gains for their corresponding terms, such as acceleration of the preceding vehicle $\ddot{x}_{i-1}$. L_{i-1} indicates the vehicle length for the preceding vehicle (all vehicle lengths are assumed to be 5m in later experiments). Figure 3.2 presents the string of vehicles in a platoon.

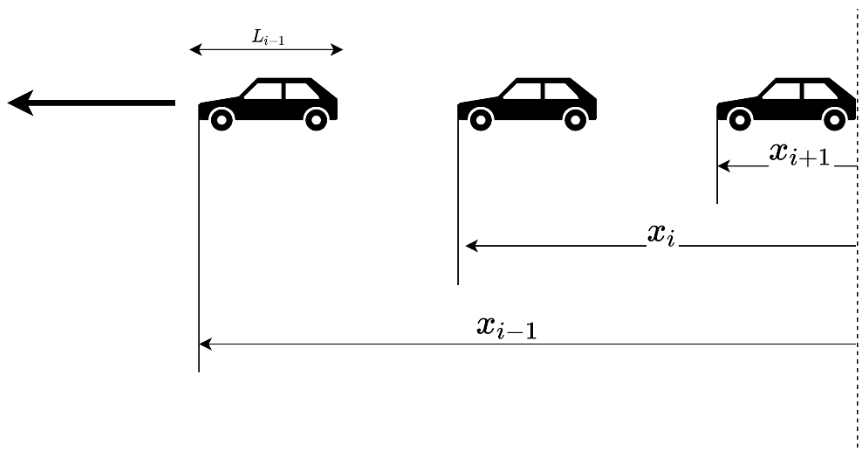


FIGURE 3.2: Sting of vehicles in a platoon

The calculations for five control gains are shown below.

$$w_1 = 1 - C_1 \tag{3.3.3.4}$$

$$w_2 = C_1 \tag{3.3.3.5}$$

$$w_3 = -\left(2 * \xi - C_1 * \left(\xi + \sqrt{\xi^2 - 1}\right)\right) * w_n \tag{3.3.3.6}$$

$$w_4 = -C_1 * \left(\xi + \sqrt{\xi^2 - 1}\right) * w_n \tag{3.3.3.7}$$

$$w_5 = -w_n^2 \tag{3.3.3.8}$$

where C_1 is the weighting factor for the acceleration rates of the leader and the preceding vehicle respectively. ξ is the damping ratio and w_n is the control bandwidth. Among these parameters, C_1, ξ and w_n are tuning parameters that can be adjusted based on research needs. Table 3.2 shows the default parameter values that are used in this research. Platoons are only detectable within a certain distance, and thus platooning control can only apply to the vehicles that are within a distance boundary D_b. According to (Segata et al., 2014), 20 m is a proper boundary for platooning control. Table 3.2 shows a summary of the values utilized in this research for the platooning control.

TABLE 3.2: Default Values for Platooning Control Parameters

Parameters	Default values
Damping ratio $\boldsymbol{\xi}$	1
Bandwidth $\boldsymbol{w_n}$	0.2 Hz
Acceleration weighting factor $\boldsymbol{C_1}$	0.5
Desired gap $\boldsymbol{g_d}$	5 m
Distance boundary for platooning $\boldsymbol{D_b}$	20 m

A small numerical simulation is conducted to test the effectiveness of platooning model given the default values. Assume a preceding vehicle and a leader vehicle with a speed of $20\,m/s$ $(44.7\,mph)$ and acceleration of $0\,m/s^2$. A third following vehicle is created with a speed of $15\,m/s$ $(33.6\,mph)$ and a gap to the preceding vehicle $20\,m$. Figure 3.3 shows how the vehicle catches up with the platoon of two vehicles using this platooning control system. From Figure 3.3, one can see that the platooning control can reduce gap error ε from 15m to 0m in about 30s. Moreover, platooning control system could maintain the desired gap size throughout the whole trip. This result validates the developed platooning control system.

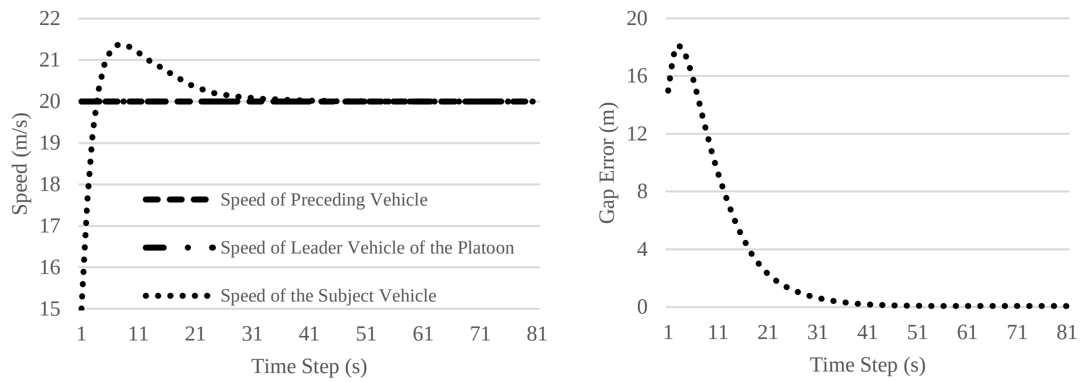


FIGURE 3.3: Numerical test for platooning model performance

Some other practical considerations needed to be added in a large-scale microscopic simulation as presented in this research. First, the vehicles can enter a platoon only when they share the same next route, which means that if the platoon is going to turn left in the upcoming intersection, then only the vehicles that also turn left are allowed to join the platoon and keep a close following distance. Second, the vehicles can enter a platoon only when they share the same lane. If the vehicle inside the platoon violates these two rules at a certain time step, then the platoon will disband, and the rest of the vehicles may reformulate a new platoon if they meet the above requirements.

CAVs should also be controlled by the default car following model when CAVs are approaching the signalized intersection. CAVs controlled by platooning mode illustrated by Eq (3.3.3.1-3.3.3.8) result in a slow approaching rate to stopped preceding vehicles, which are often seen in closely spaced signalized intersections such as superstreets. Figure 3.4 illustrates the motivation for this consideration assuming two CAVs with two different controls are approaching a stopped vehicle with a distance of 100m at the intersection. CAVs controlled by IDM reached the converged distance (IDM default desired gap 2.5m) in $20s$ while it takes $30s$ for the platooning control to reach the desired distance (platoon default desired gap 5m). If a CAV with platooning control approaches the waiting vehicles in front of intersections in a medium/high traffic volume scenario, this CAV will inevitably block other vehicles in the middle of the road. This prevents us from applying the same platooning control logic throughout the simulation.

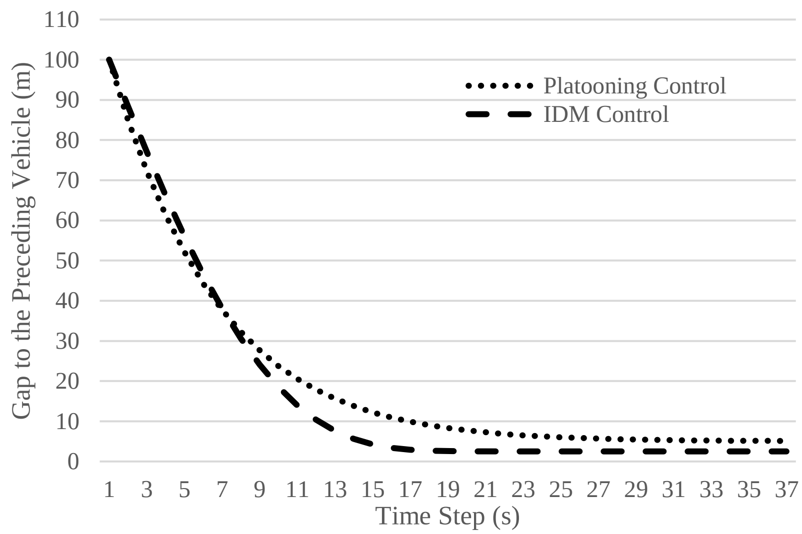


FIGURE 3.4: Gap plot for CAVs approaching a stopped vehicle with platooning control and IDM control

Based on the above discussions, the CAVs approaching the signalized intersection in the same lane, are bunched together (when their inter distance is less than 1s headway plus minimum gap, i.e., 2.5m) by sharing the same speed as their platoon leaders to pass the intersection. This design can achieve a similar effect as curve matching algorithms proposed in Gong and Du (2018) and trajectory copy in Han et al. (2020). After the CAVs exit the intersection, platoon control starts to take effect to adjust their headways properly. This research also implements the platoon split as introduced in Han et al. (2020) when the green duration is not sufficient for the whole platoon to travel through.

3.4 Trajectory Planning I with Fixed Signal Timing

3.4.1 Optimal trajectory based on accumulated absolute acceleration rates

CAVs can plan their trajectories based on the signal information obtained to achieve a certain objective, such as minimizing fuel consumption or traffic delay. The popular approach is to formulate trajectory planning as an optimal control problem whose objective can be a certain traffic performance measure. When the goal is to minimize fuel consumption or emissions, the objective function often takes a non-linear form and requires non-linear programming to obtain an optimal solution. Significant computational resources may be required in the real world. An alternative approach to achieving the optimal fuel consumption or emissions benefit is to minimize accumulated absolute acceleration rates along the trajectories according to Feng et al. (2018). First, a generalized trajectory planning problem of CAVs can be formulated with the objective of minimizing cost $\boldsymbol{C}$.

$$\min \boldsymbol{C}\,(a, v) \tag{3.4.1.1}$$

$$\begin{cases} \dot{x}(t) = v(t) \\ \dot{v}(t) = a(t) \end{cases} \tag{3.4.1.2}$$

$$\begin{cases} x(t_0) = 0 \\ v(t_0) = v_0 \end{cases} \tag{3.4.1.3}$$

$$\begin{cases} x\left(t_f\right) = D \\ v\left(t_f\right) = v\left(t_f\right) \end{cases} \tag{3.4.1.4}$$

$$-a_L \leq a(t) \leq a_{U,} \tag{3.4.1.5}$$

$$0 < v(t) < v_{max} \tag{3.4.1.6}$$

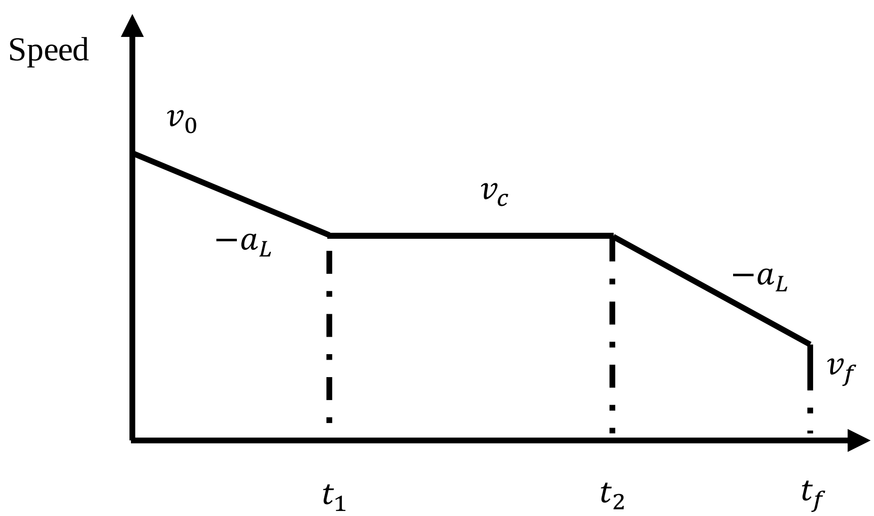
$$t_0 \leq t \leq t_f \; and \; t_f \text{ fixed} \tag{3.4.1.7}$$

where $\boldsymbol{C}(a, v)$ represents the cost function, $x(t)$ and $v(t)$ are control variables that indicate the traveled distance and instant speed value at the time step t, respectively. $a(t)$

