IMPACT OF CONNECTED AND AUTONOMOUS VEHICLES ON MOBILITY OF HIGHWAY SYSTEMS

by

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ABSTRACT

PENGFEI LIU. Impact of connected and autonomous vehicles on mobility of highway systems. (Under the direction of DR. WEI FAN)

Connected and autonomous vehicle (CAV) technologies are known as an effective way to improve safety and mobility of the transportation system. As a combination technology of connected vehicle and autonomous vehicle, CAVs share real time traffic data with each other, such as position, speed, and acceleration. CAVs are able to increase roadway capacity since they require narrower lane width and headway. And CAVs can coordinate their maneuvers while weaving in which will result an improvement of capacities at weaving areas. Also, CAVs enable the information shared between vehicles and traffic signals. The coordinated operation among CAVs and the communication between CAVs and traffic signals will improve the throughput at signalized intersections and lead to a higher intersection capacity. To evaluate the influence of CAVs on freeway capacity and intersection mobility, new guidelines should be established. Microsimulation software is used to simulate CAVs as well as AVs and regular vehicles. Case studies are conducted both on freeways and signalized intersections. It is concluded that CAVs can improve the freeway capacity and the improvement of capacity also increases with the increase of freeway speed limit. Also, CAVs can help reduce the capacity drops before and after the on-ramp, off-ramp, and weaving area as the CAV penetration rate increases. With V2I/I2V communications, CAVs can effectively improve the efficiency of signalized intersections. The vehicle emissions under all scenarios are also generated. CAVs can reduce vehicle emissions by as much as 33.47% compared to regular vehicles and 11.26% compared to AVs. The

findings in this research could establish knowledge on how CAVs will improve mobility in the highway systems.

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LIST OF ABBREVIATIONS

AACC	anticipatory adaptive cruise control
AV	autonomous vehicle
CACC	cooperative adaptive cruise control
CAV	connected and autonomous vehicle
COM	component object model
CV	connected vehicle
DLL	dynamic link library
DSRC	dedicated short range communications
EDBM	external driver behavior model
FHWA	Federal Highway Administration
GA	genetic algorithm
GBDT	gradient boosting decision tree
I2V	infrastructure to vehicle
IDM	intelligent driver model
MAE	mean absolute error
NGSIM	Next Generation Simulation
PeMS	Performance Measurement System
RMSE	root mean square error
V2I	vehicle to infrastructure
V2V	vehicle to vehicle

CHAPTER 1 INTRODUCTION

1.1 Problem Statement and Motivation

Connected and autonomous vehicle (CAV) technologies are known as an effective way to enhance safety as well as roadway mobility. As a combination technology of connected vehicle and autonomous vehicle, CAVs share real time traffic data with each other, such as position, speed, and acceleration. CAVs are able to increase roadway capacity since they require narrower lane width and headway. And CAVs can coordinate their maneuvers while weaving in which will result an improvement of capacities at weaving areas. Also, CAVs enable the information shared between vehicles and traffic signals. Traffic signals are essential in urban traffic management. Although traffic signals can increase the intersection capacity particularly when the traffic volume is high, they may also increase travel time, gas emissions and fuel consumption of vehicles. Moreover, stop-and-go traffic increases the possibility of vehicle collisions and leads to increased economic cost as a result. The coordinated operation among CAVs and the communication between CAVs and traffic signals will improve the throughput at signalized intersections and lead to a higher intersection capacity.

As the travel demand increases in recent years, traditional intersections are generating more delays and gas emissions. As such, there is an urgent need to increase intersection capacity and the throughput mobility using the emerging CAV technologies. The coordinated through or turning maneuvers of CAVs may also reduce crashes and minimize the total delay at an isolated intersection. To evaluate CAVs' influence on freeway capacity and intersection mobility, new guidelines need to be established. Due to the rapid development of CAV technologies, it can be expected that CAVs will soon penetrate into the transportation system. The impact of CAVs on traffic delay and congestion needs to be quantified under different market penetration levels of CAVs.

