Center for Advanced Multimodal Mobility Solutions and Education

Project ID: 2020 Project 03

IMPACT OF CONNECTED AND AUTONOMOUS VEHICLES ON NONTRADITIONAL INTERSECTION DESIGN: SUPERSTREETS

Final Report

by

Wei Fan (ORCID ID: https://orcid.org/0000-0001-9815-710X)
Shaojie Liu (ORCID ID: https://orcid.org/0000-0001-5330-3871)

Wei Fan, Ph.D., P.E.
Director, USDOT CAMMSE University Transportation Center
Professor, Department of Civil and Environmental Engineering
The University of North Carolina at Charlotte
EPIC Building, Room 3261, 9201 University City Blvd, Charlotte, NC 28223
Phone: 1-704-687-1222; Email: wfan7@uncc.edu

for

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

September 2021

ACKNOWLEDGEMENTS

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

DISCLAIMER

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

EXECUTIVE SUMMARY

Congestion has been becoming a critical issue for transportation professionals as it increases travel time, energy use and pollutant emissions. Thanks to recent technology development of wireless communication and artificial intelligence, connected and autonomous vehicles (CAVs) become a promising and practical approach to increasing road capacity. As many studies have been done to explore the potential application and impact of CAVs in various transportation environment and scenarios, such as freeway segments (Liu and Fan 2020), signalized intersections (Han et al., 2020), 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 at innovative intersections had received relatively less attention. This research aims to mitigate the research gaps by conducting simulation-based research to explore the impact of CAVs on the operational performances in the environment of superstreets.

In this research, several assumptions have been made on the technological features and capabilities of future CAVs. These assumptions are mainly based on communications between vehicles and vehicles, and vehicles and traffic lights. For communication between vehicles, CAVs are expected to maintain condensed platoons while they are traveling on the roads. For communication with traffic lights, the CAVs are expected to be able to adjust their trajectories according to the signal status to achieve the minimum fuel consumption. The impacts of these capabilities are examined by their operational performances in a simulated environment.

A real-world superstreet network from Leland, North Carolina, is replicated in the simulation platform with collected traffic volumes that were recorded in the existing literature. The Wiedemann 99 model and the Intelligent Driver Model (IDM) are utilized to model human traffic and CAV traffic, respectively. The genetic algorithm is employed to obtain the optimal parameters in the Wiedemann 99 model so that the simulated average speeds can match with the observed average speeds on each approach. CAVs are assumed to be able to adjust their speeds based on the Signal Phasing and Timing (SPaT) information. Different traffic volumes and market penetration rates are also considered during the evaluation of CAVs’ performance. The results demonstrate the high efficiency of the developed CAVs framework. In addition, it is also observed that the performance of CAVs varies significantly on different traffic volume scales and at different market penetration rates.

CHAPTER 1 INTRODUCTION

Connected and autonomous vehicles (CAV) is an emerging technology that has the potential to improve operations, safety, and the environment of the existing transportation system. Being able to travel on the roads with shorter headways, CAVs are expected to yield a larger capacity compared with human-driven vehicles (HDVs). Accidents caused by human improper driving behaviors can also be reduced by the introduction of such technology. In addition, since CAVs can travel on the roads with fewer speed fluctuations, CAVs may as well contribute significantly to the emission reduction and improve the environmental condition of the current transportation system.

Due to all the potential benefits of CAVs mentioned above, many studies have been conducted to explore the impacts of CAV technologies on the performances of conventional intersections, highway segments, on/off ramps, and roundabouts. Improvement in operational performances has been confirmed when the market penetration of CAVs reaches a certain rate. Innovative intersections distinguish themselves usually by creating minor intersections that are hundreds of feet ahead or downstream of the main intersection for turning movements. Superstreets are one of the innovative intersection designs which have been implemented in numerous states across the country. However, how CAVs would affect the performances of superstreets has not been explored, even to a minimum extent. To be specific, the following questions need to be answered: (1) at what market penetration rate would CAVs bring benefits towards operational performances; (2) to what extent would CAVs bring benefits towards operational performances of superstreets; (3) how would the impact of CAVs on the operational performance vary across different traffic scales and market penetration rates.

This study will fill this gap by conducting a simulation-based experiment to identify the potential impact of CAVs on superstreets regarding operational performances. The finding of this research may also be applied to other innovative intersection designs which have similar geometric and traffic patterns.

1.1 Objectives

The objectives of this project are to: (1) review and synthesize existing studies on both CAVs and superstreets; (2) conduct a simulation-based study to evaluate the impact of CAVs on the superstreet considering available SPaT information; (3) identify the threshold of market penetration rates where CAVs start to gain benefits in superstreets; (4) evaluate the impact of CAV on different traffic scales; and (5) examine the impacts of CAVs with different capabilities, i.e., platooning and trajectory planning.

1.2 Report Overview

The rest of the report is structured as follows: Chapter 2 presents a comprehensive review of the existing literature on CAVs and superstreets. For CAVs, the existing literature can be grouped into four categories, which are car following, lane changing, traversing the intersection, and merging on the freeways. For the superstreets, this chapter presents the existing literature on the operational performance of superstreets and CAVs on the innovative intersections. Chapter 3 introduces methods employed in this research, including the Wiedemann 99 and Intelligent Driver Models, simulation platform, platooning scheme, and speed planning strategies for CAVs approaching the intersection considering available SPaT information, and the illustration of selected location for the case study. Chapter 4 discusses the simulation results for the operation performances of CAVs in the environment of the superstreet with different market penetration rates and traffic scales. Chapter 5 concludes this project with a summary and discusses future research directions.

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

This chapter introduces the existing work on the CAVs and 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. Then this report discusses the existing literature on CAVs at the Intersections, the car-following model, lane changing model, and CAVs on freeways in Section 2.3, 2.4, 2.5, and 2.6, respectively. The literature for CAVs can be classified into four categories, including car-following models, lane-changing models, models for CAVs traveling through the intersection and merging on the freeways. Although in some literature, the lane-changing model is integrated with 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. As for the superstreets, most studies have been done on the operational performances compared to the conventional intersection and other innovative intersection designs. The literature about superstreets is reviewed and presented in section 2.7.

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 speed, acceleration rates, and position. In addition, connected vehicles are also expected to be capable of communicating with transportation infrastructure to obtain information like traffic volumes and traffic light information. Autonomous vehicles refer to the vehicles that can complete the driving task 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 (NHTSA, n.d.), 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, and environment

Road Capacity

Due to shorter headways, prompt reaction, and accuracy of maneuvering, CAVs can increase the road capacity, theoretically. Existing studies mainly employed two approaches in evaluating the impacts of CAVs on road capacity, including theoretical framework, and simulation of CAVs. Chen et al. (2017) developed a theoretical framework for evaluating the lane 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 while the 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 was found that the improvement of road capacity is highly correlated to the market penetration rates 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
Liu et al., 2017	54% improvement on road capacity when the market penetration rate increases from 0 to 100 percent.
Talebpour et al., 2017	With dedicated lane for automated vehicles, the 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 the market penetrate rate is 100%.
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.

H. Yu et al., 2019	Capacity increases as market penetration rates increases

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, the crash, rate could be reduced by around a third. These functions are generally supported in Automation Level 0 and Level 1. Nevertheless, though some functions have been fulfilled in automation Level 0 and Level 1, drivers' errors cannot be 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 (Derbel et al., 2013).

Li and Wagner (2019) conducted a simulation-based study on the impact of the automated vehicle on mobility, safety, emissions, and fuel consumption using the simulation platform of Simulation of Urban MObility (SUMO). A segment of the freeway 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 42s to 1s when the market penetration rate increased from 0% to 100%.

Li et al. (2017) evaluated the safety impacts of different market penetration rates of Adaptive Cruising Control (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. Also, equipped with a variable speed limit (VSL) system, the ACC system could bring a more significant improvement in safety performance.

Environment

Morrow et al. (2014) pinpointed a list of factors of AVs' implementation that could have impacts on the environment, including vehicle weight, performance, and size. The authors estimated that AVs were expected to have a positive influence over 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 influence the emission and fuel consumption regarding vehicle's performances, including vehicle operation, electrification, vehicle design, and platooning. For vehicle operation, eco-driving is important and an encouraged driving pattern that could reduce fuel consumption by 4-45%. Detailed information is summarized in Table 2-3. Autonomous vehicles have advantages in following the eco-driving pattern when the control strategy is coded into the system.

Table 2-3 Eco-Driving Impact on the Reduction of Fuel Consumption

Researchers	Reduction of Fuel Consumption
Barth and Boriboonsomsin, 2008	10-20%
Boriboonsomsin et al., 2012	13%
Gonder et al., 2012	15-20%
Brown et al., 2013	20%
National Research Council, 2013	4 -10%
Chen et al., 2017	30-45%

2.3 Existing Studies on CAVs at the Intersections

CAVs have been extensively studied in various scenarios of transportation. Before the appearance of CAVs, the car following and lane changing models have already been extensively studied in the arena of traffic engineering, often with the purpose of simulating vehicle movements controlled by humans. These models and methodologies could be extended to develop control strategies for CAVs. In general, these strategies are applied in four scenarios, including car following, lane changing, traversing intersections, and merging activities.

2.3.1 Reservation based strategies for CAVs traversing the intersection

Methods for coordinating CAVs at the intersection circulate how the spaces in the intersection are allocated for the upcoming vehicles. There are essentially two types of methods, the time and space reservation method and the trajectory planning method.

Dresner and Stone (2004) proposed a time and space reservation-based system that uses square patches as the parts of the road space to reserve. This method is 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 crossroad 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 is quite demanding for the computational 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 a traffic signal, stop sign, and emergency vehicles, which made the system more robust. With a traffic signal or a stop sign in place combined with reservation-based strategies for autonomous vehicles, the traffic mixed with both human-driven vehicles and autonomous vehicles became possible. When a traffic light is in place, 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 the traffic light information. In the study, consideration for the stop sign was also included, though it might not be practical in the real-world because of 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 the 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 for different turning movement in the intersection. The model is 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 trajectory that conflicts 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. H-AIM was not superior to AIM until more than a 10% CAV technology penetration level is reached.

Mehani and De La Fortelle (2008) also developed the 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, including: 1) one named None, in which vehicles traveled through the intersection at their full speed without concerns about collision; 2) 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 on 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 greater throughput capacity with zero collision. The Poll scenario, though also had zero collision, 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.

2.3.2 Trajectory planning based strategies 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 unsignlized traffic 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 at 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 the optimizing 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 eliminated stop delay. This model could also be used for turning traffic but with a 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 for each vehicle in order 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 in 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 is stop sign controlled. The simulation results showed that 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 analogous to Travelling Salesman Problem (TSP). In TSP, 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 De La 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 et al.	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

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 HVs and CAVs

2.3.3 CAVs at the signalized intersections

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. 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 are capable of receiving the SPaT information and can react promptly to achieve certain objectives such as minimal travel time or fuel consumption.

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 purposes. 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).

Pourmehrab et al. (2019) proposed an algorithm that minimizes the travel time by coordinating the SPaT and computed trajectories. The proposed control strategies considered different controls for the lead vehicle, following vehicle, and traffic signals, assuming two-way communication technologies between vehicle and infrastructure. The speed trajectories and signal phase were optimized simultaneously to achieve the minimum travel delay. Comparing with a fully actuated signal control, the proposed algorithm was found to reduce the average travel time by 38%-52%.