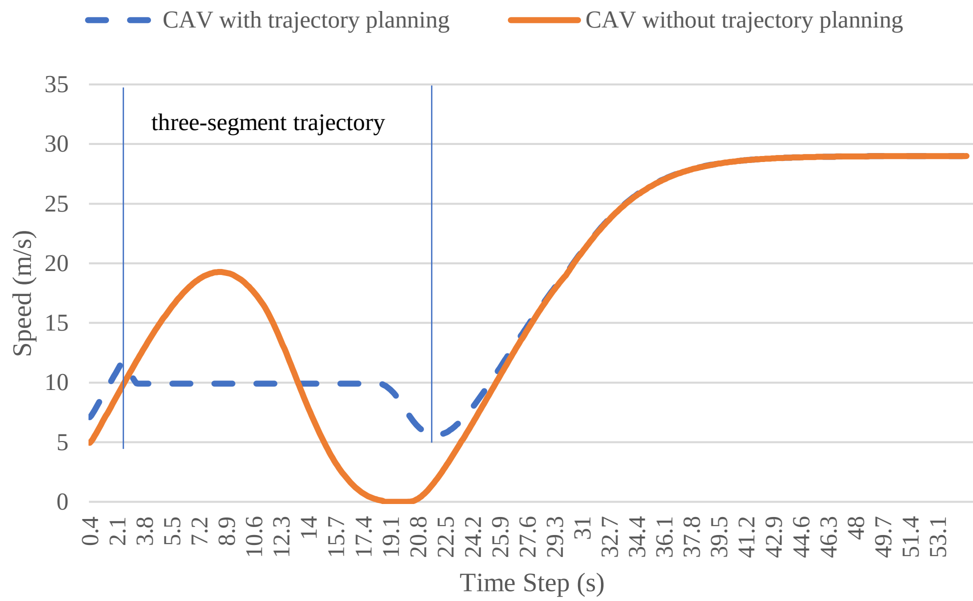
is the control variable that represents the acceleration rate at time step t. t_0 and t_f are the time steps when the CAVs start and finish the trajectory, respectively. D is the target distance that the subject vehicle needs to travel, which often is the distance between the vehicle and the intersection. The fuel consumption or emission is known to be significantly related to the acceleration rates. Feng et al. (2018) developed a trajectory planning strategy to minimize fuel consumption based on the Pontryagin's Minimum Principle (PMP). Through analysis of PMP, a generalized solution can be achieved with the objective of minimizing the accumulated absolute acceleration rates along the trajectory, which is

$$\min \boldsymbol{C} = \int_{t_0}^{t_f} |a(t)| dt \tag{3.4.1.8}$$

The solution to the optimal trajectory generally results in a three-segment trajectory, in which vehicles remain at a constant speed in the second segment. The first and the third segment have a constant either maximum acceleration or deceleration rate according to the relationship between the initial speed or final speed, as Figure 3.5a shows. Figure 3.5b provides an example comparison of when CAVs are enabled with and without such trajectory planning feature.



a. Theoretical three-segment trajectory in the deceleration case (revised from Feng et al. (2018)



b. Three-segment trajectory in simulation

FIGURE 3.5: A general optimal trajectory in the deceleration scenario

The transition time steps t_1 and t_2 can be determined given the following equations in the deceleration case ($v_0 > v_f$) and acceleration case ($v_0 < v_f$) respectively.

$$\frac{v_0 + v_c}{2} * t_1 + v_c * (t_2 - t_1) + \frac{v_f + v_c}{2} * \left(t_f - t_2\right) = D \qquad (3.4.1.9)$$

$$v_c = \begin{cases} v_0 - a_L * t_1 = v_f + a_L \left(t_f - t_2\right), & v_0 > v_f \\ v_0 + a_U * t_1 = v_f - a_U \left(t_f - t_2\right), & v_0 < v_f \end{cases} \qquad (3.4.1.10)$$

Additionally, one can obtain the lower and upper travel time boundary to guarantee that a feasible solution exists as shown below:

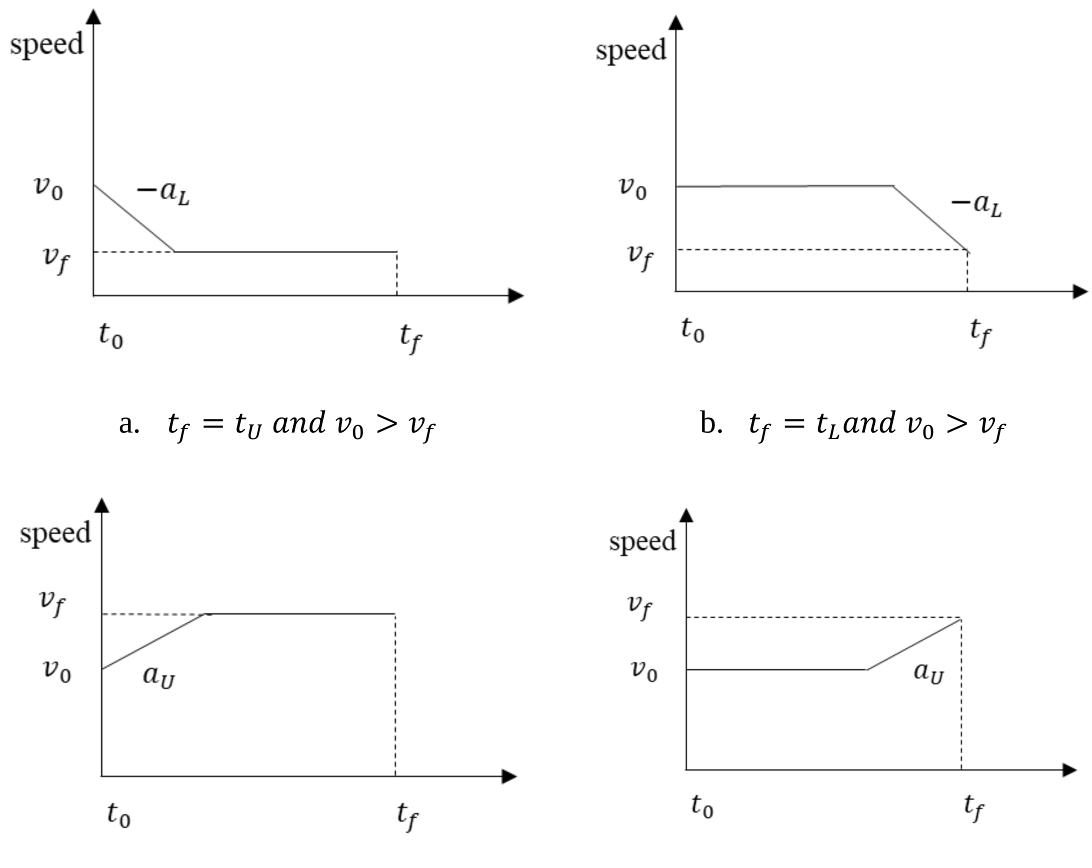
$$v_0 > v_f \begin{cases} t_L = \dfrac{D}{v_0} + \dfrac{\left(v_0 - v_f\right)^2}{2 * v_0 * \ a_L} \\ t_U = \ \dfrac{D}{v_f} - \dfrac{\left(v_0 - v_f\right)^2}{2 * v_f * \ a_L} \end{cases} \tag{3.4.1.11}$$

$$v_0 < v_f \begin{cases} t_L = \dfrac{D}{v_f} + \dfrac{\left(v_0 - v_f\right)^2}{2 * v_f * \ a_U} \\ t_U = \ \dfrac{D}{v_0} - \dfrac{\left(v_0 - v_f\right)^2}{2 * v_0 * \ a_U} \end{cases} \tag{3.4.1.12}$$

Notably, a feasible three-segment trajectory solution only exists when the vehicle arrival time t_f is strictly within the boundary of t_L and t_U, i.e.,

$$t_L < \ t_f < t_U \tag{3.4.1.13}$$

When t_f = t_L or $t_f \ = t_U$, the three-segment trajectory solution collapses into the two-segment trajectory. The lower/upper-time boundaries indicate two-segment trajectories in acceleration and deceleration respectively as shown in Figure 3.6. In a deceleration scenario, the lower boundary indicates that the vehicle keeps its current speed in the first segment and then decelerates to its final speed in the second segment. The upper boundary indicates that the vehicle first decelerates to the target final speed, and then keeps the target final speed until it arrives at the intersection. On the other hand, in an acceleration scenario, the lower boundary indicates that the vehicle first accelerates the final speed v_f and then cruises at the target speed until arriving at the intersection. When the final speed v_f is equal to the maximum speed v_{max}, such trajectory type can yield the minimum travel time $t_{minimum}$ and thus is referred to as the minimum travel time trajectory. The upper boundary in an acceleration scenario means that the vehicle first keeps its initial speed and then accelerates to its target speed. Intuitively, when the travel time is strictly within the lower- and upper-time boundaries, an optimal three-segment trajectory exists. When the travel time is equal to one of the two boundary values, a two-segment trajectory introduced above can be applied. Nevertheless, when travel time exceeds the boundary, no feasible solution exists with the given distance, acceleration rate, and initial speeds. This reflects the real-world scenarios. For example, a vehicle may not be able to decelerate to a speed of zero if the remaining distance to the intersection is too short or the initial speed is too high.



a. $t_f = t_U \ and \ v_0 > v_f$

b. $t_f = t_L and \ v_0 > v_f$

c. $t_f = t_L \ and \ v_0 < v_f$

d. $t_f = t_U \ and \ v_0 < v_f$

FIGURE 3.6: Two-segment trajectory when t_f equals to boundary values ($t_L \ and \ t_U$)

Feng et al. (2018) demonstrated that this trajectory planning strategy could successfully reduce traffic delay and fuel consumption in a standard isolated conventional intersection with a joint adaptive signal optimization algorithm. With the adaptive signal control, Equation 3.4.1.13 holds in most cases and the vehicle can avoid stops under certain traffic conditions. Nevertheless, this strategy cannot be directly transferred to a fixed signal-controlled intersection. In a fixed signal-controlled intersection, the final travel time t_f is largely dependent on the initiation time or remaining time of the target green phase in a fixed signal timing plan, where vehicles cannot avoid stopping entirely. To apply this trajectory planning scheme in a fixed signal-controlled intersection, this research also considers a constant deceleration trajectory when Equation 3.4.1.13 cannot be sufficed. For a constant deceleration trajectory, the vehicle will keep a constant deceleration rate until it arrives at the intersection with a speed of 0, as shown in Figure 3.7. The deceleration rate a_{dec} can be easily obtained through the basic kinetic law, which is described by Equation 3.4.1.14.

$$a_{dec} = \frac{v_0}{\frac{2 * D}{v_0}} \tag{3.4.1.14}$$

Based on the signal status and the next signal switch time t_{switch}, the vehicle can choose different speed trajectories as introduced above.

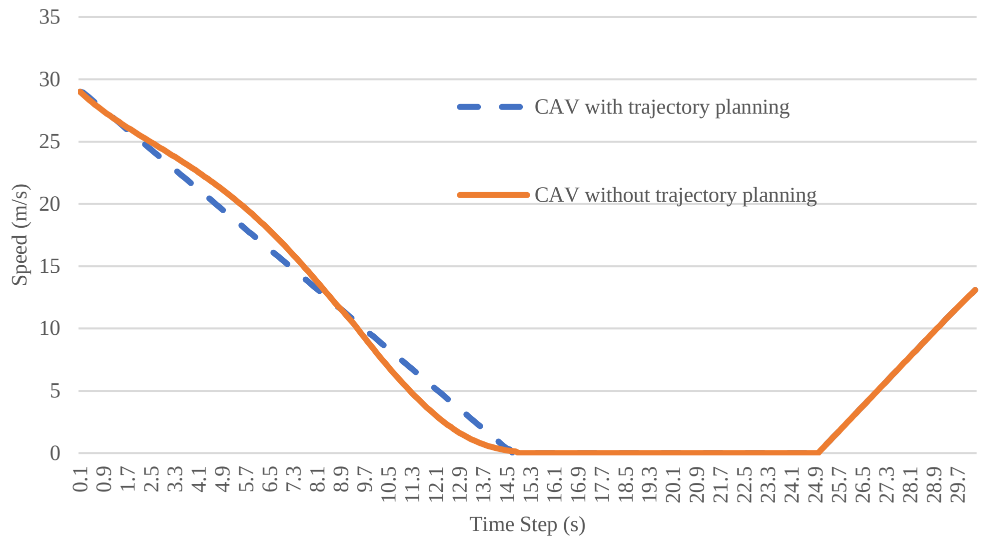


FIGURE 3.7: Constant deceleration trajectory

3.4.2 Trajectory planning at the red signal

When the upcoming signal status for the subject vehicle is red, the signal switch time t_{switch} indicates the initiation of green time. The lower time boundary obtained through Equation 3.4.1.12 is equal to the minimum travel time $t_{minimum}$ when the given final speed $v_f = v_{max}$. If the switch time t_{switch} is less than or equal to the $t_{minimum}$, then the vehicle can meet a green signal with a two-segment trajectory as shown in Figure 3.8 to achieve minimal traffic delay.