This research is intended to establish knowledge on CAVs' impact for transportation planners better preparing future highway systems under mixed traffic environment.

1.2 Study Objectives

This study is trying to complete several objectives as follows:

1. To conduct a comprehensive literature review of the cutting-edge knowledge on CAVs and their impact on freeway capacity and intersection mobility;
2. To identify suitable freeway segments and intersections for case study and develop potential scenarios;
3. To use simulation method to measure freeway capacity and intersection mobility at different CAV penetration levels;
4. To evaluate the influence of the CAV technologies on freeway capacity and intersection mobility and provide recommendations on future research directions.
5. To predict CAV trajectory in the highway system using machine learning methods.

1.3 Expected Contributions

To evaluate the influence of CAVs on freeways and signalized intersections and develop the guidelines, modeling and simulation of CAVs are conducted in this research. The outcomes from this research are expected as follows:

1. A review of CAV technologies and freeway capacity and intersection mobility analysis considering different levels of CAV penetration;
2. Identification and development of freeway and intersection scenarios and collect the characteristics of each scenario;
3. Guidelines on freeway capacity and intersection mobility at different CAV penetration levels.
4. A machine learning method that predicts CAV trajectory more accurately compared to the state-of-the-art.

1.4 Research Overview

The research is structured as shown in Figure 1.1. In this chapter, the motivation of the research has been explained, followed by the study objectives and expected outcomes.

Chapter 2 presents a comprehensive literature review of the current technologies of CAVs. Previous studies that were conducted to analyze the impact of CAVs on highway systems are classified into three categories: (1) impact of CAVs on freeway capacity; (2) impact of CAVs on intersection mobility; (3) CAV trajectory optimization.

Chapter 3 presents the basic information needed to evaluate the influence of CAVs, including the historical traffic flow and speed data used in this research. The data source used to collect real time traffic flow and speed data is introduced. Different scenarios collected from the data source are also described in detail.

Chapter 4 presents the calibration process of the microscopic traffic simulation software used in this research. The case study location and the traffic data related to the selected location are described first. The genetic algorithm and the objective function used to optimize the difference between simulation results and real world data are also discussed.

Chapter 5 discusses the simulation results of the impact of CAVs on freeway capacity based on the data described in Chapter 3. The driving behavior of CAVs will be described first. Then the influence of CAVs on freeway capacity will be examined with consideration of different CAV penetration rates.

Chapter 6 presents the simulation results of the impact of CAVs on intersection mobility. The trajectory optimization strategy of CAV approaching intersection will be described. Then the impact of CAVs on intersection mobility will be explored with different market penetration rates.

Chapter 7 presents the prediction of vehicle trajectories using the proposed machine learning models. The prediction error of the proposed approach will be measured. Potential impacts of the machine learning approach on CAV trajectory prediction will be discussed.

Chapter 8 concludes the report by summarizing the impact of CAVs on freeway capacity and intersection mobility. Suggestions for future research directions will be also provided.