2.4 Existing Studies on Longitudinal Behavior Model of CAVs

2.4.1 Overview of car-following model

Car following models is 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 model includes stimulus-response, safe-distance, desired headway, and psychophysical models. Though classic methods may suffer insufficiency in that they fail 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 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 Chandeler et al. (1958) at General Motors research laboratories and Kometani and Sasaki (1958) in Japan. The general formulation of this model is

$$a_n = c v_n^m(t) \frac{\Delta v(t-T)}{\Delta x^l(t-T)} \tag{1}$$

where a_n is the acceleration of the subject vehicle, c, m, l are the calibration parameters, Δv and Δx are the speed difference and the distance between the subject vehicle and its leading vehicle, respectively. The parameters in the GHR model have been continuously calibrated by many researchers. Chandler et al., (1958) suggested that m, l 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, 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. A simplified version of this model is presented in Equation 2 and Equation 3:

$$a_n = w_1 \Delta v(t-T) + w_2[\Delta x(t-T) - D_n(t)] \tag{2}$$

$$D_n(t) = \propto + \beta v_n(t-T) + \gamma a_n(t-T) \tag{3}$$

Where w_1 and w_2 are two calibration parameters for relative speed difference and gap between the subject vehicle and the leading vehicle; $D_n(t)$ is the desired headway, which is a function of speed and acceleration rate. $\propto$, β and γ are the calibration parameters.

Later this model was calibrated on the urban freeway under both the 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. It can take the form as Equation 4 and Equation 5 as shown below:

$$a_n = c\left[V_{opt}\left(\Delta x(t) - v_n(t)\right)\right] \tag{4}$$

$$V_{opt} = \begin{cases} 0, & \Delta x \leq \Delta x_a \\ f\,(\Delta x), & \Delta x_a < \Delta x < \Delta x_b \\ v_{max}, & \Delta x_b \leq \Delta x \end{cases} \tag{5}$$

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 is originally developed for human-driven vehicles in the single lane without consideration of lane changing (Tieiber et al, 2000). IDM can be classified as one of the OVMs. 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., 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), and was developed by combining the OVM and generalized forced model (GFM). The original OVM was biased in the aspect of too high acceleration and unrealistic deceleration compared with observations on the field. Based on the OVM, GFM was proposed, and the results showed that GFM's output is more consistent with the field data. However, GFM fails to consider the case when the velocity difference between the preceding vehicle and 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 2-5 provides a brief review of the literature on the OVM, FVDM, and IDM.

Table 2-5 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
Rachel M. 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

2.4.3 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 $T/2$, where T is the drivers' reaction time and constant for all drivers. Gipps model can take the form as follows:

$$v_n(t+T) = \begin{cases} v_n(t) + 2.5a_nT\left(1 - \frac{v_n(t)}{V_n}\right)\left(0.025 + \frac{v_n(t)}{V_n}\right)^{0.5} \\ b_nT + \left\{b_n^2T^2 - b_n\left[2\big(x_{n-1}(t) - S_{n-1} - x_n(t)\big) - v_n(t)T - \frac{{v_{n-1}}^2(t)}{\hat{b}}\right]\right\}^{0.5} \end{cases} \tag{6}$$

where a_n is the maximum acceleration, b_n is the maximum deceleration rate, $S_{n-1}$is the length of the leading vehicle plus the minimum headway, V_n is the desired speed, and $b\hat{}$ is the estimation of b_{n-1} employed by the driver of vehicle n.

2.4.4 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. The model has the form as shown below.

$$x_{n-1}(t) - x_n(t) - L_{n-1} = hv_n(t), \tag{7}$$

$$x_{n-1}(t+T) - x_n(t+T) - L_{n-1} = hv_n(t+T) \tag{8}$$

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. The visual angle changes could be captured by Equation 9.

$$\frac{d\theta}{dt} = -w(\Delta v/\Delta x)^2 \tag{9}$$

where θ is the visual angle change of the leading vehicle and w is the observed 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 the most popular model that has been applied in the microscopic simulation platform PTV VISSIM.

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 neural network learning-based models. A brief review of the literature on the artificial intelligence model is presented in Table 2-6.

Table 2-6 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 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 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 on the car following model and then many efforts were made in developing the car-following model with the same principle (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 dataset. Neural networks mimic the way that the human brain processes information. In the initial layer, the observed values of variables are put in the neurons where a coefficient would be assigned to each variable. Then the obtained results from the first layer are 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.

2.5 Existing Studies on 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 model, discrete choice-based model, artificial intelligence model and incentive-based model. (Rahman et al. 2013). The rule-based models include 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-baed 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 model (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 different models.

2.5.2 Discrete choice models

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 change to left, and lane change to the right. This step assumesthat the vehicle would make the lane change decision which results in the maximum utilization, which 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 assumes 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 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 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%.

2.5.4 Incentive-based models

Kesting et al. (2007) proposed lane-changing rules that is 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, then the driver was determined to execute a lane change. The safety criteria, which evaluate the lane changing was safe or not was 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, the vehicle was not able to make the lane change either.

2.5.5 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 2-7 provides a brief review of the literature mentioned above.

Table 2-7 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

2.6 CAVs on Freeway and On/Off Ramps

In addition to the conventional intersections, the freeways, and on/off ramps are also an important scenario where CAVs have promising implications. Due to the short reaction time and accuracy of maneuvers, merging activity conducted by CAVs could be potentially advantageous in terms of safety and efficiency. The behaviors of CAVs on freeway is not the focus of this research, and hence, this research present only several existing studies.

Milanés et al. (2010) developed a fuzzy controller for the longitudinal behaviors of the automated vehicles with two principles: one was to permit the vehicle to merge into the major road fluidly and the other one was to modify the speed of the vehicles on the main road to minimize the fluctuations on the main road caused by the merging activities. The control algorithm proposed can decide when the merging vehicle enters the main road, and a fuzzy controller was designed to control the throttle and brake to follow the reference from the control algorithm. Simulation, as well as an experiment in the real world, was conducted with both gasoline-propelled automated vehicles and electric automated vehicles. The results of the simulation and experiment showed that the proposed algorithm can predict the optimal trajectory for the merging vehicle to enter the main road.

Letter and Elefteriadou (2017) proposed a merging algorithm for automated vehicles at the on-ramp or lane drop in the freeway. The model took inputs of the vehicle's position, speed, and acceleration with an assumption of V2I equipment being in place. Once the relevant data is received, the order with which vehicles will merge is calculated based on each vehicle's potential arrival time to the merge point. Vehicle trajectories are then optimized individually according to this merging order. The objective of this model was to maximize the average travel speed through the communication zone. Two scenarios were designed using CORSIM to evaluate the proposed merging algorithm, one being the human-driven and the other being 100 % automated vehicle aided with the proposed merging algorithm. The simulation results showed that the proposed algorithm can direct automated vehicles safely and efficiently. Improvement increased as the demand increased in terms of average travel speed, total travel time, and travel time per distance traveled.

Xie et al. (2017) developed an optimal control strategy for CAVs which aims to maximize the total speed of vehicles while minimizing the variation of speeds, on the condition that a sufficient gap is available for the vehicle from ramp to merge. A simulation platform was developed based on VISSIM and MATLAB. Dedicated short-range communication (DSRC) technology was assumed to be equipped on the vehicles to enable communication for vehicles on freeways and ramps. With the VISSIM simulator and Car2X module included in it, the acceleration, speeds, and position of all vehicles in the specified areas can be obtained directly during the simulation. A case study was implemented considering two scenarios, four vehicles on the road and twenty vehicles on the road, respectively. The results showed that the proposed control strategy can regulate the vehicles as expected. Besides, average delay, average speed, and traffic throughput were evaluated considering three cases: proposed control, no control, and gradual control speed limits (reduce the speed of upstream vehicles if the speeds of downstream vehicles are low). The assumed traffic volumes ranged from 800 to 1200 vehicles per hour for the freeway and 300 to 700 vehicles per hour for on-ramp. It was found that the proposed control strategy can improve the average speed and average delay substantially.

2.7 Existing Studies on Superstreets

2.7.1 Concepts, benefit, and application of superstreets

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 relieves traffic congestions especially when unbalance traffics 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. According to different control strategies, there are three types of superstreets essentially, including signalized, stop-controlled, and merge-or yield-controlled superstreets. Figure 2.1 presents a typical design of a superstreet according to Hummer et al. (2014).

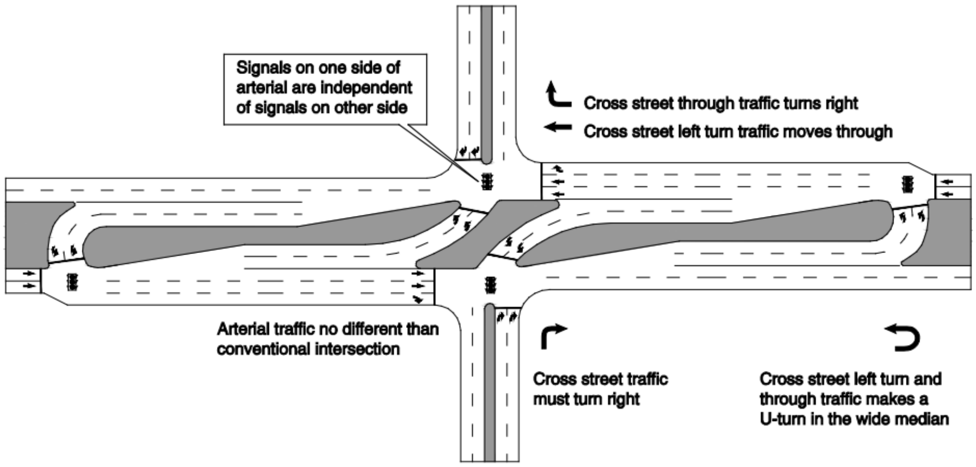

Figure 2.1 Example of signalized intersection (source: Hummer et al., 2014)

Coming along with the substantial benefits from superstreets, the construction cost for a superstreet is inevitably expensive because of the larger footprint. In addition, there are additional signal controllers that may need to be installed. Table 2-8 shows some construction costs in Hummer et al (2014).

Table 2-8 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

Xu et al. (2019) developed a two-stage control model for optimizing traffic signal control planes of signalized superstreets. 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 in 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 to combine 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 different lengths of offset proved the efficiency of the model.

Holzem et al. (2015) studied pedestrian and bicyclist accommodation strategies in the context of superstreets. 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. 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 additional measures so that shorter cycle length could also benefit the accommodation of bicyclists.

2.7.3 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 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 with 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 video camera last. Two sets of data were collected, one for calibration and the other for validation. The results show that superstreets increase the travel time for the vehicles on minor streets while decreases that of vehicles on major streets. However, overall, 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 residentials, 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 being the superstreets that must be constructed within five years. This is because drivers might not remember what the driving situation was if the superstreets have been there for more than five years. The second criterion was that there must exist road construction before the superstreet is 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 live in a neighborhood of superstreet, they thought the superstreets had increased their travel time. This might be due to that superstreets improve the traffic flow on a major road with a compromise of traffic flow in the minor road. People who live in the neighborhood, are likely to experience longer travel time while they used the minor road. As for the commuters, superstreets are difficult to navigate for half of them according to the response received. The percentage of people who find superstreets safer was greater than the percentage of people who found the otherwise by 8 percentage. 12% of commuters believed 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, jughandle, 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 the equivalent conventional intersections. It showed that travel time per vehicle were reduced. This means the superstreets could provide more capacity and lower travel time. Though signalized superstreet did not provide significant crash reduction, 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.

Table 2-9 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,
Hana Naghawi et al.	2018	signalized convention intersection	VISSIM	Improvement of LOS from F to C
Naghawi, H. H., & Idewu, W. I. A.	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

2.7.4 Replacement of conventional intersection

Numerous studies had been done to evaluate the feasibility and improvement of replacing existing conventional intersections by 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. (2010) 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, number of arrived vehicles, 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 fewest stops and lowest delays due to the effective traffic progression. Collisions were also reduced according to the SSAM analysis.