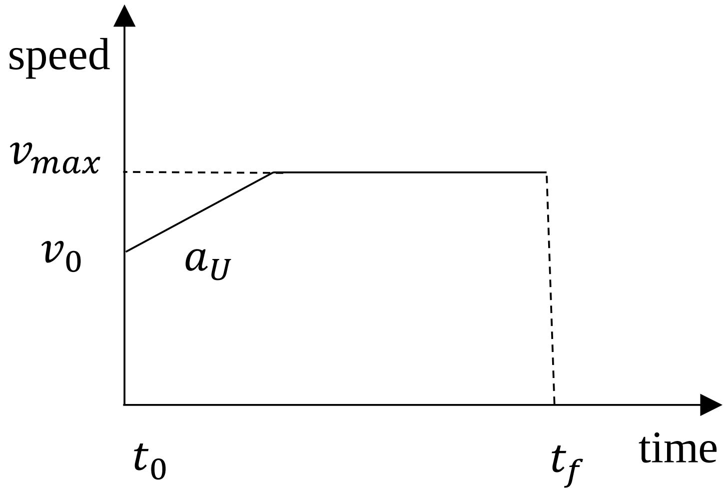


FIGURE 3.8: Speed trajectory with minimum travel time

If the switch time is greater than the minimum travel time, i.e., $t_{switch} \geq t_{minimum}$, then the vehicle with a minimum travel time trajectory will meet a red signal. In this situation, it is assumed that $t_f = t_{switch}$. From Equation 3.4.1.11 and Equation 3.4.1.12, one may obtain t_L and t_U given a final speed v_f. Hence, researchers may simply enumerate all possible final speeds $[0, v_{max})$ to obtain feasible speed candidates $\boldsymbol{V_f}$ so that Equation 3.4.2.1 stands.

$$t_L < t_{switch} < t_U \tag{3.4.2.1}$$

This research selects the max $(\boldsymbol{V_f})$ so that the subject vehicle can travel through the intersection with maximum final speed to minimize the traffic delay, where the max () function returns the maximum value among the feasible final speed list $\boldsymbol{V_f}$.

3.4.3 Trajectory planning at the green signal

If the ahead signal status is green, then $t_{signal\ switch}$ indicates the remaining green time for the subject vehicle. This research mainly considers two cases based on the relationship between signal switch time $t_{signal\ switch}$ and minimum travel time $t_{minimum}$ of the subject vehicle.

Case 1: when the subject vehicle can traverse through the intersection with minimum travel time $t_{minimum}$ (i.e., $t_{signal\ switch} \geq t_{minimum}$), then the vehicle may accelerate its maximum speed to pass the intersection to achieve the minimal traffic delay. However, this strategy may potentially increase the average fuel consumption since the fuel consumption is closely related to the acceleration rate. In some circumstances, if the $t_{signal\ switch} \geq t_{current\ speed}$, where $t_{current\ speed}$ is the travel time to the intersection when the vehicle keeps its current speed, then the decision-makers who assign a higher priority to fuel consumption may let the vehicle keep its current speed to avoid increasing fuel consumption with acceptable compromise on the traffic delay.

Case 2: $t_{signal\ switch} \leq t_{minimum}$ means that the subject vehicle cannot arrive at the intersection with the given remaining green time even if the vehicle accelerates to maximum speed. In such situation, a constant deceleration trajectory introduced above may be executed. The subject vehicle may need to check whether the vehicle can meet the second green with a given final speed within $[0\ v_{max})$ when the distance D is large.

3.4.4 Encountering preceding vehicles during trajectory planning

In the real world, the vehicles may have close preceding vehicles on the roads, and following the predetermined trajectories may lead to collisions with the preceding vehicles. Therefore, to avoid these collisions in this research, when a vehicle has preceding vehicles that are within a $3s$ headway, the vehicle will stop executing the planned trajectory and switch to the predefined car-following model, which is the IDM in this research. Note that the system constantly checks each vehicle's distance to the preceding vehicles at each time step. When the distance to the preceding vehicle is greater than $3s$ and there is an upcoming signalized intersection, then the system will plan the vehicle trajectory again for the subject vehicle to follow. With this function, the vehicles following the planned trajectory can successfully avoid collision with not only the close preceding vehicles but also the queueing vehicles in front of the intersection because of the red signal.

3.5 Adaptive Signal Control

3.5.1 Signal optimization with MILP

Adaptive signal control leverages the communication between CAVs and signalized intersection. The adaptive signal control in this research can update its phasing duration and phase sequence according to the arrival information on CAVs.

The adaptive signal control model is developed based on the work of Ding et al. (2021). In Ding et al (2021), mixed-integer quadratic programming (MIQP) was developed for CAV platoons based on the arrival times of platoon leaders and platoon length, i.e., the number of vehicles. The formulation of the MIQP model allows for a flexible phasing sequence with the introduction of Big M and auxiliary binary variables. This research utilizes the flexible phase sequence concept in the following mixed-integer linear programming (MILP) formulation. Table 3.3 illustrates the symbols that are used in the following sections.

TABLE 3.3: Descriptions of Symbols Employed in Signal Optimization Modeling

Descriptions	**Symbols**
Green start	ST

Green duration	G
Vehicle arrival time list	A
Traffic delay	D
Function returning the length of the arrival time list, i.e., the number of vehicles	$N()$
Total number of phases	P
Cycle length	C
Number of lanes	Ln
Average headway	h
Green duration set required by movements	G_M
Minimum clearance interval	c

The delay for vehicle i with a target phase p is defined as the time differences between the green start time ST_p and vehicle arrival time $A_{i,p}$, where $p \in P$ and $i \in A_p$.

$$D_{i,p} = \begin{cases} ST_p - A_{i,p}\ ; & if\ ST_p - A_{i,p} \geq 0, \\ 0; & if\ ST_p - A_{i,p} < 0 \end{cases} \tag{3.5.1.1}$$

The arrival time of vehicle i can be estimated by the remaining distance l_i divided by the current speed $v_{current,i}$.

$$A_{i,p} = \frac{l_i}{v_{current,i}} \tag{3.5.1.2}$$

Naturally, the objective function can be identified as the total accumulated delay from all the vehicles and all phases in the intersection at the current time step, i.e.,

$$\min \sum_{p \in P} \sum_{i \in A_p} D_{i,p} \tag{3.5.1.3}$$

where P is the total number of phases for the target intersection. Two crucial parameters in signal control logics are phase sequences and phase duration. Phase duration G_p can be easily determined based on traffic demand from all the movements belonging to phase p.

Assuming that traffic movement m is governed by phase p, the green duration required by movement m can be calculated as:

$$G_m = \frac{N(A_m)}{Ln_m} * h, \qquad m \in p \tag{3.5.1.4}$$

where G_m denotes the green duration required by the movement m and A_m contains the vehicle arrival times for movement m that has the target phase p. N denotes the function that returns the length of the arrival time list, i.e. number of the vehicles. Ln_m represents the number of lanes available for movement m. Let $G_{M,p}$ contain the green duration set required by each movement from phase p, then the green duration for phase p should suffice the critical traffic movement volume for phase p, i.e.,

$$G_p \geq \max(G_{M,p}) \tag{3.5.1.5}$$

Different phase sequences may cause significant performance changes in the traffic operations. Hence, this research utilizes the binary earlier indicator Ω. For a pair of conflicting phases, p and $\neg p$, constraint is presented below,

$$\Omega_{p,\neg p} + \Omega_{\neg p,p} = 1 \tag{3.5.1.6}$$

Specifically, $\Omega_{p,\neg p}$ equals to 1 when phase p turn green in advance of phase $\neg p$, which is the conflicting phase for phase p. In contrast, $\Omega_{p,\neg p}$ equals to zero when phase p turns green after its conflicting phase $\neg p$ turn green.

This research employed the formulation proposed by Ding et al. (2021) to enforce the constraint that conflicting phases do not start simultaneously. In addition, the time difference between conflicting phases should also take into account the minimum clearance time. Therefore, such constraints are presented as follows,

$$ST_p + M * \Omega_{p,\neg p} \geq ST_{\neg p} + G_{\neg p} + c \tag{3.5.1.7}$$

$$ST_{\neg p} + M * \Omega_{\neg p,p} \geq ST_p + G_p + c \tag{3.5.1.8}$$

In this research, it is assumed that the minimum clearance time is 2s. To ensure that the planned signal timing can suffice the vehicle arrivals at the current time step, the sum of the green start and green duration should be greater than the latest arrival time, i.e.,

$$ST_p + G_p \geq \max(A_p) + h \tag{3.5.1.9}$$

However, this constraint may cause the green start and green duration to become unexpectedly large, hence, penalties are added towards to green duration and green start in the objective function, which results in the final objective function as shown below.

$$\min \ w_d \sum_{p \in P} \sum_{i \in A_p} D_{i,p} + w_G * \sum_{p \in P} G_p + \ w_{ST} * \sum_{p \in P} ST_p \tag{3.5.1.10}$$

The w_G and w_{ST} are the penalty weights for the green start and green duration, respectively. These two weights need to be less than 1 since the priority objective is to minimize the traffic delay. Hence, this research selected 0.1 for these two weight values, which leaves 0.8 for the weight of the traffic delay, w_d. To sum up, the full form of the MILP model for signal optimization is presented below:

$$\min \ w_d \sum_{p \in P} \sum_{i \in A_p} D_{i,p} + w_G * \sum_{p \in P} G_p + \ w_{ST} * \sum_{p \in P} ST_p \tag{3.5.1.11}$$

$$Constraints: D_{i,p} = \max(ST_p - A_{i,p}, 0)$$

$$A_{i,p} = \frac{l_i}{v_{current,i}}$$

$$G_p \geq \max(G_M)$$

$$ST_p + G_p \geq \max(A_p) + h$$

$$\Omega_{p,\neg p} + \Omega_{\neg p,p} = 1$$

$$ST_p + M * \Omega_{p,\neg p} \geq ST_{\neg p} + G_{\neg p} + c$$

$$ST_{\neg p} + M * \Omega_{\neg p,p} \geq ST_p + G_p + c$$

The above optimization model has a MILP form that is convenient for popular commercial solvers to solve, such as CPLEX or Gurobi. This research uses Gurobi to obtain the solution in real-time.

3.5.2 Additional practical considerations for adaptive signal control

Rolling Horizon Scheme

Since vehicle arrivals vary at different time periods on the microscopic level, it is often necessary to utilize a rolling horizon scheme to update the vehicle arrival information and signal timings. In this research, the vehicle arrival information and signal timing are updated as soon as all vehicles in the previous cycle finish travelling through the intersection. This rolling horizon scheme is also illustrated in Figure 3.9, where C_n denotes the cycle length for the n^{th} cycle. The initial time for each cycle is reset as zero.

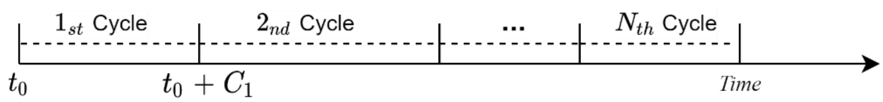
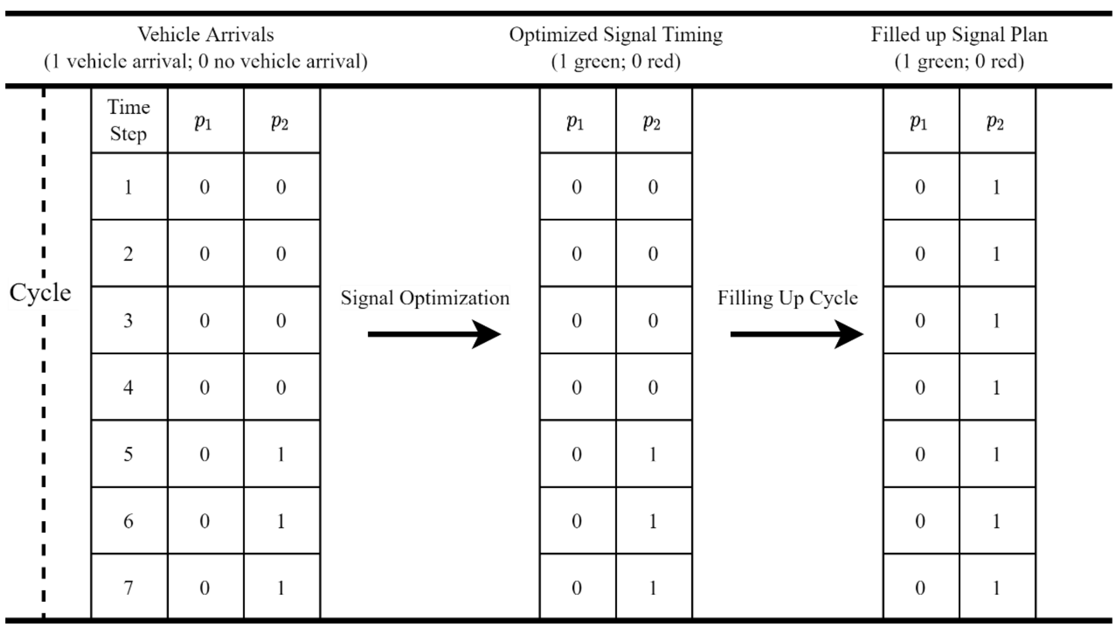


FIGURE 3.9: Rolling horizon scheme illustration

Filling up Cycle in low traffic volume scenarios

Although the proposed signal optimization model can continuously yield the optimal signal timings for vehicle arrivals in time step t, there are some extreme traffic scenarios that deserve attention. In low traffic volume scenarios, there may be no traffic for a considerable time period for a particular approach. However, the designed signal optimization scheme may produce frequent unnecessary signal switches between conflicting phases. Though these unnecessary signal switches do not compromise the traffic delay, they may cause confusion to other road users and cause extra wear on the signal displaying equipment in a real-world deployment. Therefore, when all detected vehicles belong to one phase in an intersection at time step t, the targe phase fills up all planned cycle length. Figure 3.10 illustrates this filling up cycle process.