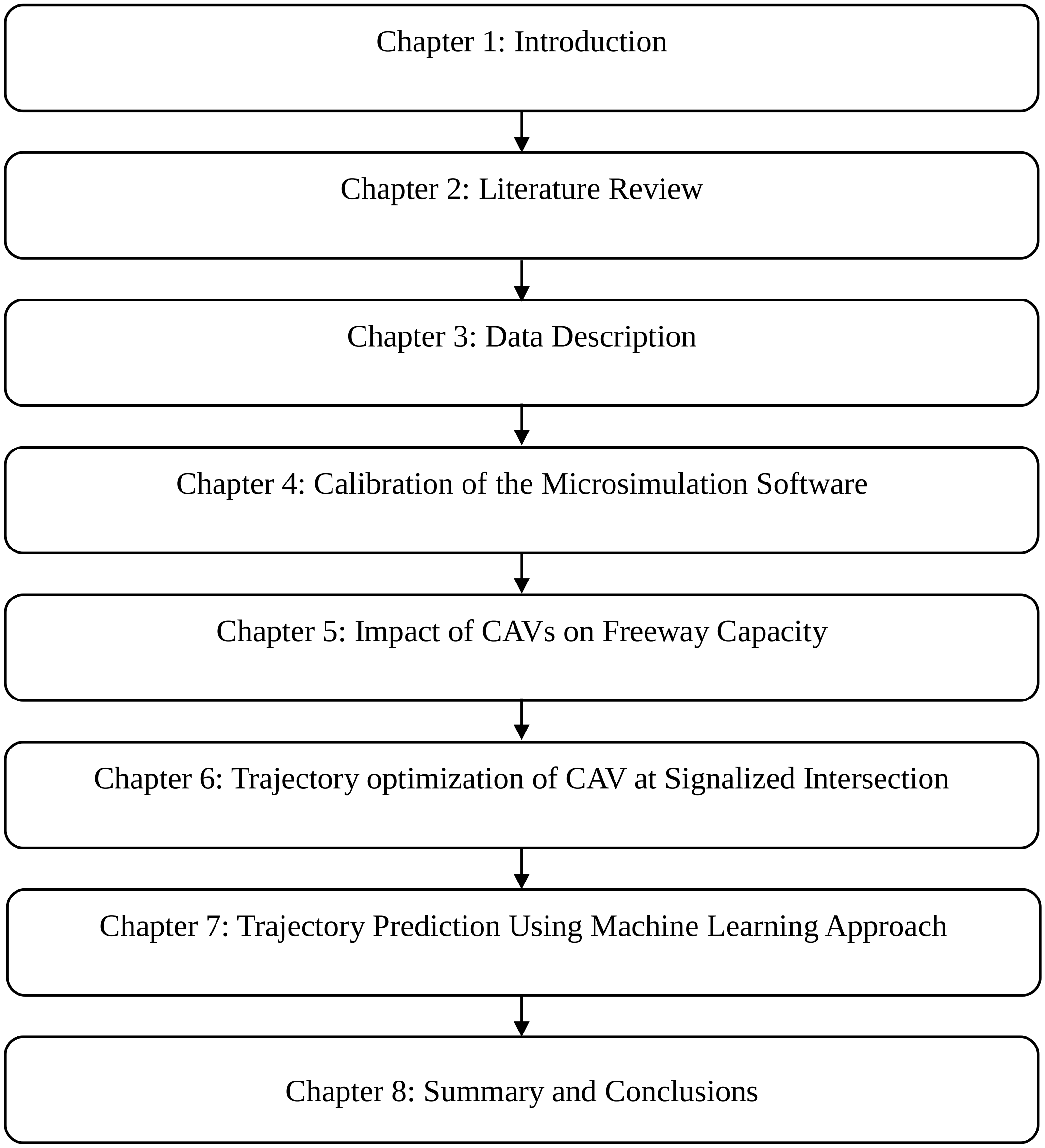

Figure 1.1 Research Structure

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

This chapter provides a comprehensive literature review of the current technologies of CAVs and various methodological approaches developed and used to analyze freeway capacity and intersection mobility with or without CAVs. This review will include previous freeway capacity and intersection mobility analysis methods with and without consideration of CAVs, possible modeling scenarios, and suitable parameters used in the estimation.

This chapter is organized as follows. Section 2.2 presents background of connected vehicle and autonomous vehicle technologies, followed by current technologies in use and benefits of CAVs. Section 2.3 details existing freeway capacity analysis methods with consideration of CAVs. Particular attention will be given to simulation-based approaches as they are capable of measuring freeway capacity under different modeling scenarios. Section 2.4 presents existing intersection analysis methods with consideration of CAVs. Particular attention will be given to trajectory optimization approaches as they are capable of measuring intersection mobility under different modeling scenarios. Finally, section 2.5 summarizes this chapter.