2.7.5 Safety performance of superstreet

The number of conflict points is a commonly accepted measure for evaluating the safety performance of transportation infrastructure. Figure 2.2 and Figure 2.3 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 superstreets compared to the conventional intersections. 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.

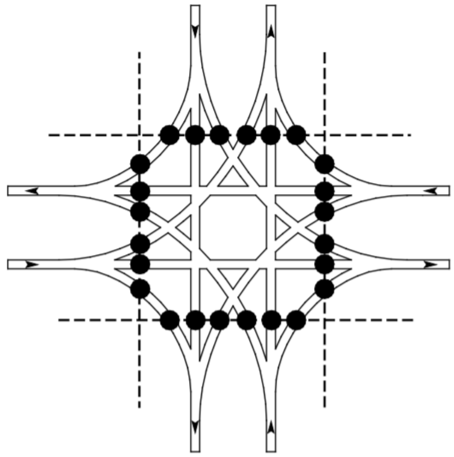

Figure 2.2 Pedestrian-vehicle conflict points at a conventional intersection (Hummer et al., 2014)

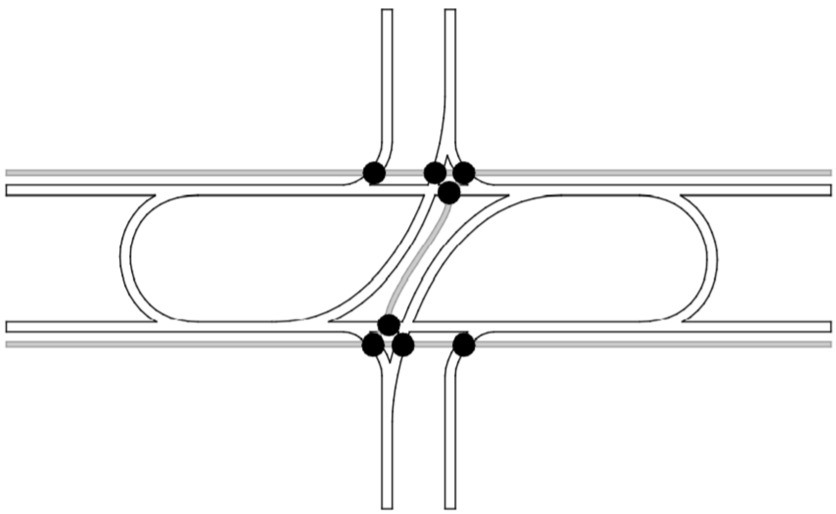

Figure 2.3 Pedestrian-vehicle conflict points in a superstreet (Hummer et al., 2014)

As for the vehicle-to-vehicle conflict points, superstreets still outperform 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 2-10.

Table 2-10 Vehicle Conflict Points Comparison in Conventional Intersection and Superstreet (Hummer et al., 2014)

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

2.7.6 The impact of CAVs on the innovative intersection

Few research efforts have been made in exploring the impacts of CAVs in the environment of superstreets. Zhong et al. (2019) investigated the operational performance of CAVs in the environments of diverging diamond intersections and restricted crossing U-turn intersections (superstreet). In this research, a standard and hypothetical superstreet network were 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 EXPERIMENTS

3.1 Introduction

This chapter presents the experiments conducted to explore the impact of CAVs with available SPaT information on superstreets. A case study is conducted based on the collected traffic data in the existing literature. The simulation model is established with SUMO, which is introduced in Section 3.2. Wiedemann 99 and IDM are illustrated in Section 3.3. The parameters in the Wiedemann 99 model are calibrated using the GA. Section 3.4 briefly illustrates the VT-Micro fuel consumption model. Section 3.5 introduces the platooning behavior of CAVs while Section 3.6 explains how the CAVs cooperate with signal timing information. Also, the signal timing information is discussed in Section 3.7.

3.2 Simulation Platform SUMO

SUMO is a microscopic multi-modal simulation platform and is considered as an open-source under General Public License (GPL). SUMO has supported multiple car-following models including Krauss, IDM, Wiedemann, Wiedemann 99, Adaptive Cruise Control (ACC), and Cooperative Adaptive Cruise Control (CACC). In addition, SUMO also allows users to define their car-following models. As for lane-changing models, three lane-changing models are supported including LC2013, SL2015 (Krajzewicz, 2010). A brief explanation for these three lane-changing models is provided in Table 3-1. This research employes the default lane-changing model of SUMO.

Table 3-1 Lane changing models supported by SUMO

Models	Descriptions
LC2013	Default lane-changing model in SUMO, developed by Jakob Erdmann based on DK2008
SL2015	Lane changing model that depicts the trajectory of lane changing

SUMO has visualized network editing and simulating platforms, known as NetEdit and SUMO GUI, which could facilitate the efficiency of network modeling and simulation. To simulate the user-defined scenarios, software users often need to change the attribute values of network objectives, such as the scenarios of the actuated traffic signals. Traffic Control Interface (TraCI) is an interface that can help users retrieve and change the attribute values of network objects during the simulation. The network objects that TraCI can edit include detector, traffic light, vehicle, route, lane, person, edge, bus stop, and so forth. TraCI supports multiple programming languages including C++, Java, MATLAB, and Python. Among the languages supported by TraCI, Python is the one that has a complete test for the functionality. As such, this project employed Python to fulfill the proposed control scheme of CAVs. The speed planning strategies proposed in this project rely on TraCI to be fulfilled. Due to its full functionality and portability, SUMO has received more and more research attention from transportation professionals, as provided in Table 3-2.

Table 3-2 Recent Studies that Utilized SUMO as Simulation Platform

Authors	Simulation Platform	Title	Year	Journal
C. Yu et al.	SUMO	Corridor level cooperative trajectory optimization with connected and automated vehicles	2019	Transportation Research Part C: Emerging Technologies
Li et al.	SUMO	Temporal-spatial dimension extension-based intersection control formulation for connected and autonomous vehicle systems	2019	Transportation Research Part C: Emerging Technologies
Yang et al.	SUMO	A Deep Reinforcement Learning-based Ramp Metering Control Framework for Improving Traffic Operation at Freeway Weaving Sections	2019	Transportation Research Record
Li et al.	SUMO	Right-of-way reallocation for mixed flow of autonomous vehicles and human driven vehicles	2020	Transportation Research Part C: Emerging Technologies

3.3 Traffic and Geometric Characteristics of the Selected Location

Hummer et al. (2010) conducted a comprehensive study on the superstreet in North Carolina to evaluate the operational and safety performance of the superstreet in comparison to equivalent conventional intersections. After reviewing this report, this study selected the location of U.S. 17 & Walmart/Gregory Road as the case study for its typical geometric design and traffic flow pattern for a superstreet. Figure 3.1 presents the aerial view of U.S. 17 & Walmart/Gregory Road from Google Maps. A complete traffic characteristic for each approach was reported as Table 3-3 and Table 3-4 that are shown below. Figure 3.2 presents the collected speed distribution for the superstreet. This study would utilize the data from the report for calibration of the car-following model.

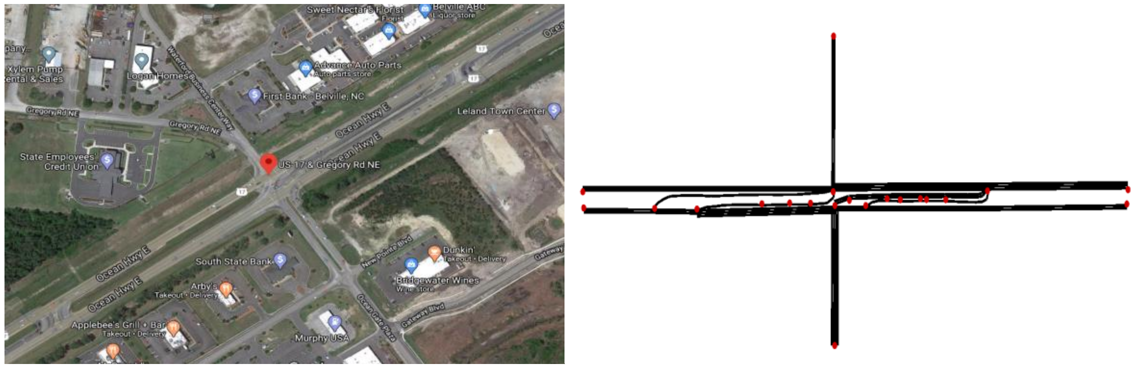

Figure 3.1 Aerial view of U.S.17 & Walmart/Gregory Road from Google Maps and SUMO

Table 3-3 Traffic Characteristics for the Superstreet Situated at U.S.17 & Walmart/Gregory Road

	Average Speed (m/s)	Hourly Traffic Volume	Average Stops	Travel Time (Minutes)
EBL	5.99	18	3	2.45
EBR	6.93	20	2	1.38
EBT	5.68	9	2	2.25
NBL	8.00	20	1	1.17
NBR	14.08	71	0	0.64
NBT	14.75	2029	0	0.81
SBL	5.72	321	1	1.26
SBR	14.26	38	0	0.4
SBT	19.58	1637	0	0.58
WBL	8.09	66	2	2
WBR	7.69	345	1	0.89
WBT	5.05	11	2	2.09

Table 3-4 Lane Configurations for the Selected Superstreet

	Northbound	Southbound	Westbound	Eastbound
Left turn	1	2	------	------
Through	2	2	------	------
Right turn	1	1	2	1

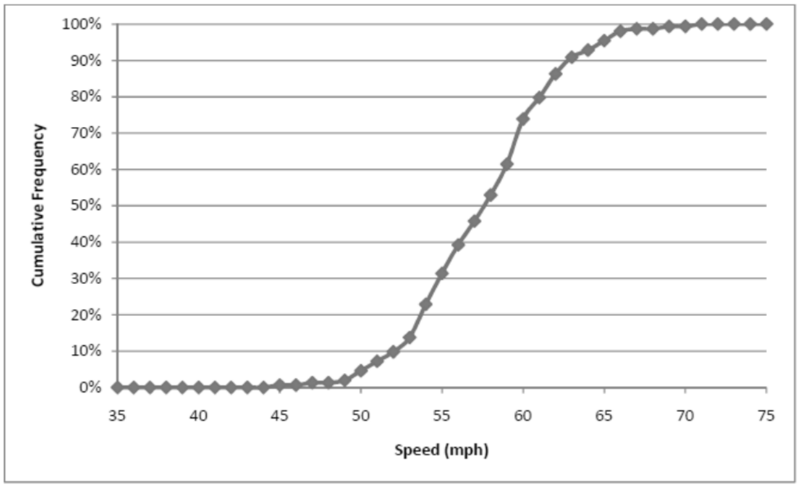

Figure 3.2 Speed distribution for U.S.17 (Source Hummer et al., 2010)

3.3 Car-Following Models

As mentioned above, this research employed Wiedemann 99 and IDM to model the HDV traffic and CAV traffic, respectively. This section presents illustrations for the two car-following models.

3.3.1 Wiedemann 99 car-following models

Wiedemann 99 car-following model is popularly applied in modeling HDV traffic. It was developed based on the Wiedemann model (Wiedemann, 1974), which was proposed to model traffic on the urban road while Wiedemann 99 model was proposed to model traffic on the freeways. The governing equation for Wiedemann 99 model is described in Equation 10.

$$v_n(t+\Delta t) = min\begin{Bmatrix} v_n(t) + 3.6 \times \left(CC8 + \dfrac{CC8 - CC9}{80} \times v_n(t)\right)\Delta t; u_f \\ 3.6 \times \dfrac{s_{n(t)} - CC0 - L_{n-1}}{v_n(t)}; u_f \end{Bmatrix}, \tag{10}$$

Where $v_n(t)$ represents the speed of the subject vehicle at the time step t; $v_n(t+\Delta t)$ is the speed of the subject vehicle after Δt seconds relative to t ; $CC8$ denotes the desired acceleration when starting from standstill condition; $CC9$ is the desired acceleration rate of the vehicle; $CC0$ represents the standstill distance; s_n is the distance between the subject vehicle and its leading vehicle; L_{n-1} is the length of the leading vehicle; and u_f is the free-flow speed.