Time Step	Vehicle Arrivals p_1	Vehicle Arrivals p_2	Optimized Signal Timing p_1	Optimized Signal Timing p_2	Filled up Signal Plan p_1	Filled up Signal Plan p_2
1	0	0	0	0	0	1
2	0	0	0	0	0	1
3	0	0	0	0	0	1
4	0	0	0	0	0	1
5	0	1	0	1	0	1
6	0	1	0	1	0	1
7	0	1	0	1	0	1

FIGURE 3.10: Filling up cycle procedure

Emergency Release in high traffic volume scenarios

In extremely high traffic volume scenarios, the minimal-traffic-delay oriented signal timing plan cause vehicles from minor approach to wait excess long periods. When vehicles have waited for two standard cycle lengths ($120s \times 2$ for this research) in front of the intersection, the signal should turn green for a sufficient duration ($3s$) so that the vehicle can pass the intersection. This operation also reflects the equity principle in traffic operations. Figure 3.11 presents the overall workflow for this adaptive signal control.

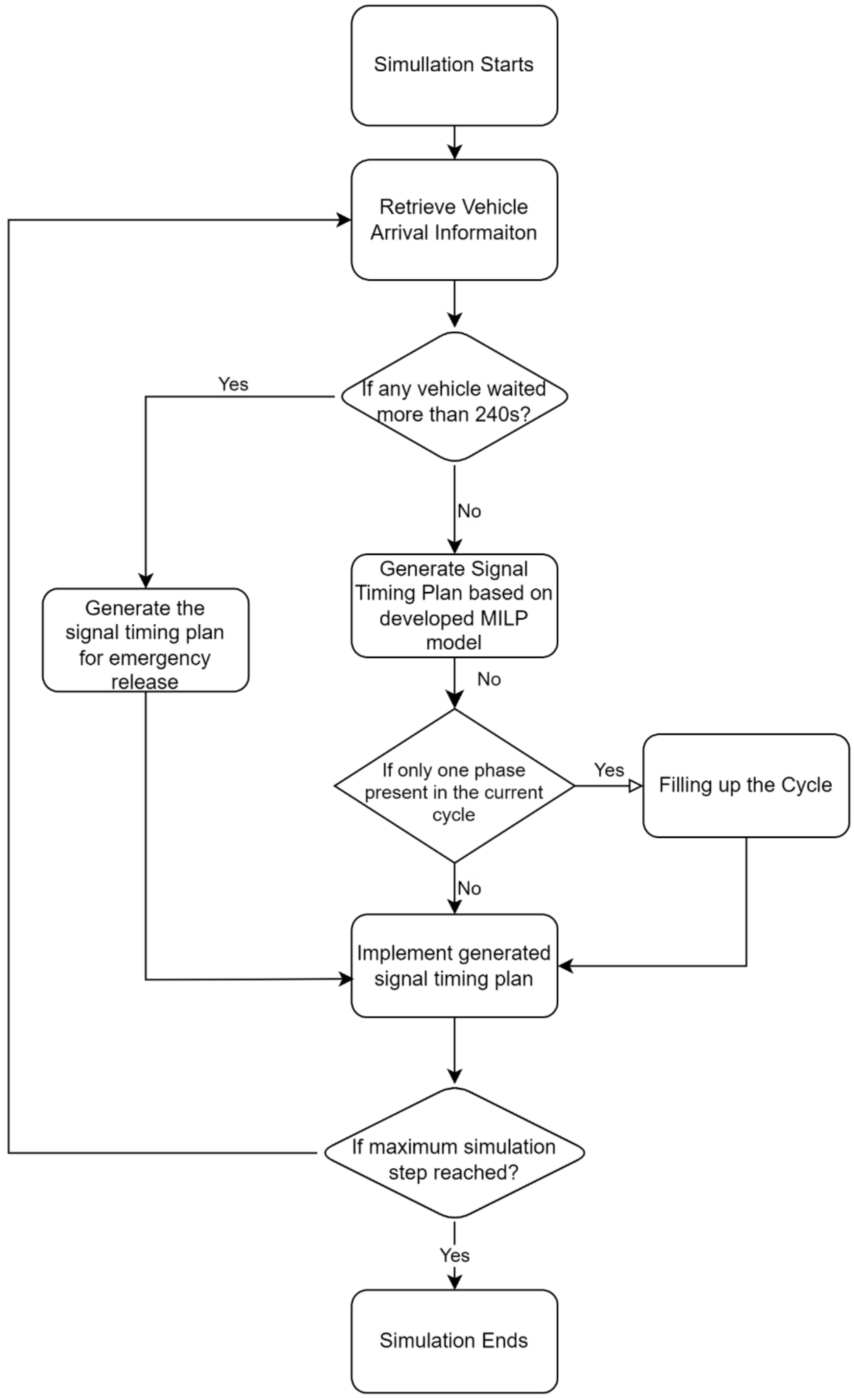


FIGURE 3.11: Overall flow chart for optimized signal timing procedures

3.5.3 Trajectory planning with adaptive signal control

For the trajectory planning under adaptive signal control, this research employs the Ding et al. (2021) model to explore the impact of CAVs. Ding et al. (2021) developed the trajectory planning based on the work of Feng et al. (2018), in which three-segment trajectory planning was proven to be an efficient approach to reduce traffic delay while preventing the fuel consumption from increasing. To avoid unstable traffic flow, Ding et al. (2021) further simplified this approach by only considering three-segment acceleration trajectories (note that two segment trajectory is a special case of three-segment trajectory when the green start time is equal to the boundary value - refer to Feng et al.(2018) and Ding et al.(2021) for more details). The discussion on trajectory planning varies based on the relationship between the earliest arrival time of vehicle i and the optimized green start ST_p. The earliest travel time i_p^e is when the vehicle accelerates with the maximum acceleration rate until it reaches the speed limits, and then it travels through the intersection with the speed limit. Equation (3.5.3.1) shows the calculation of i_p^e.

$$i_p^e = \begin{cases} \dfrac{\sqrt{\left(v_{curent,i,p}\right)^2 + 2a^U l_{i,p}} - v_{current,i,p}}{a^U}, & l_{i,p} < \dfrac{v_f^2 - v_{current,i,p}^2}{2a^U} \\ (l_{i,p} - \dfrac{v_f^2 - v_{current,i,p}^2}{2a^U})/v_f + \dfrac{v_f - v_{current,i,p}}{a^U}, & l_{i,p} \geq \dfrac{v_f^2 - v_{current,i,p}^2}{2a^U} \end{cases} \quad (3.5.3.1)$$

Case 1: $ST_p \leq i_p^e$

When the green start time for phase p is less than the earliest arrival time of vehicle i, i_p^e, the vehicle can meet a green signal with its fastest speeds, v_f. In such case, the vehicle may accelerate from its current speed $v_{current,i,p}$ with its maximum acceleration capability

a^U to the speed limits instantly, and then cruise at its maximum speed to travel through the intersection. The time required to accelerate to v_f can be obtained as follows,

$$t_1 = \frac{\left(v_f - v_{current,i,p}\right)}{a^U} \tag{3.5.3.2}$$

Case 2: $i_p^e \leq ST_p < t_{three,i,p}$

$t_{three,i,p}$ is a boundary value for vehicles that first travel with current speed, then accelerate with a^U to the speed limit, and keep driving with the speed limit to travel through the intersection. In this case, the acceleration rate of the subject vehicle experiences three stages, $\{0, a^U, 0\}$. $t_{three,i,p}$ can be obtained as follows:

$$t_{three,i,p} = \frac{l_{i,p}}{v_{current,i,p}} - \frac{\left(v_f - v_{current,i,p}\right)^2}{2 * v_{current,i,p} * a^U} \tag{3.5.3.3}$$

where $l_{i,p}$ denotes the remaining distance to the stop line. The two transition point time points t_1, t_2 for this three-segment trajectory can be calculated as follows:

$$t_1 = \frac{v_f * ST_p - l_{i,p}}{v_f - v_{current,i,p}} - \frac{\left(v_f - v_{current,i,p}\right)}{2 * a^U} \tag{3.5.3.4}$$

$$t_2 = \frac{v_f - v_{current,i,p}}{a^U} \tag{3.5.3.5}$$

Case 3: $ST_p = t_{three,i,p}$

When the boundary value $t_{three,i,p}$ equals to the green initiation time ST_p for the subject vehicle i, the three-segment trajectory collapse into two segments, in which the subject vehicle first keeps its current speed and then accelerate to its maximum allowed speed with a^U. Then the acceleration segments would be $\{0, a^U\}$. The subject vehicle reaches its maximum speed and the stop line simultaneously in this case. The split time t_1 for the two-segment acceleration trajectory can be easily calculated as follows:

$$t_1 = ST_P - \frac{v_f - v_{current,ip}}{a^U} \tag{3.5.3.6}$$

Case 4: $t_{three,i,p} < ST_p < t_{v_{current},i,p}$

$t_{v_{current,i,p}}$ is the time for the subject vehicle i to arrive at the intersection with current speed. When the green start time ST_p falls between $t_{three,i,p}$ and $t_{v_{current},i,p}$, the subject vehicle i can only reach the free speed if there is a deceleration segment. Nevertheless, a deceleration three-segment may cause unstable traffic flow and larger fuel consumption may be incurred. Therefore, to make the trajectory planning efficient and robust, a two-segment control scenario is employed, that is, {0, a^U}. The subject vehicle needs to keep the current speed long enough so that it can reach a target speed $v_f{}'$ ($v_f' < v_f$) with maximum acceleration capacity. Similar to the discussions above, the calculation of t_1 is given in Equation (3.5.3.7).

$$t_1 = ST_p - \sqrt{2 * \frac{l_{i,p} - v_{current,i,p} * ST_p}{a^U}} \tag{3.5.3.7}$$

This finishes the illustration of the trajectory planning model. Nevertheless, another issue arises when implementing trajectory planning in simulation environments. By following the predetermined trajectories, CAVs may collide with each other when the preceding vehicles slow down, and the following vehicle speeds up to catch the upcoming green signal. Due to this issue, CAVs must stop following the predetermined trajectories when their inter gap is close to a threshold. Through a trial-and-error experiment, this research selected a 1.5s headway gap as such threshold considering both safety and efficiency. This means that CAVs would switch back to default IDM car following mode when their distance is smaller or equal to 1.5s headway. Also, if i_p^e of vehicle i is greater than the sum of the green start and green duration of its target phase, then this vehicle cannot meet a green signal in the currently planned cycle. In this case, the subject vehicle will keep moving based on IDM and will not enter the trajectory planning module until the next planned cycle initiates.

3.6 Information on the Selected Location for Case Study

A superstreet situated in Leeland, NC is identified for the case study. This superstreet is selected for its typical geometric design and traffic flow characteristics. The traffic characteristic information on the selected superstreet is available in Hummer et al. (2010). Figure 3.12 shows the selected superstreet and signal locations in Google Maps and Table 3.4 provides the traffic characteristics information. The maximum speed limits are set as 29 m/s (i.e., $65mph$) for the main road and 15.6 m/s (i.e., $35mph$) for the minor road. The four minor intersections in the superstreet system are all signal controlled with a cycle length of $120s$.