2.2 Connected Vehicle and Autonomous Vehicle Technology

2.2.1 Connected Vehicle Technology

Connected vehicles are defined as vehicles that use a number of different communication technologies to communicate with the driver, other cars on the road (V2V), roadside infrastructure (V2I), and the “Cloud” (V2C) (NHTSA 2016). V2V technology can enable applications such as crash alerts and hazard warnings, while also enabling cooperative braking. V2I technology is able to provide real time traffic information such as speed, volume, travel time, queue length, and stops (Shladover 2017). The USDOT's Connected Vehicle program is dedicated to new technologies that will enable V2V and V2I, by cooperating with state and local transportation agencies and stakeholders (Hong et al. 2014).

By applying connected vehicle technologies, drivers can be noticed in advance with the traffic information, such as traffic delay or an accident occurred ahead. Such information can greatly help drivers adjust their strategy of driving, which could reduce their travel time and also the probability of being involved in a crash. However, the total travel time may still increase due to the increased travel demand (Minelli 2015). According to National Highway Traffic Safety Administration (NHTSA), connected vehicles can reduce as much as 80 percent of crashes. Connected vehicles are a combination of technologies in the following categories:

- In-vehicle or mobile equipment is the most end equipment that provides useful information to drivers, such as vehicle speed and travel time.
- Roadside equipment will interact with connected vehicles with information, including both traffic signal and other connected vehicles to support better traffic management.
- Core systems enable the data exchange process between vehicles and infrastructure.
- Support systems create and operate a security credential management system that allows connected vehicle applications to establish trust relationships.

- Communications systems comprise the data communications infrastructure that provides connectivity for other equipment and systems in the connected vehicle environment. Dedicated Short Range Communications (DSRC) technology was developed specifically for connected vehicle communications with a 5.9 GHz frequency. DSRC provides a low-latency communications link. While the least stringent latency requirement for Active Safety is 1 second and most stringent latency requirement for Active Safety is 0.2 second, DSRC has a latency of 0.0002 second.

Applications-specific systems refer to the equipment supporting specific connected vehicle applications. For example, a software system acquires data from connected vehicles and integrates them into traffic management systems.

2.2.2 Autonomous Vehicle Technology

NHTSA defines autonomous vehicle as “self-driving vehicles which can execute steering, acceleration, and braking without interfering of human drivers.” Society of Automotive Engineers (SAE) international defines six levels of vehicle automation from level 0 to level 5. Table 2.1 shows different levels of vehicle automation.

Table 2.1 Summary of Different Levels of Vehicle Automation

Level	**Description**
Level 0	No automation
Level 1	Driver assistance: Human driver is assisted with acceleration and deceleration.
Level 2	Partial automation: Vehicle undertakes acceleration and deceleration.
Level 3	Conditional automation: Automated driving system with human driver intervention to a request.
Level 4	High automation: Vehicle undertakes all dynamic driving task.
Level 5	Full automation: No human driver needed.

Autonomous vehicles use a "sense-plan-act" design like other robotic systems. A suite of in-vehicle sensors gather information from the surroundings of the vehicle. The automated driving system will analyze sensor data and decide the next step actions, such as decelerating or lane changing. Autonomous vehicles use a combination of sensors to realize their automotive driving, which include radar, cameras, Lidar, GPS, and so on.

- Radar systems used in autonomous vehicles contain two ranges: short range and long range. Short range radar is used when vehicle speed is relatively low, detecting the vehicle's surroundings within a short distance. And long range radar is used when vehicle speed is relatively high, detecting over long distance.
- Cameras are equipped by autonomous vehicles to work as the human's eyes. Videos are captured and processed so that roadside infrastructure can be recognized, such as signage, lane markings, and traffic lights.
- Lidar creates 3D representations of the vehicle's surroundings. Although Lidar makes high resolution profiles, it is also easily disrupted by a temporary change of the surroundings, such as rain and snow.
- GPS receives real time position of the vehicle and provides navigation.