Wiedemann 99 model contains ten parameters that can either increase or decrease so that the simulated traffic can be matched with observed traffic. The observed difference is usually minimized until a certain threshold is reached. Based on the work of Manjunatha et al. (2013), 15% difference between observed and simulated traffic is regarded as acceptable performance. This research would utilize the collected traffic data reflected in the work of Hummer et al. (2010).

3.3.2 Wiedemann 99 car-following models' calibration with Genetic Algorithm

According to Lownes and Machemehl (2006), $CC0$ and $CC1$ (time gap) are parameters that not only affect the capacity of a roadway but also have interactions with parameters of $CC8$, $CC4$ and $CC5$. Durrani et al. (2016) concluded that it is necessary to calibrate all the parameters since interaction exists among ten parameters. Hence, this research calibrated all ten parameters. In this research, the traffic volumes are regarded as the direct input in the simulation while the calibration objective is to minimize the difference between observed average speeds and simulated average speeds for all approaches in the superstreet, namely the Normalized Mean Absolute Error (NMAE), which gives Equation 11.

$$\min \text{NMAE}(v) = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|u_i^{observed} - u_i^{simulated})\right|}{u_i^{observed}} \tag{11}$$

Subject to constraints:

$$l_{pi} \leq pi \leq u_{pi} \tag{12}$$

Where $v_{sim,i}$ and $v_{obs,i}$ represent the simulated average speed and observed average speed for approach i, respectively; N denotes the total number of approaches; pi represents the ith parameter for calibration in the Wiedemann 99 model; and l_{pi} and u_{pi} are the lower bound and upper bound for ith parameter.

The calibration is conducted using the genetic algorithm (GA), which could find near-optimal solutions for the target objective. GA is a search heuristic that is inspired by natural selection based on Darwin's theory of evolution. In genetic algorithm, a population of candidate solutions is randomly generated. Then the candidate solutions are taken as inputs to the objective function to obtain the results for evaluation. The best candidates are selected from the population to produce the new generation. The new generation is produced by the crossover and mutation process. Such an evolution process would terminate when either the maximum number of generations or a certain objective is reached. In this research, the maximum number of generations is set to 20 and the population size is assumed to be 10 based on the existing literature (Liu and Fan, 2020). The values of the objective function in each generation are plotted in Figure 3.3 against the number of generations. According to Figure 3.3, it can be observed that the average difference in the generated population is approaching the minimal difference closer and closer. The minimal difference in percentage is 14.18 %, which represents an acceptable performance for this research. The obtained parameters' values that achieved the minimal difference are shown in Table 3-5.

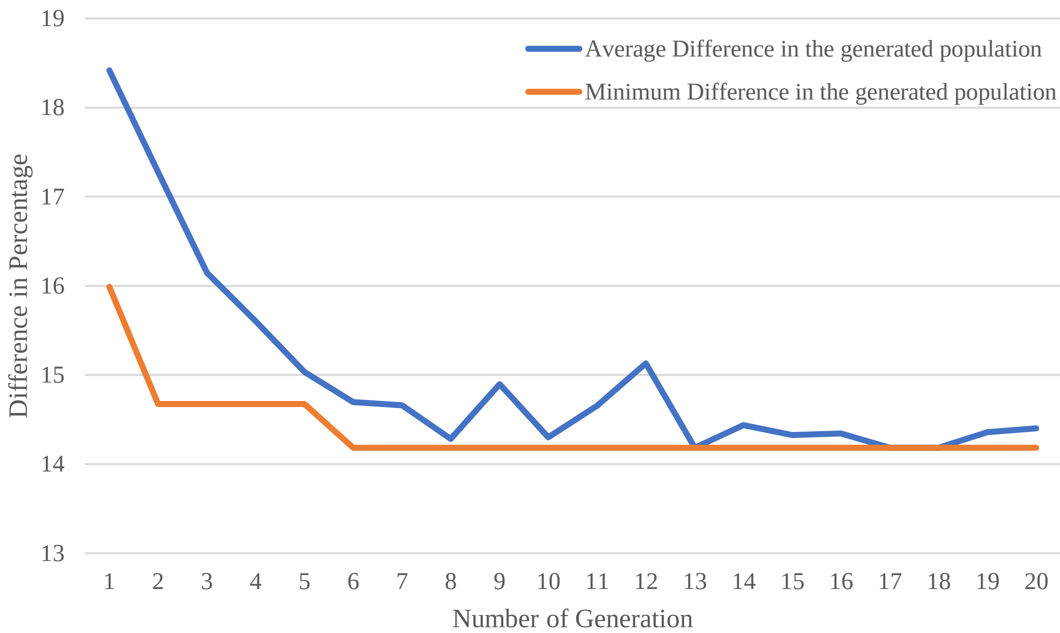

Figure 3.3 GA calibration process

Table 3-5 Wiedemann 99 Model Parameters, Interpretation, Default and Calibrated Values

Parameters	Interpretation	Default Values	Calibrated Values
CC0	average standstill distance (meter)	1.4	2.585922
CC1	headway (seconds)	1.2	0.757596
CC2	longitudinal oscillation (meters)	8	7.122266
CC3	start of deceleration process (seconds)	-12	11.45669
CC4	minimal closing Δv(m/s)	-1.5	0.8544
CC5	minimal opening Δv(m/s)	2.1	0.753872
CC6	speed dependency of oscillation (10^{-4} rad/s)	6	7.738532
CC7	oscillation acceleration - m/s^2	0.25	0.267392
CC8	acceleration rate when starting (m/s2)	2	0.899741
CC9	acceleration behavior at 80 km/h (m/s^2)	1.5	4.551409

3.3.3 IDM Formulation

IDM was firstly proposed by Treiber et al. (2000). The model has several advantages: 1) collision-free, 2) intuitively measurable parameters with good interpretability, and 3) capable of fast numerical simulation. Due to these advantages, the IDM has been widely used in modeling CAVs (Liu and Fan, 2020; Do et al., 2019; Lu et al., 2019). The acceleration rates are dependent on the velocity, the gap, and the velocity difference to the leading vehicle, as Equations 13 and 14 show below:

$$a(s, v, \Delta v) = a_m \left(1 - \left(\frac{v}{v_d}\right)^{\propto} - \left(\frac{s^*(v, \Delta v)}{s}\right)^2\right) \tag{13}$$

$$s^*(v, \Delta v) = s_0 + vT + \frac{v \times \Delta v}{2\sqrt{a_m b}} \tag{14}$$

Where a represents the acceleration rate; a_m denotes the maximum acceleration rates; v is the current speed; v_d is the desired speed; Δv represents the speed difference between the subject vehicle and its leading vehicle; $\propto$ means the acceleration exponent; s is the current headway between the subject vehicle and its leading vehicle; $s^*(v, \Delta v)$ represents the minimum desired headway; s_0 is the jam distances; T is the desired headway, and b denotes the desired deceleration rate. Note that the values of these parameters are set as default values in SUMO.

3.4 VT-Micro Fuel Consumption Model

Although SUMO provides tools and an interface to evaluate the fuel consumption and emissions, most of them are at an aggregated level and a simple fuel consumption prediction model is still required to optimize the CAVs' trajectory. Many fuel consumption and emission estimation have been proposed in previous studies, including VT-Micro (Ahn, 1998, Fiori et al., 2018), CMEM (Zhang and Isoannou, 2016), and MOVES (Koupal et al., 2002). Note that emissions and fuel consumption are significantly correlated with each other, which means that when fuel consumption is higher, the emissions are most likely to be higher. Hence, this research simply takes minimal fuel consumption as the objective to determine the trajectory. This research employs the VT-Micro fuel consumption model to estimate the fuel consumption from the candidate trajectories. VT-Micro fuel consumption models can predict the fuel consumption in real-time given speed and acceleration rates as inputs. The form of the VT-Micro model is presented below.

$$E\big(v(t), a(t)\big) = \exp\left\{\sum_{i=0}^{3}\sum_{j=0}^{3} K_{ij}(a(t))(\lfloor v(t)\rceil_{0}^{120\frac{km}{h}})(\lfloor a(t)\rceil_{-\frac{5\frac{km}{h}}{s}}^{\frac{13\frac{km}{h}}{s}}))\right\} \tag{15}$$

Where $v(t)$ and $a(t)$ represents the speed and acceleration rate at time step t; and the coefficient $K_{ij}(a(t))$ is dependent on the sign of $a(t)$. Table 3-6 shows the common parameters for the VT-Micro fuel consumption model (Ma et al., 2017).

Table 3-6 Parameter for VT-Micro Fuel Consumption Model

	$a(t)$ is positive				$a(t)$ is negative			
i\j	0	1	2	3	0	1	2	3
0	-7.73452	0.22946	-0.00561	9.77E-05	-7.73452	-0.01799	-0.00427	0.0001883
1	0.02799	0.0068	-0.0008	8.40E-06	0.02804	0.00772	0.000837	-3.40E-05
2	-0.00022	-4.40E-05	7.90E-07	8.17E-07	-0.00022	-5.20E-05	-7.40E-06	2.77E-07
3	1.10E-06	4.80E-08	3.30E-08	-7.80E-09	1.08E-06	2.47E-07	4.87E-08	3.79E-10

3.5 Platooning Behavior of CAVs

In a defined platoon, CAVs can travel on the roads with shorter headways and the same speed. To reach the full potential of platooning, the minimum headway is set as 0.5 seconds to ensure CAVs can form stable and compact platoons. While the vehicle is out of a platoon, headway is reset to a default value (i.e., 1s in this research). In addition, the minimum standing distance between vehicles is set as 0.5 and 2.5 meters for vehicles inside and outside of platoons, respectively. Two platooning behaviors are defined in this research, platoon creation and platoon merging. When the subject vehicle cannot identify any feasible platoons to merge, then the vehicle will form a platoon by itself, namely platoon creation. A feasible platoon should meet two requirements: 1) it should be within a close distance (5 meters in this research) and 2) the path of the platoon should be identical with the subject vehicles. When these two requirements are met, the subject vehicle will conduct the platooning behavior (i.e., same speed and shorter headway). Otherwise, the subject vehicle itself will form a platoon (only the subject vehicle is in the defined platoon). The overall framework for the platooning behavior of CAVs is presented in Figure 3.4.