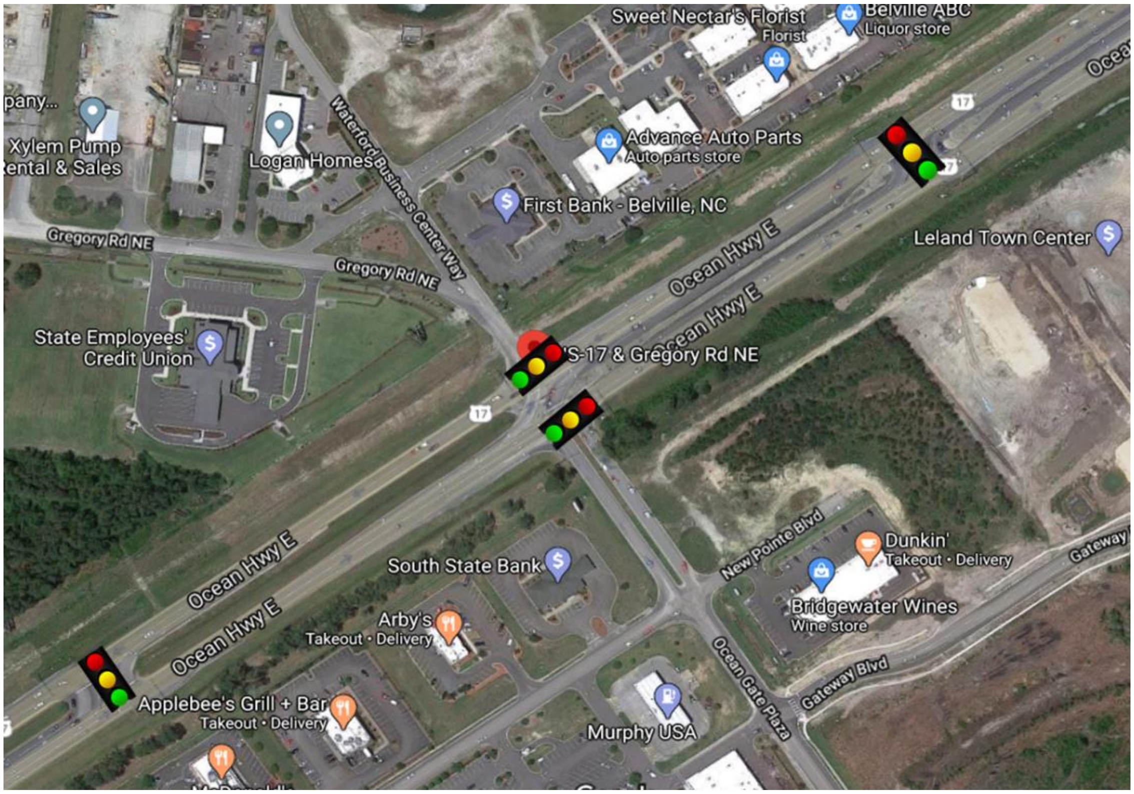


FIGURE 3.12: Selected superstreet for the case study and signal locations (adapted from the screenshot of Google Maps)

TABLE 3.4: Traffic Characteristic Information on the Superstreet at Leeland, NC

Approach	Average speed (m/s)/(mph)	Peak hour demand	Average stops	Travel time (Minutes)
EBL	5.99/13.40	18	3	2.45
EBR	6.93/15.50	20	2	1.38
EBT	5.68/12.71	9	2	2.25
NBL	8.00/17.90	20	1	1.17
NBR	14.08/31.50	71	0	0.64
NBT	14.75/33.00	2029	0	0.81
SBL	5.72/12.80	321	1	1.26
SBR	14.26/31.90	38	0	0.4
SBT	19.58/43.80	1637	0	0.58
WBL	8.09/18.10	66	2	2
WBR	7.69/17.20	345	1	0.89
WBT	5.05/11.30	11	2	2.09

3.7 Simulation Scenarios and Relevant Settings

An equivalent conventional intersection with the same road segment length, lane configuration, and maximum speed is designed in the simulation platform. The cycle length is also set the same as the superstreet in the real world, i.e., 120s, to make a fair comparison. The green splits for each approach are determined by their volume ratios. To account for different traffic conditions, this research tests four different traffic scales including 25%, 50%, 75%, and 100% of peak hour traffic volumes from Table 3.2. Furthermore, a market penetration analysis is conducted on the 100% peak hour traffic volumes. 25%, 50%, and 75% of CAV market penetration rates are considered in the simulation. Every scenario is run five times with different random seeds to account for the randomness. To make the system more robust and increase calculation accuracy, the simulation resolution is set as 10HZ, which means that the simulation runs 10 time steps every second. Once the vehicle enters the roadway network, the vehicle is assumed to enter the Vehicle-to-Infrastructure (V2I) communication range, which is reasonable since the selected superstreet has a rather short road segment length in all approaches before the traffic signals (less than 300m). Average traffic delay (delay per vehicle) and fuel consumption (fuel consumption per vehicle) are the performance indicators that are used for this research. Traffic delay is measured by the ideal travel time (free-flow speed without any stop) minus actual travel time. Fuel consumption is measured by the default emission model from SUMO, i.e., HBEFT.3 (Krajzewicz et al., 2015). In the following chapter, the traffic delay and fuel consumption are denoted as TD and FC respectively. The maximum acceleration rates and deceleration rates for IDM are set as 2.5 m/s^2. Considering drivers' comfort, the maximum acceleration rate and deceleration rate in CAV trajectory planning are 2 m/s^2. The simulation experiment for Section 4.2 and the adaptive signal control in Section 4.3 last for 3600s. The remaining experiments from Section 4.3 last for 1800s to facilitate this research.

CHAPTER 4 RESULTS AND DISCUSSIONS

4.1 Introduction

This chapter discusses the simulation results in different scenarios as defined in Chapter 3. The results and discussions are divided into two parts. The first part focuses on the results of platooning control I and trajectory planning I at fixed signal timing, while the second part circulates the platooning control II and adaptive signal control signal timing. The results and discussions cover different traffic scales, different environments, and different performance indicators.

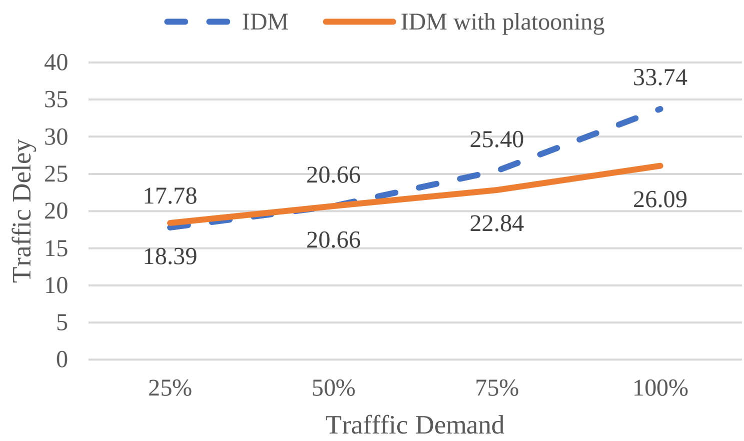
4.2 Platooning Control I and Trajectory Planning Control I with Fixed Signal Timing Strategy

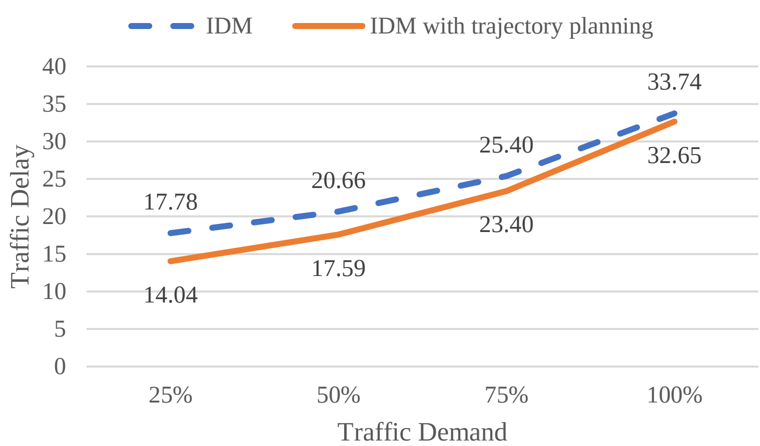
4.2.1 The performance of CAVs in conventional intersections

4.2.1.1 Traffic delay

To provide an initial understanding of the performance of CAVs, this research first obtains the simulation results of CAVs for the equivalent conventional intersection. The traffic delays results are presented in Figure 4.1. From Figure 4.1, it can be observed that the developed platooning, trajectory planning, and platooning-based trajectory planning can reduce the traffic delay in most scenarios. The exception is CAVs with platooning at the 25% demand level. When CAVs are enabled with platooning, the speed of the following vehicles is influenced by the leading vehicle in the same platoon and may not be able to achieve their maximum speeds even in light traffic volume scenario. This may potentially explain that no benefit is gained for platooning in the traffic demand of 25%

and 50% peak hour traffic volume scenarios. The traffic delay improvements for CAV with platooning increase as the traffic demand increases.





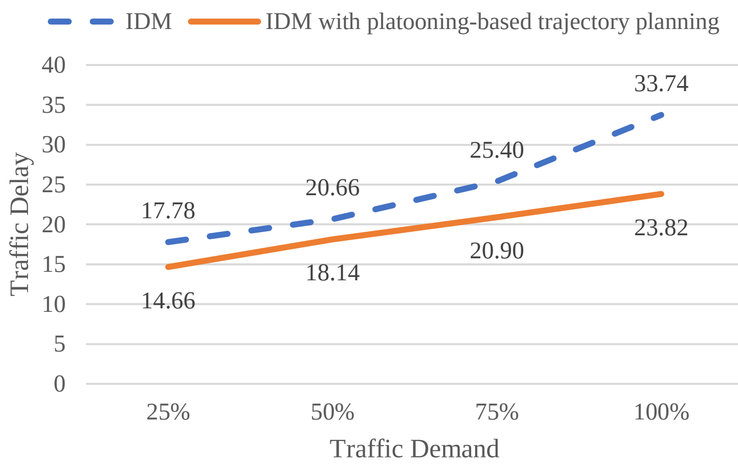
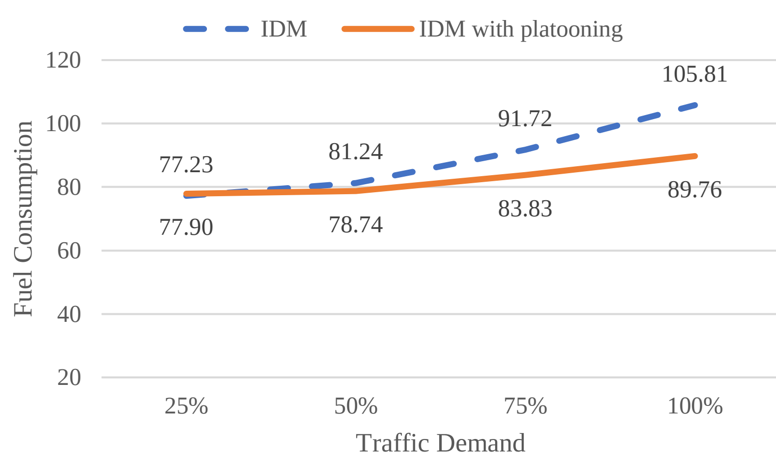


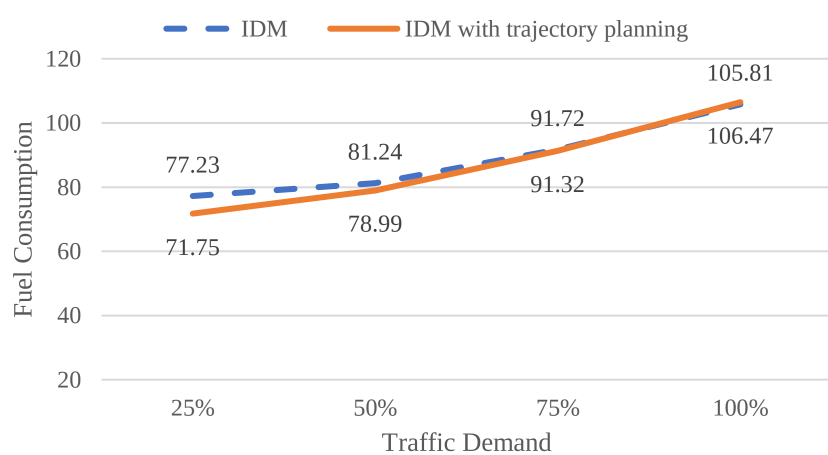
FIGURE 4.1: Average traffic delay (s) of CAVs in the equivalent conventional intersection

Trajectory planning can reduce traffic delay to a larger extent in light traffic volume scenarios, and the improvement magnitudes shrink as the traffic volumes increase. These results can be explained by the trajectory planning modeling framework. As mentioned in the methodology section, to avoid collisions with preceding vehicles and queueing vehicles in front of the intersection, CAVs with trajectory planning may switch to the default car following model frequently in high traffic demand scenarios. For CAV with platooning-based trajectory planning, the traffic delays share a similar trend as the ones from CAV with platooning. Notably, platooning-based trajectory planning also successfully reduces the traffic delay in low traffic demand scenarios.

4.2.1.2 Fuel consumption

From Figure 4.2, it can be observed that platooning could provide larger benefits in terms of fuel consumption in high traffic volume scenarios. The improvement magnitudes are also consistent with existing studies on platooning (Alam et al., 2015). The proposed trajectory planning framework reduces the average fuel consumption to a certain extent in low traffic volume scenarios. However, the fuel consumption benefits from trajectory planning are less significant compared to platooning. In addition, the trajectory planning framework may produce adverse effects towards fuel consumption in high traffic volume scenarios, as observed in 100% peak hour traffic volume scenarios. In high traffic volume scenarios, CAVs with trajectory planning capability change to the car following model frequently because of the presence of preceding vehicles, which may produce speed fluctuations and higher fuel consumption. CAV with platooning-based trajectory planning produces the optimal fuel consumption results on most traffic demand levels.