Litman (2014) explored the influence of AVs on travel demands and transportation planning. The analysis indicated that most impacts, including reduced traffic congestion and increased safety, will probably take place after 2040.

2.2.3 Connected and Autonomous Vehicle Technology

Connected and autonomous vehicle technology is a combination of CV and AV technology. CAV can be self-driving as well as communicate with its surroundings.

Some examples of existing CAV technologies are active lane keeping assistance, active park assistance, automatic braking, blind spot detection, cross traffic alert systems, and forward collision warning. USDOT is working closely with state DOTs to catch up with the rapid deployment of CAV technologies (Yang et al. 2017).

By incorporating the two technologies together, CAV has many more benefits compared to CV alone, AV alone, and traditional vehicles in the following aspects:

- Increase safety. By eliminating driver errors during driving, CAVs will significantly reduce the number of crashes. CAVs may reduce economy loss by over 126 billion dollars per year due to crashes in the United States (Kockelman et al. 2016).

- Increase capacity. CAVs will allow lower headways between vehicles, which will increase roadway capacity.

- Increase mobility. CAVs can increase mobility by providing opportunities to people less likely travelling due to various reasons (Duncan 2015, NHTSA 2016).

- Reduce emissions. By communicating with each other, CAVs could drive more smoothly than human drivers, which will reduce vehicle emissions and improve air condition.

- Save time. During in-vehicle time, people can perform any activity as necessary instead of driving. When arrived, CAVs can park themselves which will also save time for the both drivers and passengers.

- Improve road design. CAVs require narrower lanes and less traffic control methods such as median barriers and traffic lights, maximizing land use and increasing traffic efficiency. The need for human-centered design for parking areas will be significantly reduced (Chapin et al. 2016).

Policy should be made to maximize the positive impact of CAVs on public transit (Zmud 2017). It is predicted that by 2045 there will be 25% level 4 AV in the market (Bansal and Kockelman 2017).

2.3 Freeway Capacity Analysis Methods

One critical issue for CAV technology is that higher level of automation is still in its infancy. Therefore, there is inadequate historical data of CAVs and associated impacts yet. Most researchers used macro and micro simulation, driving simulators, field test and analytical methods to estimate the impact of CAVs on freeway capacity (Milakis et al. 2017).

2.3.1 Empirical Based Methods

2.3.1.1 Ni et al.'s research work

Ni et al. (2012) analyzed the impact of connected vehicle technology (CVT) on highway capacity. The model formulation was derived based on Gipps' car following model. The modeling strategy used different driver perception-reaction time for different driving modes, such as CVT-automated mode, CVT-assisted mode, and non-CVT mode. An illustrative example was conducted by employing different market penetration rates of CVT. The result showed that connected vehicle technology could increase highway capacity by 20% to 50% depending on the penetration rate. One limitation of this study was that the model assumed equilibrium flow and homogeneous type of vehicles.

2.3.1.2 Shi and Prevedouros's research work

Shi and Prevedouros (2016) examined the possible impact of driverless cars on freeway capacity based on Highway Capacity Manual 2010 methodologies. The quantification analysis used adjusted average headway and traffic demand flow rate. Two case studies were conducted on a basic freeway segment and a freeway weaving segment. Two types of driverless cars were considered (i.e., autonomous driverless cars and connected driverless cars), by setting different headways. It is concluded that the level of service can be improved by increasing the penetration rate of driverless cars in traffic and shortening the driverless car following headways.

2.3.1.3 Michael et al.'s research work

Michael et al. (1998) presented a methodology to calculate highway capacity as a function of inter-vehicle cooperation. The Automated Highway System was assumed to be dedicated for use by fully automated vehicles. Under the required spacing between inter-platoon vehicles, collisions can be avoided in the Automated Highway System. Various system parameters were set for capacity calculation. The minimum inter-vehicle separation was constrained for safe operation. It was concluded that highway capacity increases as a result of the increasing of inter-vehicle cooperation.