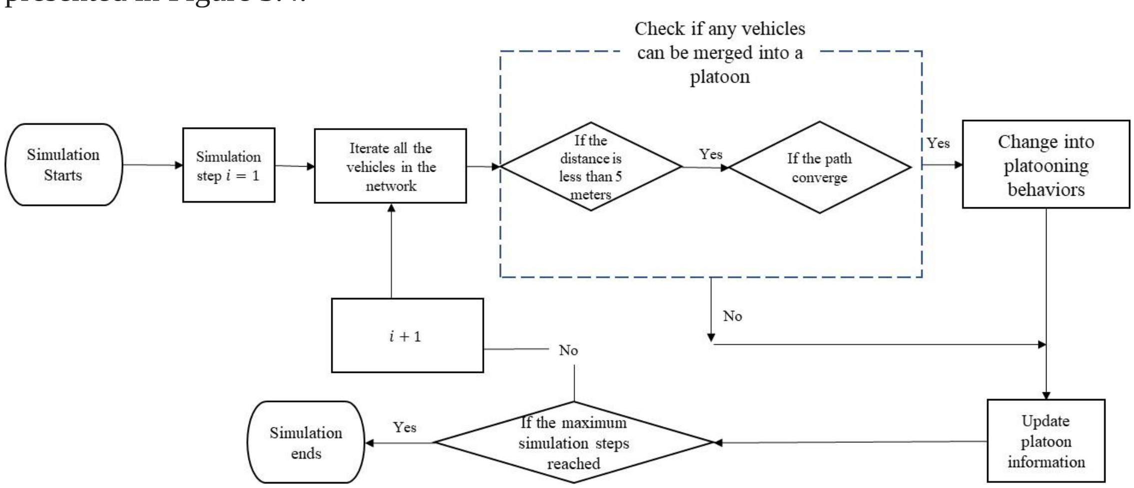

Figure 3.4 Flow chart for simulated platooning behaviors

3.6 Trajectory Planning of CAVs

According to the platoon scheme illustrated above, the CAVs in the simulation system are either in a platoon merging or platoon creation process. The trajectory of the following vehicle is largely dependent on the trajectories of leading vehicles. Therefore, in this research, the trajectory planning process is conducted on the leading vehicle of the platoon only. However, there are some time steps when some vehicles just disbanded from the platoon because of inconsistency in path choice. Hence, in this research, the leading vehicles and the vehicles that are not in any defined platoons are captured for trajectory planning at each time step. The goal of the trajectory planning process is to achieve a speed trajectory that can produce minimal fuel consumption while CAVs is predicted to meet red signals. Ideally, CAVs can accelerate to their maximum speeds and cruise through the intersection to save travel time. Nevertheless, acceleration may lead to rear-end crashes between CAVs and HDVs in a mixed traffic environment. Hence, the trajectory planning is applied to the CAVs that cannot avoid the red signal only.

The trajectory planning procedures mainly require two inputs, the signal status of the upcoming intersection and the distance to the upcoming intersection. The distance to the upcoming intersection also needs to be subtracted by the queue length to obtain the real traveling distance for the vehicles. In this research, the length of all vehicles, either CAVs or HDVs, is set as 5 meters. This information is expected to be available in the simulation environment. In this two-segment trajectory planning strategy, CAVs will maintain a constant speed during the first segment and then decelerate with a constant deceleration rate during the second segment of the planned trajectory. A generalized optimization function is provided in Equation 16:

$$\min FC(l) = \int_{x(0)}^{x(l)} f(\dot{x}(t),0) + \int_{x(l)}^{x(L)} f(\dot{x}(t),\ddot{x}(t)) \tag{16}$$

Where l is the optimal deceleration position, $x(0)$ denotes the time step when the subject vehicle enters the communication range, $x(l)$ represents the time step when the subject vehicle exit the first segment of speed trajectory, $x(L)$ represents the time step when the subject vehicle arrives at the intersection and L represents the distance to the intersection, $\dot{x}(t)$ is the first derivative of the position of the subject vehicle (or speed), $\ddot{x}(t)$ represents the second derivative of $x(t)$ (or acceleration rate), and f denotes the fuel consumption function.

Considering the trajectory planning is applied on the CAVs that would encounter the red signal, the final velocity is naturally 0; then, the initial velocity is assumed to be the speed at which the CAVs enter the communication range. Then the travel time and deceleration rate in the second segment of the trajectory at different deceleration points can be obtained through basic kinematic law. Candidate trajectories that result in unrealistic deceleration rates will not be considered; and the maximum deceleration capability is set as $-4.5\ m/s^2$ (Rahman and Abdel-Aty, 2018).

It should be noted that, when the CAVs are conducting the planned optimal trajectories, red signal may switch to the green signal. In such cases, excessive delay and fuel consumption are introduced if the vehicle is still decelerating based on previously planned trajectories. With the assumed connectivity between CAVs and intersections, the remaining switch time $t_{signal\ switch}$ from red to green, and the remaining travel time $t_{travel\ time}$ to arrive at the intersection with the current speed, should be available for CAVs. With available $t_{signal\ switch}$, it can be checked whether the subject vehicle can meet the next green signal with its current speed. Figure 3.5 provides a visualization of the trajectories when CAVs encounter a signal switch from red to green. Essentially, the CAVs would stop decelerating when the upcoming signal switches from red to green and continue to travel to the intersection based on the default speed (i.e., controlled by the car-following model).

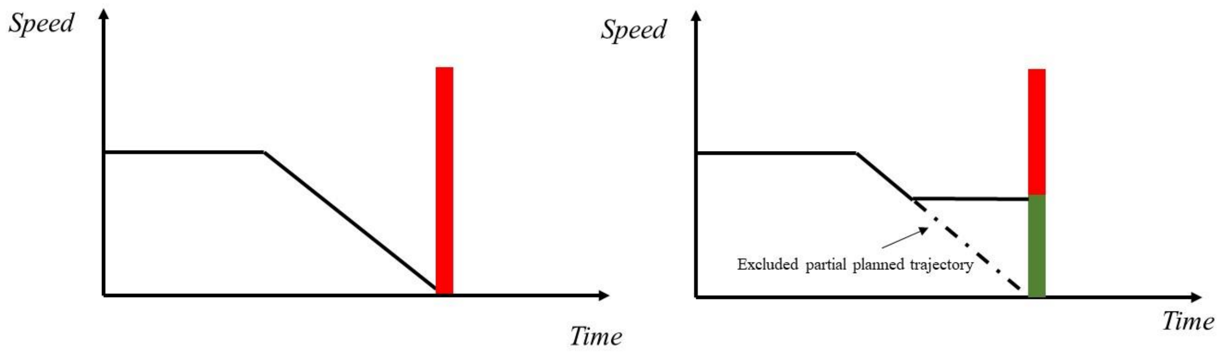

Figure 3.5 Two possible planned trajectories based on the signal status

The fuel consumption prediction models are often non-linear functions and seldom there is an analytic solution available during the optimization process. This research simplifies the trajectory planning by assuming several decision points while CAVs are approaching the intersection. First, the communication range between CAVs and intersections is assumed to be 200 meters. After the CAVs enter the communication range, the remaining distance is equally split to generate ten deceleration decision points. The accelerations are assumed to be a constant before and after the deceleration decision points. This way, ten different trajectory profiles can be generated according to ten deceleration points. These ten trajectory profiles are further evaluated using the fuel consumption estimation model, and the one generated the minimal fuel consumption will be selected and executed by CAVs. Figure 3.6 illustrates the overall procedures of trajectory planning.

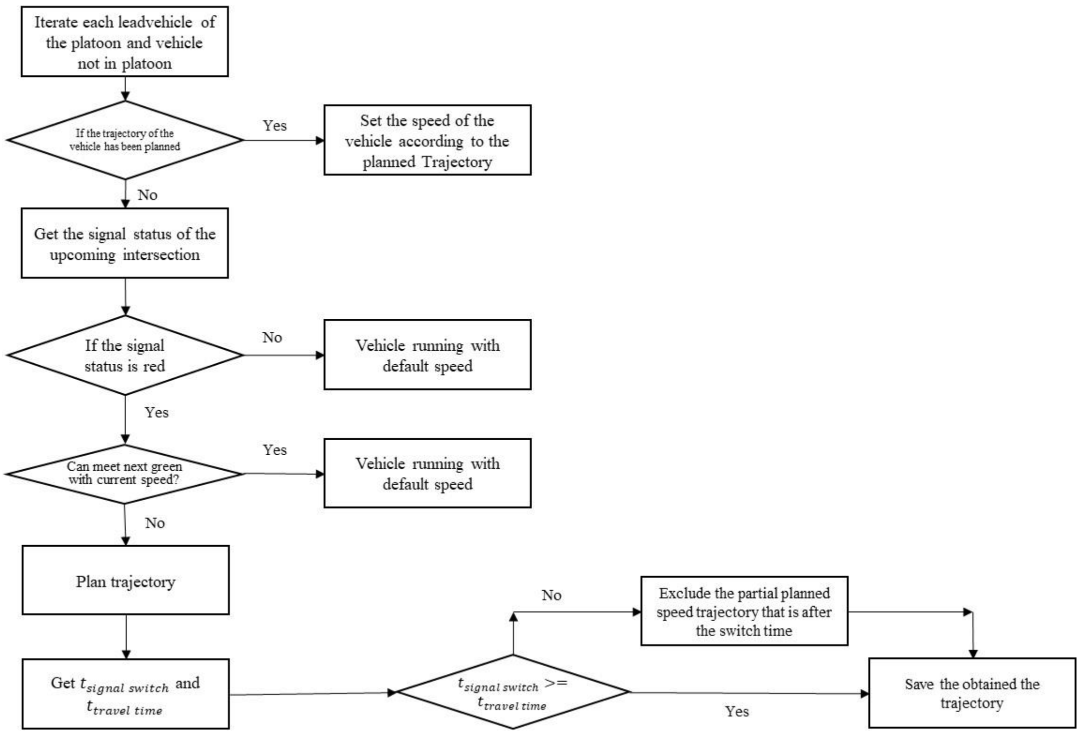

Figure 3.6 Flow chart for the trajectory planning

3.7 Signal Timing for Superstreets

Signal timing of a superstreet, especially the cycle length and phase splits, can have a significant influence on the operational performance of a superstreet. Exceedingly long cycle lengths can increase the waiting time of vehicles in front of the intersection. On the other hand, a traffic light with a short cycle length might result in insufficient phase splits to clear the queued vehicles in front of the intersection. In addition, in the superstreet, signal progression is an essential component of the signal's design since a major portion of the vehicles would come across two signals consecutively when they are traveling through the superstreet. As the traffic of through movement from the major street is significantly greater than the other approaches, this research mainly guarantees the progressions for the traffic of through movement on the main street, which is accomplished by adjusting the offset between the relevant signals. The offset can be calculated as Equation 17.

$$OS = \frac{D}{v} \tag{17}$$

Where OS and D are the offset between two signals, D is the distance between two intersections, and v is the vehicle speed. The cycle lengths for U.S.17 were provided in Hummer et al., 2010, and were employed in this research. The cycle length for the main intersection is 120s and 100s for the crossover intersections. In the environment of superstreets, two phases are sufficient for all intersections. The phase splits for the two phases can be determined based on the ratio of critical lane volumes, as demonstrated by Equation 18.

$$G_i = (C - l) \times \frac{V_i}{V_t} \tag{18}$$

Where G_i denotes the green splits for phase i, C is the cycle length, l denotes the total lost time for all phases (10 seconds for two phases in this study), V_i means the critical lane volumes for the phase i and V_t is the sum of critical lane volumes in the intersection. Note that if the calculated G_i based on Equation 18 is less than the minimum green splits to clear the queue, then G_i should be the minimum green split instead.

3.6 Simulation setting

In this section, some important settings in the SUMO simulation are introduced. Experiment scenarios are designed to account for different traffic scales and CAV market penetrations. For traffic scales, four traffic demand levels are considered, including 25% peak demand, 50% peak demand, 75% peak demand, and 100% peak demand. As for market penetration, this research also explores the same four levels of market penetration rates under 100% and 50% demand levels. Each scenario has 10 simulation runs and each run last for 3600 seconds. The operational performance is evaluated by using two measures, fuel consumption and traffic delays. Although the trajectory planning strategy introduced above focuses on minimal fuel consumption, it is still worth exploring how the strategy would influence the traffic delay. In SUMO, users can extract vehicle trajectory output and trip information output. Since the trajectory planning strategy only works when CAVs are approaching the intersection, this research only evaluated the fuel consumptions on the road segment before the intersection. Trip information output from SUMO includes the number of vehicles that have finished their trips and associated traffic delays. In other words, the unfinished trips are not recorded in the final output.