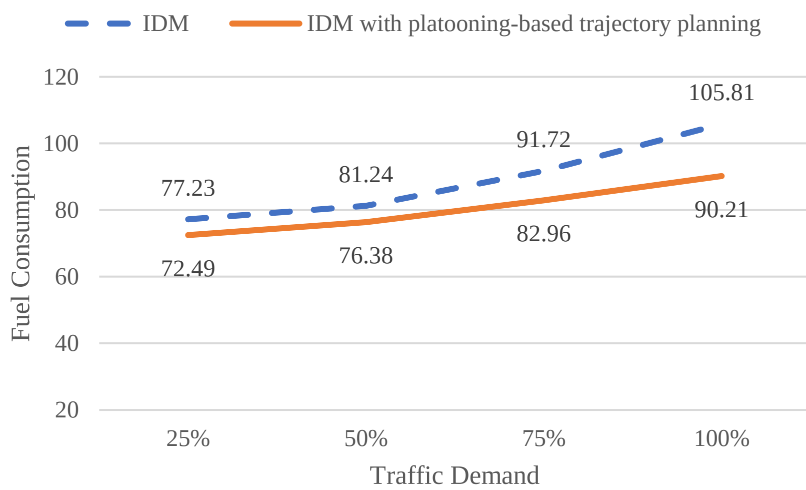


FIGURE 4.2: Average fuel consumption (ml) of CAVs in the equivalent conventional intersection

4.2.1.3 Comparison between CAVs and HDVs with calibrated W99

This research examines the performance of the calibrated W99 model, IDM model, IDM with platooning, IDM with trajectory planning, and IDM with platooning-based trajectory under 100% peak hour traffic volume, respectively.

Although it is expected that CAVs outperform HDVs, it may not be necessarily always true in the real world. For instance, when the vehicle travels through a congested intersection, HDVs are likely to have shorter headways and practice emergency deceleration or acceleration to achieve the minimal travel time or avoid collisions, while CAVs cannot exceed the predetermined boundary of safe headway and acceleration rates. According to Figure 4.3, the results from calibrated W99 and IDM prove this assumption since they have similar average delays and fuel consumptions.

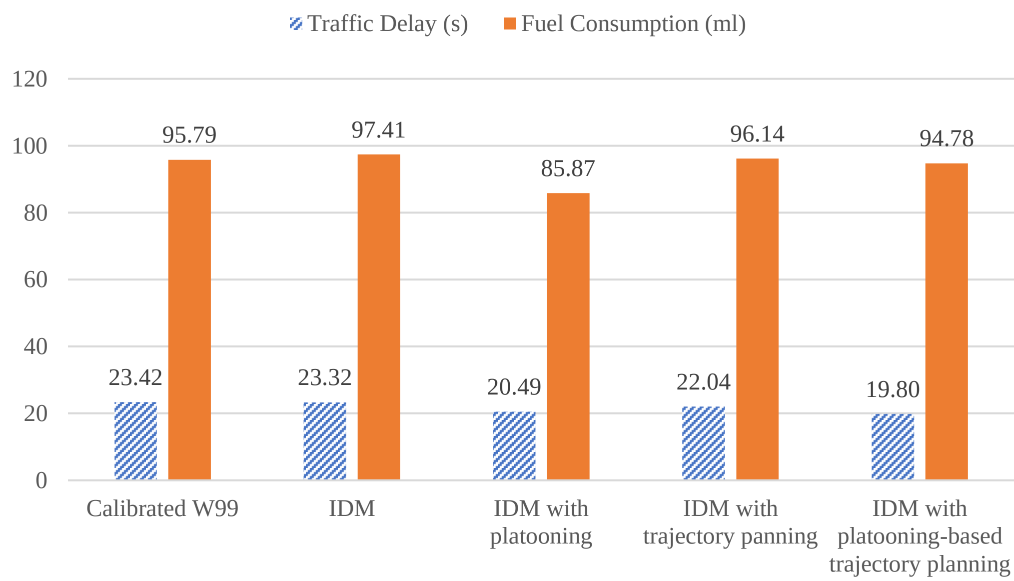


FIGURE 4.3: Traffic performances in different scenarios

However, when CAVs are enabled with platooning and trajectory planning, the CAVs may be superior to HDVs. For the proposed platooning model, compared to the IDM model, the traffic delay decreases from 23.42 to 20.49 (around 13% reduction), while the fuel consumption decreases from 95.79 to 85.87 (around 10% reduction). Since HDVs with calibrated W99 have similar traffic delay and fuel consumption, similar improvements can be found when comparing CAV with platooning against HDVs with calibrated W99.

The outstanding performance of platooning performances may be related to the large traffic volume in this scenario. On the other hand, IDM with trajectory planning has few benefits in terms of both traffic delay and fuel consumption compared to IDM only. As described in the previous section, CAVs will change into the car following model when they detect vehicles that are within a 3s headway. In a congested traffic condition such as 100% peak hour traffic volume, the advantages of trajectory planning are significantly compromised. As for CAVs with platooning-based trajectory planning, the traffic delay decreases and reaches the lowest traffic delay (19.80s) among all scenarios, while the fuel consumption is lower compared to CAVs with trajectory planning and higher compared to CAVs with platooning. CAVs with platooning and trajectory planning, when vehicles are close to each other, form a platoon so that trajectory planning can be executed, which explains the greater traffic delay reduction in CAVs with platooning-based trajectory planning. The fuel consumption of platooning-based trajectory planning is higher than ones of platooning but lower than the ones of trajectory planning.

4.2.2 The performances of CAVs in superstreets

4.2.2.1 Traffic delay

Figure 4.4 presents the average traffic delay when CAVs are enabled with platooning, trajectory planning, and platooning-based trajectory planning. CAVs with platooning have similar performances as they do in the equivalent conventional intersection. When the traffic scale is at 25% of the peak hour traffic volume, the CAVs with platooning fails to reduce the average traffic delay. Nevertheless, when the traffic demand is greater or equal to 50% of the peak hour traffic volume, the CAVs starts to reduce the traffic delay in the superstreet.

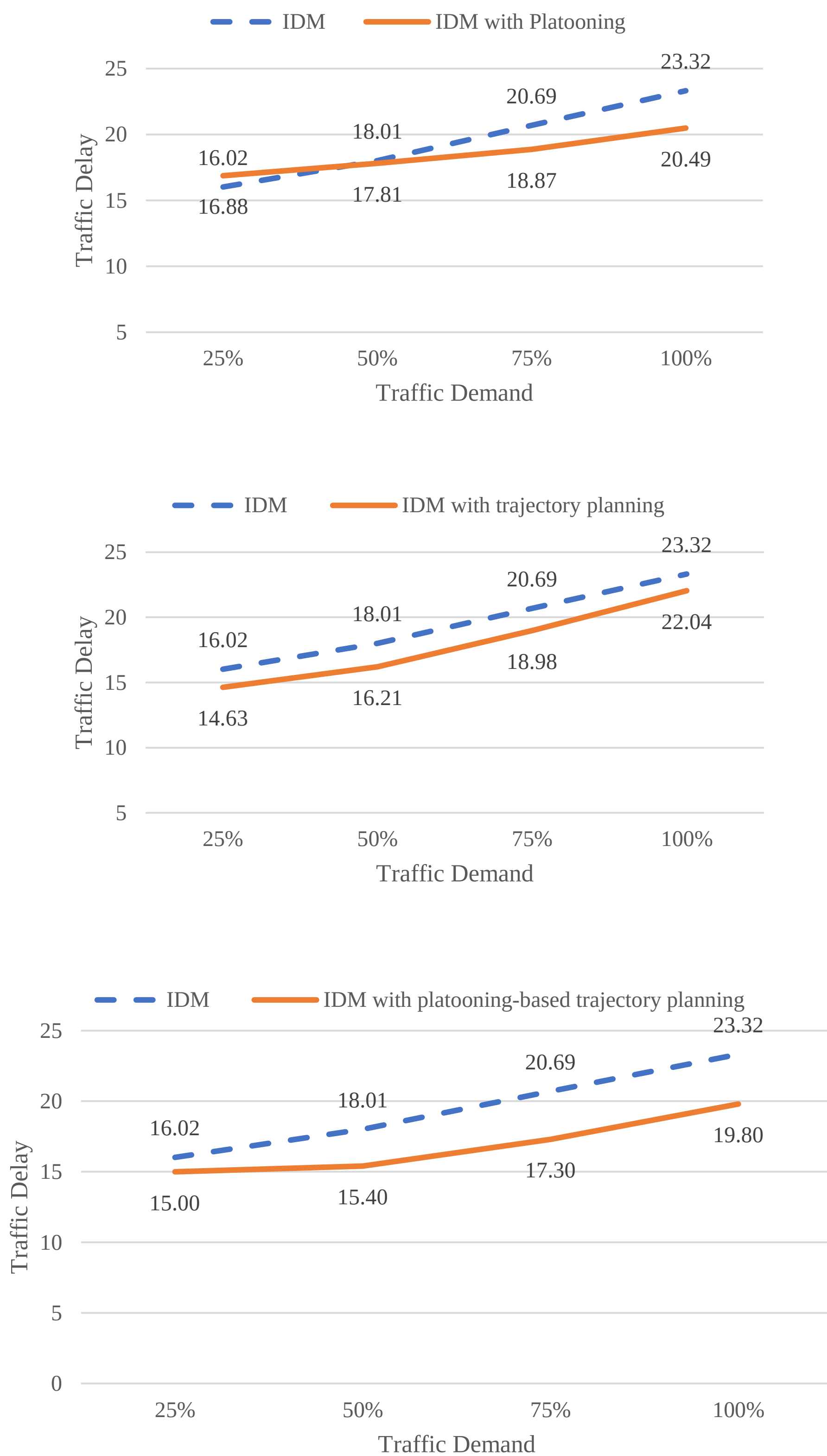


FIGURE 4.4: Average traffic delay (s) of CAVs in the superstreet

As for trajectory planning, the reductions of traffic delay in different demands are relatively constant compared to the ones in the conventional intersection. In superstreet, the road capacity often is larger than the equivalent conventional intersection. Therefore, CAVs might not have to switch to the car-following model frequently as they do in the equivalent conventional intersection in a 100% peak hour traffic volume demand, which explains the relevant constant traffic delay reduction.

CAVs with platooning-based trajectory planning still produces minimal traffic delays at nearly all demand levels (except in the 25% peak hour traffic demand scenario). The general trend of traffic delays is similar to that in platooning scenarios as in the equivalent conventional intersection.

4.2.2.2 Fuel consumption

Figure 4.5 presents the fuel consumption of CAVs in the superstreet. Platooning yields similar fuel consumption trends as it does in the traffic delay results. Nevertheless, CAVs with trajectory planning produce higher average fuel consumption, especially in the lower traffic demand scenarios. The increased average fuel consumption is potentially attributed to two reasons: 1) the acceleration behavior of CAVs with trajectory planning to catch the remaining green or initiation green time; 2) CAVs with trajectory planning may stop at the second consecutive intersection after passing the first intersection with acceleration in the superstreet system. In high traffic volume scenario, the adverse effects of fuel consumption are alleviated since CAVs with trajectory planning do not have much freedom of accelerating before the intersection. This result demonstrates the necessity of incorporating information on two consecutive signals in designing a trajectory planning framework when two signals are closely spaced. The adverse effects on fuel consumption are alleviated when CAVs are enabled with platooning-based trajectory planning.

FIGURE 4.5: Average fuel consumption (ml) of CAVs in the superstreet

4.2.2.3 CAVs with different market penetration rates

The dominance of CAVs on the roads is a gradual process in which technology, political and legal challenges continuously remain. The policymakers may be interested in the performances of CAVs at different levels of market penetration rates. Therefore, this research also conducts a sensitivity analysis of the market penetration where HDVs controlled by calibrated W99 and CAVs controlled by IDM with platooning-based trajectory planning coexist. 25%, 50%, and 75% CAV market penetration rates are tested under the 100% peak hour traffic volume scenario. When CAVs are following HDVs, CAVs are often assumed to have a larger headway (Yu and Fan, 2018). Therefore, when CAVs are following HDVs, the CAV headway is set the same as HDVs, i.e., 1.6s. Figure 4.6 provides the results of the market penetration analysis. Based on Figure 4.6, it can be observed that traffic delay starts to fall at the market penetration of 75% CAVs where the fuel consumption is similar to that of 0% CAV. The fuel consumption and traffic delay are highest when the market penetration rate of CAVs is at the 50% level. Overall, the more mixed the vehicle types are (i.e., equal market penetration rate of CAVs and HDVs), the worse the traffic performance is.