2.3.1.4 VanderWerf et al.'s research work

VanderWerf et al. (2002) examined the impacts of autonomous and cooperative adaptive cruise control systems on highway capacity. Three mathematical models were developed and used to represent vehicles driven by human drivers, Anticipatory Adaptive Cruise Control (AACC) system, and Cooperative Adaptive Cruise Control (CACC) system. Monte Carlo simulations approach was used to estimate the lane capacity. To keep it realistic, the on-ramp and off-ramp vehicles were set small enough so that they would not disturb the merging processes both upstream and downstream. It was concluded that the AACC system has a small effect on highway capacity even under the most favorable conditions. CACC system can increase highway capacity significantly by reducing the time gap between pairs of CACC vehicles. The lane capacity with a full penetration of CACC vehicles can accommodate more than 4,200 vehicles per hour.

2.3.1.5 Authority and Pinjari's research work

Authority and Pinjari (2013) pointed out that at low autonomous vehicle penetration rates, little improvement of the highway capacity and congestion reduction was expected. The reason is human drivers would more likely to keep a longer distance from AVs with consideration of safety. As AVs increases, the influence on highway capacity could get greater. AVs can improve traffic both on freeways and at intersections. It can also avoid traffic collisions at intersections from a safety perspective.

2.3.1.6 Tientrakool et al.'s research work

Tientrakool et al. (2011) assessed the influence of V2V technology on highway capacity. Different safe inter-vehicle distances were analyzed in different cases, such as leading vehicle can communicate and following vehicle can communicate. The authors developed a Reliable Neighborcast Protocol which allows vehicle to communicate with the surrounding vehicles within a specified distance. The vehicles with sensors would always keep a safe following distance with the leading vehicle. The estimated highway capacity will increase by about 43% by vehicles with sensors. If all vehicles are communicating vehicles, the capacity could increase significantly by about 3.7 times compared to the highway capacity with human driver vehicles.

2.3.1.7 Treiber et al.'s research work

Treiber et al. (2000) developed an intelligent driver model (IDM). The IDM model calculates vehicle acceleration rate with vehicle speed, headways, and the distance between vehicles. Further, the authors improved IDM by defining a limitation for a safe acceleration. By using the empirical boundary conditions, the simulation results were consistent with a previous theoretical on-ramp phase diagram.

2.3.1.8 Le Vine et al.'s research work

Le Vine et al. (2016) assessed the relationship between AVs and intersection capacity using VISSIM, which is a microsimulation software. The four-way signalized intersection is simulated with speed limit 50 km/h. Vehicle turning speed was defined manually because VISSIM does not calculate automatically. The results suggested that automated cars may have higher flow rates than regular vehicles. It is anticipated that autonomous cars will increase roadway capacity and reduce congestion. The traffic streams could be controlled without conflicting and the control methods can be more flexible.

2.3.1.9 Campbell and Alexiadis's research work

Campbell and Alexiadis (2016) comprehensively assessed CAVs in transportation planning. The authors summarized the needs generated by CAVs. The authors also pointed out the limitation of traffic simulation models. They cannot be used to model certain real-world driver behaviors or situations, such as inattention or collisions. Traffic simulation models require a significant level of input data, such as origin-destination tables for each travel mode. Traffic simulation models also require a substantial investment of time and effort, including the time needed for the software to perform the simulation once the model is ready.

2.3.1.10 Talebpour and Mahmassani's research work

Talebpour and Mahmassani (2016) simulated CAVs with different models and assumptions. This study presented a method to model CAVs with a deterministic acceleration rate. Since CAVs can only observe vehicles within its detection range, CAVs should be able to control their speed in order to stop at the sensors' detection range. It was found that CAVs will increase the throughput by more than 100%.

2.3.1.11 Meyer et al.'s research work

Meyer et al. (2017) used the Swiss national transport model to simulate AVs. Three scenarios were considered: extra-urban situations, vehicles can be operated fully automated in all situations, and a pre-set vehicle-sharing scheme. The results showed that AVs could cause quantum leap in roadway accessibility.