Three control strategies are examined respectively, including base control, platoon control, platoon with trajectory planning control. In the base control scenarios, the superstreet is filled with HDV traffic only. In the platoon control scenarios, the superstreet has CAVs which are enabled with platoon capability only. In the platooning with trajectory planning scenarios, the superstreet has CAVs which are enabled with platooning and trajectory planning capabilities.

CHAPTER 4 SIMULATION RESULTS AND DISCUSSIONS

4.1 Introduction

This chapter presents and discusses the simulation results from scenarios defined previously. Section 4.2 introduces the results for different control strategies while Section 4.3 explains the findings for scenarios with different market penetration rates.

4.2 Different Control Strategies Under Different Traffic Scales

The operational performances for three different control strategies are presented in Table 4-1. According to Table 4-1, CAVs with platooning control can significantly reduce fuel consumption at all demand levels. The magnitude of reduction is highest (25%) when the demand is 75%. When the demand level is 100%, the reduction magnitude of fuel consumption becomes less significant. This may be attributed to the increased capacity with platooning control. Due to shorter headways, more vehicles are waiting in front of the intersection and therefore the fuel consumption increases overall. Notably, platooning with trajectory planning can further decrease fuel consumption at most demand levels relative to platooning control. This benefit is not that significant at demand levels of 75% and 50%, in which fuel consumption is almost equal to the one in platooning control only, showing the overall effectiveness of the proposed trajectory planning strategy.

Platooning control does not have a significant benefit in the traffic delay, especially in lower-traffic demand scenarios. This is reasonable since vehicles in platoons do not have much freedom in achieving their maximum speed; while in base control, individual vehicles can obtain their maximum speed especially when there is no congestion on the roads, i.e., at less demand levels. Notably, in scenarios of platooning and trajectory planning control, the traffic delays are often lower compared to platooning control only. In platooning and trajectory planning control scenarios, CAVs can terminate deceleration upon the detection of signal change from red to green. In such scenarios, CAVs may arrive at the intersection at a medium speed. Without trajectory planning control, CAVs may keep running at their original speed and encounter the red signal, and then make a full stop. In this scenario, the vehicle would have to accelerate from 0 to travel through the intersection. The decrease in traffic delay from trajectory planning may be attributed to avoiding such occasions. Also, when the traffic demand is less than 50%, platooning control and platooning with trajectory planning control increase delays compared to base control; this may be explained by the freedom in achieving maximum speed described above.

Table 4-1 Operational Performances in Three Control Strategies

	Base			Platooning[3]			Platooning with Trajectory Planning[4]		
	FC[1]	Delay[2]	Trips	FC	Delay	Trips	FC	Delay	Trips
100% Peak Demand	0.0201	28.7633	3804	0.0192 (-4%)	28.7849 (0%)	4165 (9%)	0.0184 (-4%)	25.8975 (-10%)	4163 (0%)
75% Peak Demand	0.0175	23.701	3202	0.0131 (-25%)	22.0473 (-7%)	3378 (5%)	0.0131 (0%)	21.6833 (-2%)	3378 (0%)
50% Peak Demand	0.0124	18.3352	2258	0.0113 (-8%)	18.9007 (+3%)	2257 (0%)	0.0112 (-1%)	18.8753 (0 %)	2257 (0%)
25% Peak Demand	0.0110	15.8547	1136	0.0100 (-9%)	16.8723 (+6%)	1136 (0%)	0.0099 (-2%)	16.8664 (0%)	1136 (0%)

Note: 1 represents fuel consumption, the unit is liter; 2 represent average traffic delay, the unit is second; 3 numbers inside parenthesis indicate the comparison results between the platooning control and the base control; 4 numbers inside parenthesis indicate the comparison results between the platooning with trajectory planning and the platooning control.

4.3 Results of Different Market Penetration Rates

This research examines the performances of different market penetration rates under two different demand levels, 100% peak demand and 50% peak demand, representing congested and uncongested traffic flow, respectively. The average fuel consumption and average traffic delays are presented in Table 4-2 and Table 4-3, respectively. Under the congested traffic scenarios, the improvement in both fuel consumption and traffic delays increases with the increase of the market penetration rate overall. However, this increasing trend is unstable as the improvement magnitude has fluctuations. Under the uncongested traffic flow scenarios, the fuel consumption can still be reduced with CAVs. However, adverse effects are shown in traffic delays under different market penetration rates. Unstable effects under different market penetration rates are also observed.

Table 4-2 Performances in Different Market Penetrations with 100% Peak Demand

Market Penetration Rate	Fuel consumption[1]	Delay[1]
100% CAV	0.0187 (-8%)	25.8975 (-10%)
75% CAV	0.0182 (-10%)	26.4534 (-8%)
50% CAV	0.0188 (-7%)	27.1856 (-5%)
25% CAV	0.0192 (-5%)	26.4651 (-8%)
0% CAV (base)	0.0203	28.7633

Note: 1 numbers inside parenthesis indicate the improvement compared to the base

Table 4-3 Performances in Different Market Penetrations with 50% Peak Demand

Market Penetration Rates	Fuel consumption[1]	Delay[1]
100% CAV	0.0123 (-5%)	18.8753 (3%)
75% CAV	0.0124 (-4%)	19.7078 (7%)
50% CAV	0.0120 (-7%)	19.5642 (7%)
25% CAV	0.01329 (2%)	19.0496 (4%)
0% CAV (base)	0.0130	18.3352

Note: 1 numbers inside parenthesis indicate the improvement compared to the base

CHAPTER 5 SUMMARY AND FUTURE RESEARCH

5.1 Summary

CAVs as an emerging technology can bring substantial benefits in improving operational performance including fuel consumption, capacity, and traffic delay. Extensive studies have tested CAV technologies at conventional intersections, freeway segments, roundabouts, on/offramps, while the impact of CAVs in the alternative intersection designs has received relatively less attention. This research attempts to mitigate this research gap by investigating the potential impact of CAV technology on the operational performance of superstreets, one of the popular alternative intersection designs in the US. The CAVs in this study are assumed to have advanced features including platooning and trajectory planning. Platooning means the CAVs can travel on roads with shorter headway and harmonized speed relative to their preceding vehicles. For trajectory planning, a two-trajectory planning strategy is proposed when CAVs detect that the upcoming traffic light is red. These features were tested separately to examine their impacts on the operational performance separately, on different traffic scales and at different market penetration rates. This research considered four different traffic scales including 25% peak demand, 50% peak demand, 75% peak demand, and 100% peak demand. As for market penetration rates, this research accounted for 25%, 50%, 75%, and 100% market penetration rates of CAVs at two different traffic demand levels, 100%, and 50% traffic scales, representing congested traffic flows and uncongested traffic flows.

The simulation results showed that platooning control and platooning with trajectory planning can both yield benefits in fuel consumption. In addition, platooning with trajectory planning showed advantages in further reducing average fuel consumption and traffic delay in all demand levels. However, the superiority of CAVs over HDVs was influenced by traffic demand significantly, as the results showed that the demand is less than 50%, platooning and platooning with trajectory platooning cannot yield benefit in improving the operational performances. Notably, some unstable effects of CAVs were also observed in mixed traffic environments where both CAVs and HDVs were present.

5.2 Future Research

This research has utilized simple platooning and trajectory planning strategies to test the performances of CAVs on different traffic scales and at different market penetration rates. Future research can develop and consider more sophisticated platooning and trajectory planning strategies for CAVs. Also, dynamic signal timing strategies may deserve further consideration since the arrival information on CAVs is expected to be available in the future.

REFERENCES

Aghabayk, K., Sarvi, M., & Young, W. (2015). A state-of-the-art review of car-following models with particular considerations of heavy vehicles. *Transport reviews*, *35*(1), 82-105.

Ahn, K. (1998). *Microscopic fuel consumption and emission modeling* (Doctoral dissertation, Virginia Tech).

Aron, M. (1988). Car following in an urban network: Simulation and experiments. Proceedings of Seminar D, 16th PTRC meeting, Bath, Somerset, England, UK, pp. 27–39.

Azimi, R., Bhatia, G., Rajkumar, R., & Mudalige, P. (2012). Intersection management using vehicular networks (No. 2012-01-0292). SAE Technical Paper.

Bando, M., Hasebe, K., Nakanishi, K., Nakayama, A., Shibata, A., & Sugiyama, Y. (1995). Phenomenological study of dynamical model of traffic flow. Journal de Physique I, 5(11), 1389-1399.

Barth, M., & Boriboonsomsin, K. (2008). Real-world carbon dioxide impacts of traffic congestion. *Transportation Research Record*, *2058*(1), 163-171.

Bekey, G. A., Burnham, G. O., & Seo, J. (1977). Control theoretic models of human drivers in car following. *Human Factors*, *19*(4), 399-413.

Bento, L. C., Parafita, R., & Nunes, U. (2012, September). Intelligent traffic management at intersections supported by V2V and V2I communications. In 2012 15th International IEEE Conference on Intelligent Transportation Systems (pp. 1495-1502). IEEE.

Boriboonsomsin, K., Barth, M. J., Zhu, W., & Vu, A. (2012). Eco-routing navigation system based on multisource historical and real-time traffic information. *IEEE Transactions on Intelligent Transportation Systems*, *13*(4), 1694-1704.

Brown, A., Repac, B., & Gonder, J. (2013). *Autonomous vehicles have a wide range of possible energy impacts* (No. NREL/PO-6A20-59210). NREL, University of Maryland.

Burnham, G. O., & Bekey, G. A. (1976). A heuristic finite state model of the human driver in a car following situation. IEEE Transactions on Systems, Man and Cybernetics SMC, 6(8), 554–562.

Bullen, A. G. R. (1982). Development of computerized analysis of alternative parking management policies. *Transportation Research Record*, *845*, 31-37.

Ceder, A., & May, Jr., A. D. (1976). Further evaluation of single and two regime traffic flow models. Transportation Research Record: Journal of Transportation Research Board, 567, 1–30.

Chandler, R. E., Herman, R., & Montroll, E. W. (1958). Traffic dynamics: studies in car following. *Operations research*, *6*(2), 165-184.

Chen, D., Ahn, S., Chitturi, M., & Noyce, D. A. (2017). Towards vehicle automation: Roadway capacity formulation for traffic mixed with regular and automated vehicles. *Transportation research part B: methodological*, *100*, 196-221.

Chong, L., Abbas, M. M., Flintsch, A. M., & Higgs, B. (2013). A rule-based neural network approach to model driver naturalistic behavior in traffic. *Transportation Research Part C: Emerging Technologies*, *32*, 207-223.

Click, S. M., Berry, C., & Mahendran, A. (2010). Evaluation of traditional and nontraditional interchange treatments to preserve service life of narrow over-and underpass roadways. Transportation research record, 2171(1), 21-32.

Colombo, A., & Del Vecchio, D. (2012, April). Efficient algorithms for collision avoidance at intersections. In Proceedings of the 15th ACM international conference on Hybrid Systems: Computation and Control (pp. 145-154).

Das, S., Bowles, B. A., Houghland, C. R., Hunn, S. J., & Zhang, Y. (1999). A fuzzy logic model of freeway driver behaviour. Proceedings of the international ICSC congress on computational intelligence methods and applications, New York.

Derbel, O., Peter, T., Zebiri, H., Mourllion, B., & Basset, M. (2013). Modified intelligent driver model for driver safety and traffic stability improvement. IFAC Proceedings Volumes, 46(21), 744-749.

Do, W., Rouhani, O. M., & Miranda-Moreno, L. (2019). Simulation-based connected and automated vehicle models on highway sections: a literature review. *Journal of Advanced Transportation*, 2019.