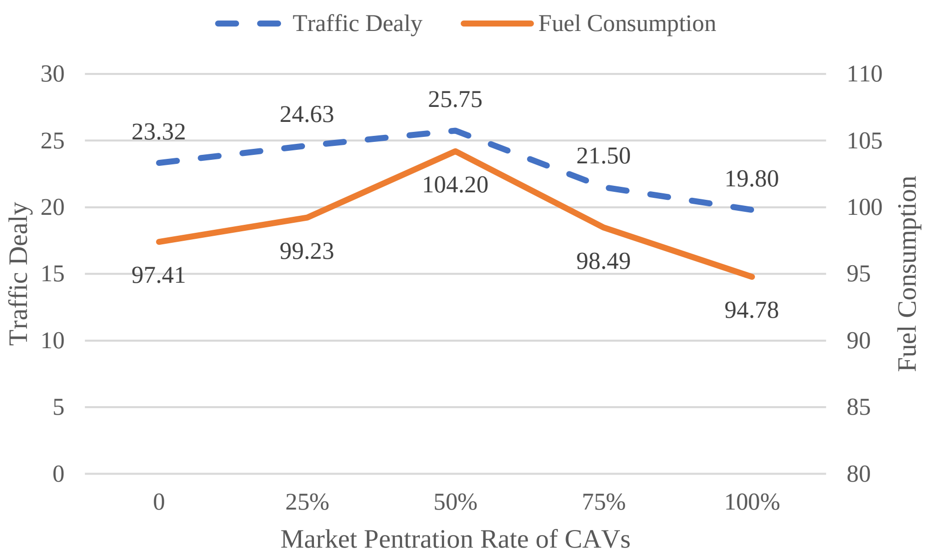


FIGURE 4.6: Analysis for different CAV market penetration rates

4.2.3 A comparison between conventional intersection and superstreet

Figure 4.7 and Figure 4.8 compare the average traffic delay and fuel consumption of CAVs in the equivalent conventional intersection and superstreet, respectively. Based on Figure 4.7, with IDM vehicles, the superstreet can consistently outperform equivalent conventional intersection regarding average traffic delay. However, it could also be observed that the average traffic delay differences between the conventional intersection and superstreet are reduced in platooning and platooning-based trajectory planning scenarios.

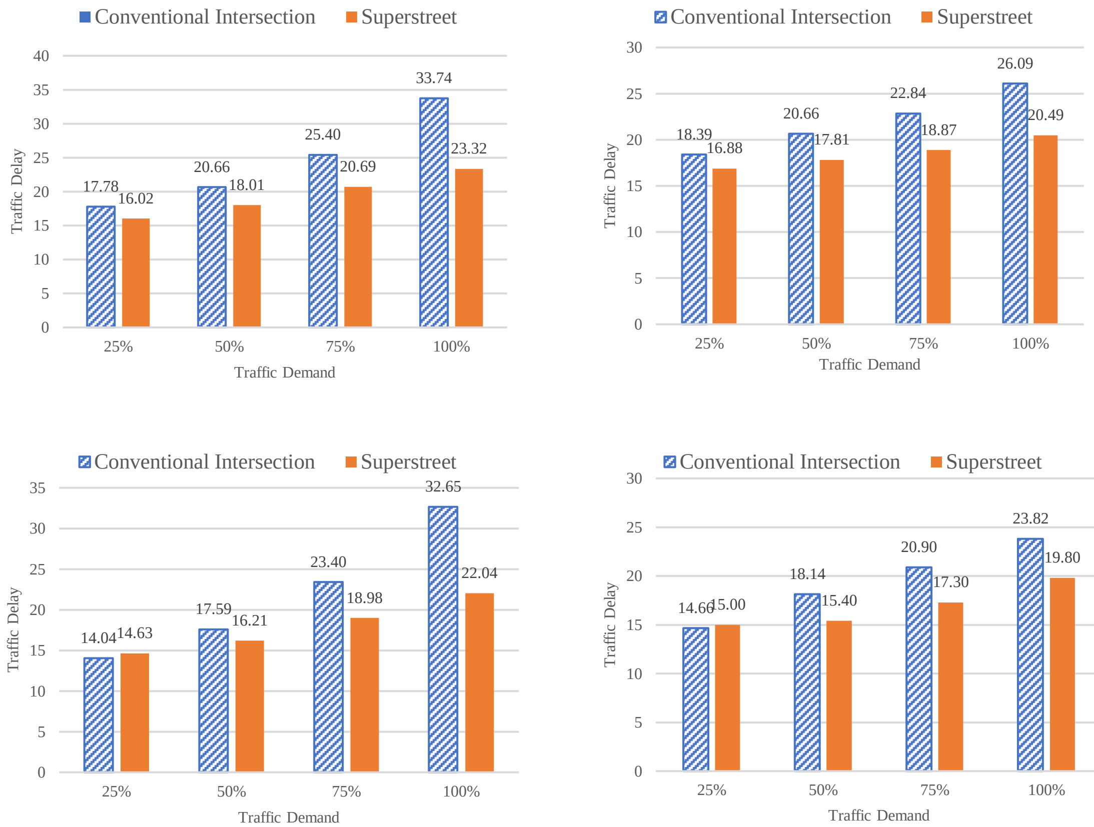
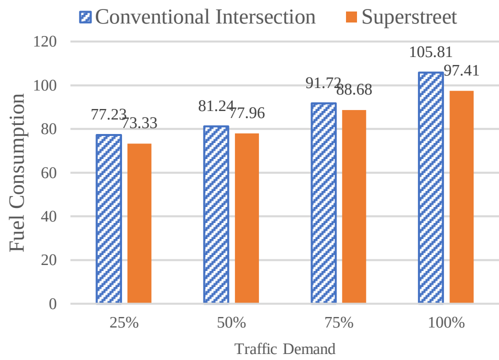
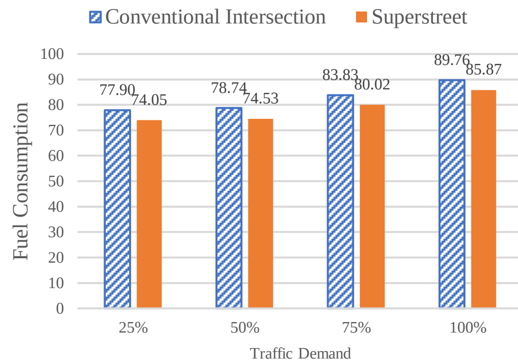


FIGURE 4.7: Average traffic delay(s) comparison of CAVs between the conventional intersection and superstreet

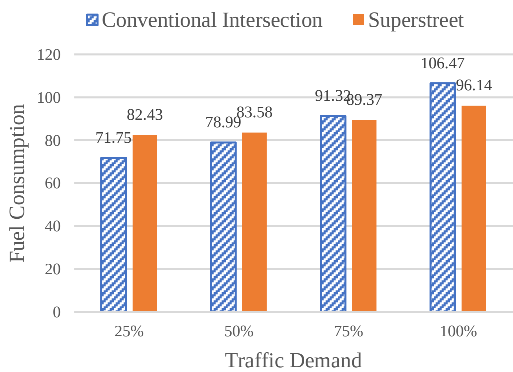
As for fuel consumption, Figure 4.8 shows that the average fuel consumptions of CAVs with trajectory planning are higher when they are in the superstreet under 25% and 50% peak hour traffic volume scenarios. When CAVs are enabled with platooning-based trajectory planning, they have higher average fuel consumption on all demand levels in the superstreet. As explained in the previous section, this may potentially result from the lack of consideration on two closely spaced signalized intersections when developing the trajectory planning control framework.



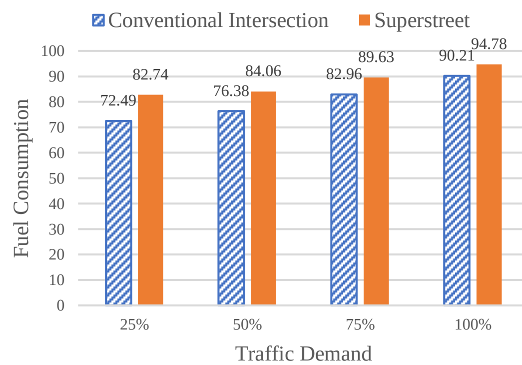
a. IDM



b. IDM with platooning



c. IDM with trajectory planning



d. IDM with platooning-based trajectory planning

FIGURE 4.8: Average fuel consumption (ml) comparison of CAVs between the conventional intersection and superstreet

4.3 Platooning Control II and Adaptive Signal Control

4.3.1 Platooning control II

The platooning control system is designed primarily to maintain a constant close distance, and the fuel consumption may increase when the following vehicles accelerate to achieve a close headway. Nevertheless, the fuel consumption and traffic delay are expected to be reduced when CAV platoons allow more vehicles to traverse the intersection given a short green signal duration. The simulation results for CAV with and without platooning control under a fixed signal timing control are presented in Table 4.1 and Table 4.2. When

CAVs are equipped with platooning control, average traffic delay is reduced for both superstreet and conventional intersections. They also show a similar increasing trend of improvement magnitudes as the traffic volume increases. This is expected since when there are more vehicles, there are more chances that platooning control can take effect. The fuel consumption benefits are relatively less significant for these two environments but still show a similar trend. A notable result is that, with light traffic volumes, platooning can still yield fuel consumption reduction (1%) in superstreet but not in the conventional intersection (-1%). The reason for this slight difference is most likely to be the multiple signalized intersections for vehicles to travel through in the superstreet environment. When multiple intersections are present, CAVs have less chance to burn gasoline to accelerate even in platooning control systems. When the traffic volume is 100% of the peak hour volume, the equivalent conventional intersection is far more congested than the superstreet, and therefore, platooning can deliver more improvement in traffic delay and fuel consumption.

TABLE 4.1: CAVs With and Without Platooning in the Superstreet

Traffic Scale	**25%**		**50%**		**75%**		**100%**	
Control	With Platooning	No Platooning	With Platooning	No Platooning	With Platooning	No Platooning	With Platooning	No Platooning
TD (s)	16.10	16.77	16.09	18.22	16.60	20.78	18.32	24.42
Improvement	**4%**		**12%**		**20%**		**25%**	
FC (ml)	73.46	74.37	77.83	79.15	88.49	92.67	98.71	104.17
Improvement	**1%**		**2%**		**5%**		**5%**	

TABLE 4.2: CAVs With and Without Platooning in the Equivalent Conventional Intersection

Traffic Scale	**25%**		**50%**		**75%**		**100%**	
Control	With Platooning	No Platooning	With Platooning	No Platooning	With Platooning	No Platooning	With Platooning	No Platooning
TD (s)	16.81	17.50	18.42	20.85	19.75	24.87	21.14	32.92
Improvement	**4%**		**12%**		**21%**		**36%**	
FC (ml)	79.56	78.94	83.67	83.40	92.39	95.43	100.37	110.41
Improvement	**-1%**		**0%**		**3%**		**9%**	

4.3.2 Adaptive signal control

Figure 4.9 presents the traffic delay and fuel consumption reductions when the adaptive signal control in Section 3.5.1 and Section 3.5.2 is implemented. The proposed signal timing strategy can yield significant benefits in terms of both traffic delay and fuel consumption. The highest traffic delay reaches up to 75% when light traffic volume is present. As for the fuel consumption, the reduction ranges from 9% to 17% at different traffic scales. A general trend is that the improvement magnitudes decrease as the traffic volume increases in superstreet.

Figure 4.10 shows the effects of proposed signal timing with CAVs in the environment of conventional intersection. It can be easily seen that the optimized signal timing with CAVs also has a good performance, and the performance also deteriorates as the traffic volumes increase in the conventional intersection. The better performance observed in the superstreet may be attributed to the fact that superstreet have fewer conflicting movements in the intersections, which gives more flexibility in signal optimization.