Dresner, K., & Stone, P. (2004, July). Multiagent traffic management: A reservation-based intersection control mechanism. In *Proceedings of the Third International Joint Conference on Autonomous Agents and Multiagent Systems-Volume 2* (pp. 530-537). IEEE Computer Society.

Dresner, K., & Stone, P. (2006, May). Human-usable and emergency vehicle-aware control policies for autonomous intersection management. In Fourth International Workshop on Agents in Traffic and Transportation (ATT), Hakodate, Japan.

Dresner, K., & Stone, P. (2008). A multiagent approach to autonomous intersection management. Journal of artificial intelligence research, 31, 591-656.

Durrani, U., Lee, C., & Maoh, H. (2016) Calibrating the Wiedemann's vehicle-following model using mixed vehicle-pair interactions. *Transportation research part C: emerging technologies*, . 67, 227-242.

Elhenawy, M., Elbery, A. A., Hassan, A. A., & Rakha, H. A. (2015, September - 2015, September). An Intersection Game-Theory-Based Traffic Control Algorithm in a Connected Vehicle Environment. In 2015 IEEE 18th International Conference on Intelligent Transportation Systems (pp. 343–347). IEEE. https://doi.org/10.1109/ITSC.2015.65

Evans, L., & Rothery, R. (1973). Experimental measurement of perceptual thresholds in car following. Highway Research Record, 64, 13–29.

FHWA. (2008). The Next Generation Simulation (NGSIM) [Online]. Available: <http://www.ngsim.fhwa.dot.gov/> (Accessed).

Fiori, C., Ahn, K., & Rakha, H. A. (2018). Optimum routing of battery electric vehicles: Insights using empirical data and microsimulation. Transportation Research Part D: Transport and Environment, 64, 262-272.

Gao, Q., Hu, S., & Dong, C. (2008). The modeling and simulation of the car-following behavior based on fuzzy inference. Proceedings of the international workshop on modelling, simulation and optimization, WMSO, Hong Kong, pp. 322–325.

Ghaffarian, H., Fathy, M., & Soryani, M. (2012). Vehicular ad hoc networks enabled traffic controller for removing traffic lights in isolated intersections based on integer linear programming. IET intelligent transport systems, 6(2), 115-123.

Gipps, P. G. (1981). A behavioral car-following model for computer simulation. *Transportation Research Part B: Methodological*, *15*(2), 105-111.

Gipps, P. G. (1986). A model for the structure of lane-changing decisions. *Transportation Research Part B: Methodological*, *20*(5), 403-414.

Gonder, J., Earleywine, M., & Sparks, W. (2012). Analyzing vehicle fuel saving opportunities through intelligent driver feedback. *SAE International Journal of Passenger Cars-Electronic and Electrical Systems*, *5*(2012-01-0494), 450-461.

Gonzalez-Rojo, S., Slama, J. G., Pereira, A. L., & Mora-Camino, F. (2002). A fuzzy logic approach for car-following modelling. Systems Analysis Modelling Simulation, 42(5), 735–755.

Gregoire, J., Bonnabel, S., & de La Fortelle, A. (2014). Priority-based coordination of robots.

Halati, A., Lieu, H., & Walker, S. (1997). CORSIM-corridor traffic simulation model. In *Traffic Congestion and Traffic Safety in the 21st Century: Challenges, Innovations, and OpportunitiesUrban Transportation Division, ASCE; Highway Division, ASCE; Federal Highway Administration, USDOT; and National Highway Traffic Safety Administration, USDOT.*.

Haley, R. L., Ott, S. E., Hummer, J. E., Foyle, R. S., Cunningham, C. M., & Schroeder, B. J. (2011). Operational effects of signalized superstreets in North Carolina. Transportation Research Record, 2223(1), 72-79.

Hanken, A., & Rockwell, T. H. (1967). A model of car following derived empirically by piece-wise regression analysis. In vehicular traffic science. In *Proceedings of the Third International Symposium on the Theory of Traffic Flow Operations Research Society of America*.

Helly, W. (1959). Simulation of bottlenecks in single lane traffic flow. Proceedings of the symposium on theory of traffic flow, Research Laboratories, General Motors, New York, pp. 207–238.

Herman, R., & Potts, R. B. (1959). Single lane traffic theory and experiment. Proceedings of the symposium on theory of traffic flow, Research Labs, General Motors, New York, pp. 147–157.

Heyes, M. P. and R. Ashworth. (1972). "Further Research on Car-Following Models." *Transportation Research* 6(3):287–91.

Hidas, P. (2005). Modelling vehicle interactions in microscopic simulation of merging and weaving. *Transportation Research Part C: Emerging Technologies*, *13*(1), 37-62.

Hoefs, D. H. (1972). Entwicklung einer Messmethode uber den Bewegungsablauf des Kolonnenverrkehrs. Germany: Universitat (TH) Karlsruhe.

Holzem, A. M., Hummer, J. E., Cunningham, C. M., O'Brien, S. W., Schroeder, B. J., & Salamati, K. (2015). Pedestrian and bicyclist accommodations and crossings on superstreets. Transportation research record, 2486(1), 37-44.

Hongfei, J., Zhicai, J., & Anning, N. (2003). Develop a car-following model using data collected by 'five-wheel system'. Proceedings of the IEEE intelligent transportation system, Vol. 1, China, pp. 346–351.

Hummer, J., Haley, R. L., Ott, S. E., Foyle, R. S., & Cunningham, C. M. (2010). Superstreet benefits and capacities. *Department of Civil, Construction and Environmental Engineering, North Carolina State University, Raleigh, NC*.

Hummer, J., Ray, B., Daleiden, A., Jenior, P., & Knudsen, J. (2014). *Restricted crossing U-turn: informational guide* (No. FHWA-SA-14-070). United States. Federal Highway Administration. Office of Safety.

Insurance Institute for Highway Safety (May, 2010), "New Estimates of Benefits of Crash Avoidance Features on Passenger Vehicles," Status Report, Vol. 45, No. 5.

Jiang, H., Hu, J., An, S., Wang, M., & Park, B. B (2017). Eco approaching at an isolated signalized intersection under partially connected and automated vehicles environment. *Transportation Research Part C: Emerging Technologies*, 2017. 79, 290-307.
Jiang, R., Wu, Q., & Zhu, Z. (2001). Full velocity difference model for a car-following theory. Physical Review E, 64(1), 017101.
Kamal, M. A. S., Imura, J. I., Ohata, A., Hayakawa, T., & Aihara, K. (2013, October). Coordination of automated vehicles at a traffic-lightless intersection. In 16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013) (pp. 922-927). IEEE.
Kesting, A., & Treiber, M. (2008). Calibrating car-following models by using trajectory data: Methodological study. Transportation Research Record, 2088(1), 148-156.
Kesting, A., Treiber, M., & Helbing, D. (2007). General lane-changing model MOBIL for car-following models. Transportation Research Record, 1999(1), 86-94.
Kesting, A., Treiber, M., & Helbing, D. (2010). Enhanced intelligent driver model to access the impact of driving strategies on traffic capacity. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 368(1928), 4585-4605.
Khodayari, A., Ghaffari, A., Kazemi, R., & Braunstingl, R. (2012). A modified car-following model based on a neural network model of the human driver effects. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, *42*(6), 1440-1449.
Kita, H. (1999). A merging–giveway interaction model of cars in a merging section: a game theoretic analysis. *Transportation Research Part A: Policy and Practice*, *33*(3-4), 305-312.
Kometani, E. I. J. I., & Sasaki, T. S. U. N. A. (1958). On the stability of traffic flow (report-I). *J. Oper. Res. Soc. Japan*, *2*(1), 11-26.
Kometani, E., & Sasaki, T. (1959). Dynamic behaviour of traffic with a nonlinear spacing-speed relationship. Proceedings of the symposium on theory of traffic flow, Research Laboratories, General Motors, New York, pp. 105–119.
Koupal, J., Michaels, H., Cumberworth, M., Bailey, C., & Brzezinski, D. (2002, April). EPA's plan for MOVES: a comprehensive mobile source emissions model. In Proceedings of the 12th CRC On-Road Vehicle Emissions Workshop, San Diego, CA (pp. 15-17).
Krajzewicz, D. (2010). Traffic simulation with SUMO–simulation of urban mobility. In *Fundamentals of traffic simulation* (pp. 269-293). Springer, New York, NY.
Lee, D. N. (1976). A theory of visual control of braking based on information about time to collision. Perception, 5(4), 437–459.
Lee, J., & Park, B. (2012). Development and evaluation of a cooperative vehicle intersection control algorithm under the connected vehicles environment. IEEE Transactions on Intelligent Transportation Systems, 13(1), 81-90.
Letter, C., & Elefteriadou, L. (2017). Efficient control of fully automated connected vehicles at freeway merge segments. Transportation Research Part C: Emerging Technologies, 80, 190-205.
Levin, M. W., & Boyles, S. D. (2016). A multiclass cell transmission model for shared human and autonomous vehicle roads. *Transportation Research Part C: Emerging Technologies*, *62*, 103-116.
Li, D., & Wagner, P. (2019). Impacts of gradual automated vehicle penetration on motorway operation: a comprehensive evaluation. European Transport Research Review, 11, 1–10. URL: https://link.springer.com/track/pdf/10.1186/ s12544-019-0375-3. doi:10.1186/s12544-019-0375-3

Li, T., Guo, F., Krishnan, R., Sivakumar, A., & Polak, J. (2020). Right-of-way reallocation for mixed flow of autonomous vehicles and human driven vehicles. *Transportation Research Part C: Emerging Technologies*, *115*, 102630.

Li, Y., Li, Z., Wang, H., Wang, W., & Xing, L. (2017). Evaluating the safety impact of adaptive cruise control in traffic oscillations on freeways. Accident Analysis & Prevention, 104, 137-145.

Li, Z., Wu, Q., Yu, H., Chen, C., Zhang, G., Tian, Z. Z., & Prevedouros, P. D. (2019). Temporal-spatial dimension extension-based intersection control formulation for connected and autonomous vehicle systems.. *Transportation Research Part C: Emerging Technologies*, *104*,. 234-248.

Liu, P., & Fan, W. Exploring the impact of connected and autonomous vehicles on freeway capacity using a revised Intelligent Driver Model. *Transportation planning and technology*, 2020. 43(3), 279-292.

Liu, Y., Guo, J., Taplin, J., & Wang, Y. (2017). Characteristic analysis of mixed traffic flow of regular and autonomous vehicles using cellular automata. Journal of Advanced Transportation, 2017, 1–10. URL: https://doi.org/10.1155/2017/8142074. doi:10.1155/2017/8142074.

Lownes, N. E., & Machemehl, R. B. (2006) VISSIM: a multi-parameter sensitivity analysis. In Proceedings of the 2006 Winter Simulation Conference (pp. 1406-1413). IEEE. 2006, December.

Lu, C., Dong, J., Hu, L., & Liu, C. (2019).An ecological adaptive cruise control for mixed traffic and its stabilization effect. *IEEE Access*, 7, 81246-81256.

Ma, J., Li, X., Zhou, F., Hu, J., & Park, B. B. (2017). Parsimonious shooting heuristic for trajectory design of connected automated traffic part II: computational issues and optimization. Transportation Research Part B: Methodological, 95, 421-441.

Ma, X. (2004, November). Toward an integrated car-following and lane-changing model based on neural-fuzzy approach. In *Helsinki summer workshop*.

Malinauskas, R. (2014). The intelligent driver model: Analysis and application to adaptive cruise control.

Manjunatha, P., Vortisch, P., & Mathew, T. V. (2013, January). Methodology for the Calibration of VISSIM in Mixed Traffic. In *Transportation research board 92nd annual meeting* (Vol. 11). Transportation Research Board Washington, DC, United States.

Mehani, O., & De La Fortelle, A. (2007, February). Trajectory planning in a crossroads for a fleet of driverless vehicles. In *International Conference on Computer Aided Systems Theory* (pp. 1159-1166). Springer, Berlin, Heidelberg.

Mena-Oreja, J., Gozalvez, J., & Sepulcre, M. (2018). Effect of the configuration of platooning maneuvers on the traffic flow under mixed traffic scenarios. In O. Altintas (Ed.), 2018 IEEE Vehicular Networking Conference (VNC) (pp. 1–4). [Piscataway, New Jersey]: IEEE. doi:10.1109/VNC.2018.8628381.

Michaels, R. M., & Cozan, L. W. (1963). Perceptual and field factors causing lateral displacements. Public Roads, 32, 233–240

Milanés, V., Godoy, J., Villagrá, J., & Pérez, J. (2010). Automated on-ramp merging system for congested traffic situations. *IEEE Transactions on Intelligent Transportation Systems*, *12*(2), 500-508.

Morrow, W. R., Greenblatt, J. B., Sturges, A., Saxena, S., Gopal, A., Millstein, D., ... & Gilmore, E. A. (2014). Key factors influencing autonomous vehicles' energy and environmental outcome. In *Road vehicle automation* (pp. 127-135). Springer, Cham.

Moon, J. P., Kim, Y. R., Kim, D. G., & Lee, S. K. (2011). The potential to implement a superstreet as an unconventional arterial intersection design in Korea. *KSCE Journal of Civil Engineering*, *15*(6), 1109-1114.

Nagel, K., Wanger, P., & Woesler, R. (2003). Still flowing: Approaches to traffic flow and traffic jam modelling.Operational Research, 51(5), 681–710.

Naghawi, H. H., & Idewu, W. I. A. (2014). Analyzing delay and queue length using microscopic simulation for the unconventional intersection design Superstreet. Journal of the South African Institution of Civil Engineering, 56(1), 100-107.

Naghawi, H., AlSoud, A., & AlHadidi, T. (2018). The possibility for implementing the superstreet unconventional intersection design in Jordan. Periodica Polytechnica Transportation Engineering, 46(3), 122-128.

National Research Council. (2013). *Transitions to alternative vehicles and fuels*. National Academies Press.

National Highway Traffic Safety Administration (NHTSA, n.d.), *Automated vehicle for safety*. https://www.nhtsa.gov/technology-innovation/automated-vehicles-safety

Olia, A., Razavi, S., Abdulhai, B., & Abdelgawad, H. (2018). Traffic capacity implications of automated vehicles mixed with regular vehicles. Journal of Intelligent Transportation Systems, 22, 244–262. doi:10.1080/15472450.2017.1404680.

Ott, S. E., Fiedler, R. L., Hummer, J. E., Foyle, R. S., & Cunningham, C. M. (2015). Resident, Commuter, and Business Perceptions of New Superstreets. Journal of Transportation Engineering, 141(7), 04015003.

Ott, S. E., Haley, R. L., Hummer, J. E., Foyle, R. S., & Cunningham, C. M. (2012). Safety effects of unsignalized superstreets in North Carolina. Accident Analysis & Prevention, 45, 572-579.

Panwai, S., & Dia, H. (2007). Neural agent car-following models. IEEE Transactions on Intelligent Transportation Systems, 8(1), 60–70.

Pourmehrab, M., Elefteriadou, L., Ranka, S., & Martin-Gasulla, M (2019). Optimizing signalized intersections performance under conventional and automated vehicles traffic. *IEEE Transactions on intelligent transportation systems*. .

Qian, X., Gregoire, J., Moutarde, F., & De La Fortelle, A. (2014, October). Priority-based coordination of autonomous and legacy vehicles at intersection. In 17th international IEEE conference on intelligent transportation systems (ITSC) (pp. 1166-1171). IEEE.

Rahman, M., Chowdhury, M., Xie, Y., & He, Y. (2013). Review of microscopic lane-changing models and future research opportunities. *IEEE transactions on intelligent transportation systems*, 14(4), 1942-1956.

Rahman, M. S., & Abdel-Aty, M. (2018). Longitudinal safety evaluation of connected vehicles' platooning on expressways. *Accident Analysis & Prevention*, *117*, 381-391.

Reid, J. D., & Hummer, J. E. (2001). Travel time comparisons between seven unconventional arterial intersection designs. Transportation Research Record, 1751(1), 56-66.

Rickert, M., Nagel, K., Schreckenberg, M., & Latour, A. (1996). Two lane traffic simulations using cellular automata. *Physica A: Statistical Mechanics and its Applications*, *231*(4), 534-550.

Rockwell, T. H., Ernst, R. L., & Hanken, A. (1968). A sensitivity analysis of empirically derived car-following models. *Transportation Research/UK/*.

Salvucci, D. D., Mandalia, H. M., Kuge, N., & Yamamura, T. (2007). Lane-change detection using a computational driver model. Human factors, 49(3), 532-542.

Schakel, W. J., Knoop, V. L., & van Arem, B. (2012). Integrated lane change model with relaxation and synchronization. *Transportation Research Record*, *2316*(1), 47-57.

Schepperle, H., Böhm, K., & Forster, S. (2007, May). Towards valuation-aware agent-based traffic control. In Proceedings of the 6th international joint conference on Autonomous agents and multiagent systems (pp. 1-3).

Sharon, G., & Stone, P. (2017, May). A protocol for mixed autonomous and human-operated vehicles at intersections. In International Conference on Autonomous Agents and Multiagent Systems (pp. 151-167). Springer, Cham.

Shladover, S. E., Su, D., & Lu, X. Y. (2012). Impacts of cooperative adaptive cruise control on freeway traffic flow. *Transportation Research Record*, *2324*(1), 63-70.a

Taiebat, M., Brown, A. L., Safford, H. R., Qu, S., & Xu, M. (2018). A review on energy, environmental, and sustainability implications of connected and automated vehicles. *Environmental science & technology*, *52*(20), 11449-11465.

Talebpour, A., Mahmassani, H. S., & Elfar, A. (2017). Investigating the effects of reserved lanes for autonomous vehicles on congestion and travel time reliability. Transportation Research Record: Journal of the Transportation Research Board , 2622, 1–12. doi:10.3141/2622-01

Toledo, T., Koutsopoulos, H. N., & Ben-Akiva, M. (2007). Integrated driving behavior modeling. *Transportation Research Part C: Emerging Technologies*, *15*(2), 96-112.

Toledo, T., Koutsopoulos, H. N., & Ben-Akiva, M. E. (2003). Modeling integrated lane-changing behavior. Transportation Research Record, 1857(1), 30-38.

Treiber, M., & Kesting, A. (2017). The intelligent driver model with stochasticity-new insights into traffic flow oscillations. Transportation research procedia, 23, 174-187.

Treiber, M., Hennecke, A., & Helbing, D. (2000). Congested traffic states in empirical observations and microscopic simulations. *Physical review E*, *62*(2), 1805.

Wei, C., Wang, Y., Asakura, Y., & Ma, L. (2019). A nonlinear programing model for collision-free lane-change trajectory planning based on vehicle-to-vehicle communication. Journal of Transportation Safety & Security, 1-21.

Wiedemann, R. (1974). Simulation des straßenverkehrsflusses, Schriftenreihe Heft 8, Institute for Transportation Science, Karlsruhe, Germany.

Wiedemann, R., & Reiter, U. (1992). Microscopic traffic simulation: The simulation system MISSION. CEC Project ICARUS (V1052), Final Report.

Wu, J., Abbas-Turki, A., & El Moudni, A. (2012). Cooperative driving: an ant colony system for autonomous intersection management. Applied Intelligence, 37(2), 207-222.

Xin, Q., Fu, R., Yuan, W., Liu, Q., & Yu, S. (2018). Predictive intelligent driver model for eco-driving using upcoming traffic signal information. Physica A: Statistical Mechanics and its Applications, 508, 806-823.

Xiong, B.-K., Jiang, R., & Tian, J.-F. (2019). Improving two-dimensional intelligent driver models to overcome overly high deceleration in car-following. Physica a: Statistical Mechanics and Its Applications, 534, 122313. https://doi.org/10.1016/j.physa.2019.122313

Xu, L., Yang, X., & Chang, G. L. (2017). Computing the Minimal U-Turn Offset for an Unsignalized Superstreet. Transportation Research Record, 2618(1), 48-57.

Xu, L., Yang, X., & Chang, G. L. (2019). Two-stage model for optimizing traffic signal control plans of signalized Superstreet. Transportmetrica A: transport science, 15(2), 993-1018.

Yan, F., Dridi, M., & El Moudni, A. (2009, October). Autonomous vehicle sequencing algorithm at isolated intersections. In 2009 12th International IEEE conference on intelligent transportation systems (pp. 1-6). IEEE.

Yang, H., Akiyama, T., & Sasaki, T. (1992). A neural network approach to the identification of real time origin-destination flows from traffic counts. In *International Conference on Artificial Intelligence Applications in Transportation Engineering, 1992, San Buenaventura, California, USA*.

Yang, M., Li, Z., Ke, Z., & Li, M. (2019). *A Deep Reinforcement Learning-based Ramp Metering Control Framework for Improving Traffic Operation at Freeway Weaving Sections* (No. 19-03788).

Yoon, J. W., & Kim, B. W. (2016). Vehicle position estimation using nonlinear tire model for autonomous vehicle. *Journal of Mechanical Science and Technology*, *30*(8), 3461-3468.

Yu, C., Feng, Y., Liu, H. X., Ma, W., & Yang, X (2019). Corridor level cooperative trajectory optimization with connected and automated vehicles. *Transportation Research Part C: Emerging Technologies*, . *105*, 405-421.

Yu, H., Tak, S., Park, M., & Yeo, H. (2019). Impact of autonomous-vehicle-only lanes in mixed traffic conditions. Transportation Research Record: Journal of the Transportation Research Board, 18, 036119811984747. doi:10.1177/0361198119847475.

Zhang, Y., & Ioannou, P. A. (2016). Environmental impact of combined variable speed limit and lane change control: a comparison of MOVES and CMEM model. IFAC-PapersOnLine, 49(3), 323-328.

Zhao, X. M., & Gao, Z. Y. (2005). A new car-following model: full velocity and acceleration difference model. The European Physical Journal B-Condensed Matter and Complex Systems, 47(1), 145-150.

Zheng, P., & McDonald, M. (2005). Application of fuzzy systems in the car-following behaviour analysis. Proceedings of the 2nd international conference on fuzzy systems and knowledge discovery, Vol. 3613, Changsha, China, pp. 782–791.

Zhong, Z., & Lee, E. E. Alternative Intersection Designs with Connected and Automated Vehicle. In 2019 IEEE 2nd Connected and Automated Vehicles Symposium (CAVS). (2019), September. (pp. 1-6). IEEE.

Zhou, L. J., Wang, D. H., & Li, W. Q. (2009). Application of artificial neural network and particle Swarm optimization in car-following model [J]. *Journal of Jilin University (Engineering and Technology Edition)*, *4*.

Zhou, M., Qu, X., & Jin, S. (2016). On the impact of cooperative autonomous vehicles in improving freeway merging: a modified intelligent driver model-based approach. IEEE Transactions on Intelligent Transportation Systems, 18(6), 1422-1428.

Zhu, F., & Ukkusuri, S. V. (2015). A linear programming formulation for autonomous intersection control within a dynamic traffic assignment and connected vehicle environment. Transportation Research Part C: Emerging Technologies, 55, 363-378.