FIGURE 4.9: Comparison between fixed signal (FS) timing and optimized signal (OS) timing with CAVs in terms of traffic delay and fuel consumption in the superstreet

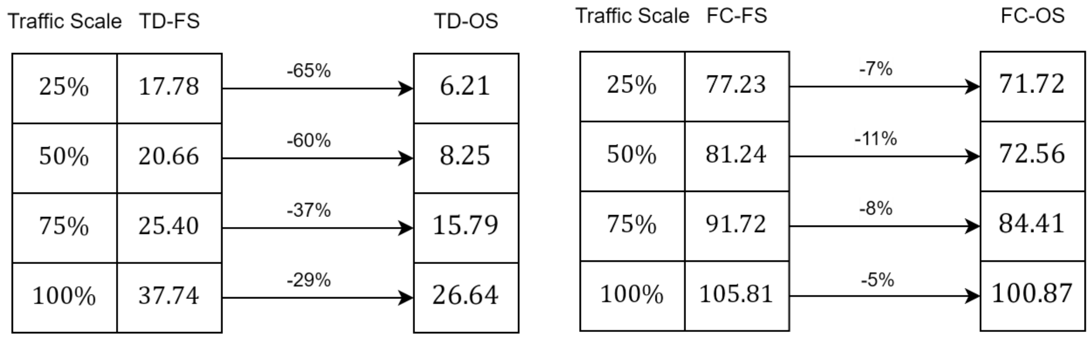


FIGURE 4.10: Comparison between fixed signal (FS) timing and optimized signal (OS) timing with CAVs in terms of traffic delay and fuel consumption in the equivalent conventional intersection

Adaptive signal control in superstreet with different arm length

Superstreet presents various forms in the real world to suit local needs. Therefore, it is necessary to test whether the signal timing optimization can have consistently good performance with different configurations. With the same lane configuration and traffic volume information provided in Table 3.4, this research tests different arm lengths for the minor intersections in superstreet (original length is about $150m$ for the minor street and $250m$ for the main street). According to Table 4.3, the proposed signal control can have stable performances with different arm lengths for superstreet.

TABLE 4.3: Adaptive Signal Control with Different Arm Lengths in Superstreet

		FS	**OS**	**Improvement**
200m	TD	24.26	14.87	38%
	FC	93.64	86.44	8%
300m	TD	25.37	15.33	40%
	FC	115.59	106.61	8%
400m	TD	26.79	15.93	41%
	FC	141.06	130.94	7%

4.3.3 Trajectory planning II under adaptive signal control

Table 4.4 presents the average traffic delay and fuel consumption results with and without trajectory planning (denoted as TP in Table 4.4 and Table 4.5) under signal optimization in superstreet. The improvement magnitudes decrease when the traffic scale becomes larger. This is understandable since the trajectory planning module needs to be switched back to the default car following model frequently when CAVs encounter preceding vehicles in medium/high traffic volumes scenarios. The improvement magnitudes drop from 7% to 0% when traffic volumes increase from 25% to 100%. The fuel consumption is relatively insignificant, which is likely to be attributed to the unstable traffic flow caused by multiple sub intersections in superstreet. According to Table 4.4, the equivalent conventional intersection has relatively more advantages as the traffic flow is more stable due to fewer intersections. The reduction in traffic delay shows a similar trend as that in superstreet. The highest improvement for conventional intersection reaches 10% in terms of traffic delay in low traffic volume scenarios. The fuel consumption reduction brought by trajectory planning is around 2% in different traffic scales, which is still better than it does in superstreet.

TABLE 4.4: Traffic Delay and Fuel Consumption for CAVs With and Without TP under Signal Optimization in Superstreet

Traffic Scale	**25%**		**50%**		**75%**		**100%**	
Control	With TP	No TP	With TP	No TP	With TP	No TP	With TP	No TP
TD (s)	3.85	4.13	5.32	5.59	9.00	9.06	13.75	13.81
Improvement	**7%**		**5%**		**0%**		**0%**	
FC (ml)	61.63	61.37	66.00	66.24	80.47	80.49	95.36	94.69
Improvement	**0%**		**0%**		**0%**		**0%**	

TABLE 4.5: Traffic Delay and Fuel Consumption for CAVs With and Without TP under Signal Optimization in Conventional Intersection

Traffic Scale	**25%**		**50%**		**75%**		**100%**	
Control	With TP	No TP	With TP	No TP	With TP	No TP	With TP	No TP
TD (s)	5.5	6.12	8.54	9.26	16.07	17.42	26.91	27.86
Improvement	**10%**		**8%**		**8%**		**3%**	
FC (ml)	70.44	71.37	73.48	75.07	85.63	89.41	105.44	107.13
Improvement	**1%**		**2%**		**3%**		**2%**	

4.4 Platooning and Trajectory Planning Approach Comparison

This section compares two sets of platooning controls and trajectory planning controls. Since two sets of platooning controls and trajectory planning controls have different assumptions and model structures, this section only discusses the improvement magnitudes. Figure 4.11 and Figure 4.12 show the improvement magnitudes of traffic delays and fuel consumption between two platooning controls in the conventional intersection and superstreet. Platooning control II clearly has better performances in terms of traffic delay but not fuel consumption. This may be attributed to more acceleration behaviors to maintain close headway when vehicles leave the intersections in platooning control II. Figure 4.13 and Figure 4.14 show the comparison between trajectory planning I and trajectory planning II in terms of traffic delay and fuel consumption respectively. For trajectory planning controls, trajectory planning control I shows superiority in terms of traffic delay but not fuel consumption, which is understandable as the trajectory planning control II does not consider the deceleration cases to avoid unstable traffic flows. Unstable traffic flows are likely to cause fuel consumption to increase in trajectory planning control I.

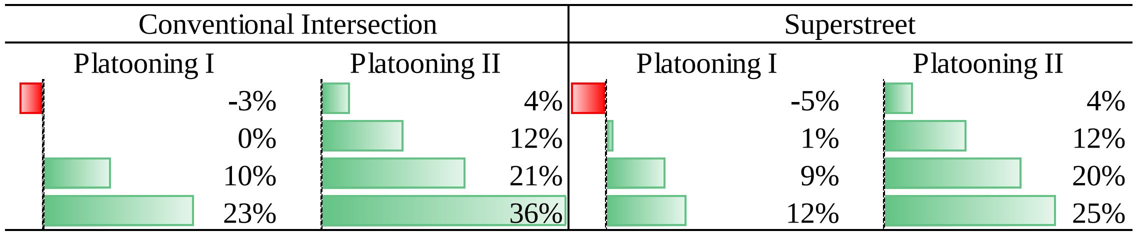


FIGURE 4.11: Traffic delay improvement magnitudes between two platooning controls

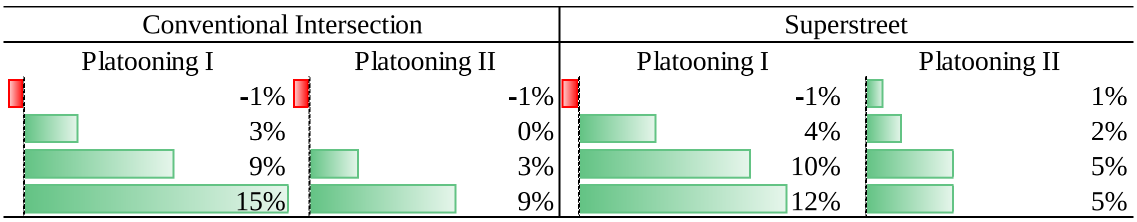


FIGURE 4.12: Fuel consumption improvement magnitudes between two platooning controls

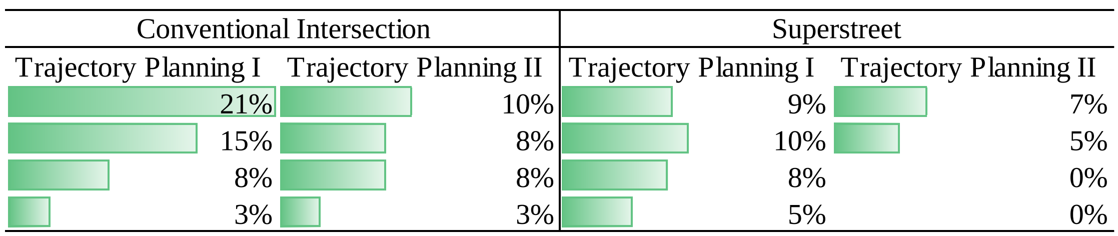


FIGURE 4.13: Traffic delay improvement magnitudes between two trajectory planning controls

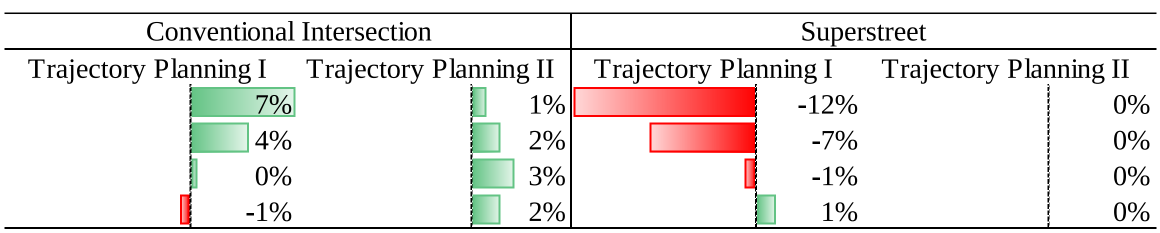


FIGURE 4.14: Fuel consumption improvement magnitudes between two trajectory planning controls

CHAPTER 5 CONCLUSIONS

5.1 Summary of Research Findings

This research investigated the performances of CAVs and HDVs in the environments of the superstreet and conventional intersection. CAVs were modeled with the IDM car-following model while HDVs were modeled with the W99 car-following model. A real-world superstreet situated in Leeland, NC, was replicated in the simulation platform to test the performances of CAVs and HDVs under different traffic conditions. In addition, to fully examine the potentiality of CAVs, platooning control, adaptive signal control, and trajectory planning strategy were developed for CAVs respectively. In this research, the W99 model was calibrated with GA so that the W99 model can better represent the local drivers' behaviors.

5.1.1 Platooning control I and trajectory planning I at fixed signal timing

The simulation results indicated that, without platooning and trajectory planning, CAV modeled by IDM did not have significant improvement compared to HDVs modeled by W99. The developed platooning strategy can successfully reduce the traffic delay and fuel consumption in relatively high traffic demand scenarios (50%, 75%, and 100% peak hour volume) in both the superstreet and the conventional intersection. Trajectory planning could reduce the traffic delay in both superstreet and conventional intersection environments but with different impacts on fuel consumption. CAVs with trajectory planning produced higher fuel consumption in the superstreet in the lower traffic demand scenarios, especially in traffic demands being 25% and 50% of peak hour traffic volumes. A potential reason is that CAVs which accelerate to pass the first intersection may fail to pass the consecutive second intersection in the environment of superstreet. In the market penetration rate analysis of CAVs, it was found that the mixed traffic environment can compromise the benefit when the CAVs market penetration rates were at 25% and 50% peak hour traffic volume. CAVs have better performances when the market penetration rate was about 75% and above.

This research also compared the traffic performances of CAVs in the conventional intersection and superstreet. A notable finding was that the proposed trajectory planning control strategy can successfully reduce the average traffic delay without increasing the average fuel consumption in the conventional intersection. This was different from superstreet where CAVs enabled with trajectory planning increase the fuel consumption at certain scenarios. This demonstrated the efficiency of the proposed trajectory planning strategy in an isolated intersection. However, this result also indicated that the trajectory planning without considering special features of two closely spaced signalized intersections may suffer adverse effects of fuel consumption. Overall, the improvement magnitude of platooning and trajectory planning was larger than that in the conventional intersection.

5.1.2 Platooning control II and adaptive signal control

The research findings suggested that adaptive signal control with CAVs can yield the largest improvement compared to trajectory planning and platooning in terms of both traffic delay and fuel consumption, and the improvement rates showed an increasing trend as the traffic scales rise. Platooning control can also yield traffic delay and fuel consumption benefits, and the highest improvement was more than 30% in terms of traffic delay in the 100% peak hour traffic volume scenario. In contrast to platooning and adaptive signal control, the effects of trajectory planning were attenuated when traffic volume increases, which was understandable since CAV must stop following predetermined trajectories when encountering close preceding vehicles. The unstable traffic flow caused by multiple intersections made the improvement for fuel consumption even less significant in the environment of superstreet. For most cases, performances of CAVs with different features showed a similar trend in the equivalent conventional intersection as they were in superstreet. CAV with trajectory planning performed better in conventional intersection design while CAVs with adaptive signal control performed better in superstreet. Table 5.1 provides a summary for performance comparison with different CAV techniques.

TABLE 5.1: A Summary on the Environment of Greater Improvement for Different CAV Techniques

	TD		**FC**	
	Light Traffic	**Heavy Traffic**	**Light Traffic**	**Heavy Traffic**
Platooning control I	Similar	Conventional Intersection	Superstreet	Conventional Intersection
Adaptive Signal Control	Superstreet	Superstreet	Superstreet	Superstreet
Trajectory Planning II Under Adaptive Signal Control	Conventional Intersection	Conventional Intersection	Conventional Intersection	Conventional Intersection

5.2 Future Research Direction Discussions

In the research findings, it was observed that trajectory planning control may have little or even adverse effects on the fuel consumption in the multiple close spaced intersection environment. Therefore, a more sophisticated trajectory planning algorithm that takes into account two consecutive signalized intersections can be developed. In the recent CAV studies, machine learning models such as reinforcement learning have become a reliable approach in obtaining the optimal control strategies without defining a specific model for both trajectory planning and signal optimization. The research may consider implementing the artificial intelligence approach to obtain the trajectory planning strategies in multiple intersection environments.

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