2.3.1.12 Delis et al.'s research work

Delis et al. (2015) used macroscopic methods to model the ACC and CACC vehicles. The first method was developed to analyze vehicle's speed change due to the accelerating or decelerating of its leading vehicle. The second method considered the time gap between vehicles which equipped with ACC or CACC systems. The conclusion was that CACC vehicles produce more stable traffic flow compared to ACC vehicles. The proposed methods could identify and release the on-ramp bottlenecks by improving the dynamic equilibrium.

In summary, car following models are capable of evaluating the impacts of various types of freeway capacity analysis strategies. A variety of empirical-based freeway capacity analysis studies considering CAV technologies have been conducted to achieve this goal. Table 2.2 exhibits a summary of the empirical based freeway analysis studies.

Table 2.2 Summary of Existing Empirical Based Freeway Capacity Analysis Studies

No.	**Author, Year**	**Vehicle Type**	**Model**	**Project Purpose**	**Capacity Impact**
1	Ni et al., 2012	CV	Gipps' car following model	Highway capacity	Increase 20% to 50%
2	Shi and Prevedouros, 2016	CV, AV	HCM 2010	Freeway and weaving segment	Improve LOS
3	Michael et al., 1998	AV	-	Highway capacity	Increase as platoon length increases
4	VanderWerf et al., 2002	AACC, CACC	Three mathematical models	Highway traffic flow capacity	AACC small, CACC 4,200 vph
5	Pinjari, 2013	AV	-	Highway capacity	Little improvement
6	Tientrakool et al., 2011	Sensors and V2V communication	-	Highway capacity	43% for sensors and 3.7 times for V2V
7	Treiber et al., 2000	ACC	Intelligent driver model	Traffic near on-ramps	-
8	Le Vine et al., 2016	AV	Wiedemann-1999	-	Higher flower rates

9	Campbell and Alexiadis, 2016	CAV	-	Transportation planning process	-
10	Talebpour and Mahmassani, 2016	CAV	-	throughput	100%
11	Meyer et al., 2017	AV	Swiss national transport model	accessibility	Quantum leap in accessibility
12	Delis et al., 2015	ACC, CACC	-	Traffic flow	CACC increase the stabilization of traffic flow

2.3.2 Simulation Based Methods

Simulation based method is widely used in CAV related studies. Compared to other approaches, simulation based method is imperative for practical decision making in transportation planning and operations. Several representative studies of simulation based methods are summarized.

2.3.2.1 Atkins's research work

Atkins (2016) analyzed the influence of CAVs on traffic flow capacity with VISSIM. Various simulation models, simplified link and junction models and complex real-world situations, were developed to examine the potential effects of CAVs under different traffic situations. It is concluded that CAVs can increase road capacity due to faster acceleration and shorter headways. However CAVs may reduce roadway capacity by as much as 40% if they are more cautious than regular vehicles.

2.3.2.2 Shelton et al.'s research work

Shelton et al. (2016) tested CAVs with traffic modeling software in a complex urban roadway network. In order to approximate real-world conditions, a multi-resolution model was used, including macroscopic, mesoscopic, and microscopic models. The results showed that traffic volume will increase with the increase of CAVs' market penetration level. Under a simplified test network, CAVs can increase the capacity to around 4,000 vehicles per hour per lane.

2.3.2.3 Hartmann et al.'s research work

Hartmann et al. (2017) employed microscopic traffic simulation to assess the influence of automated vehicles on freeway capacity. A number of individual freeway component segments were set as input in VISSIM for the simulation, including basic, merge, diverge, and weaving segments. It is concluded that AVs could only increase road capacity by 7%. CAVs could increase roadway capacity by 30% due to shorter headways and the coordinated maneuvering.

2.3.2.4 Shladover's research work

Shladover et al. (2012) employed AIMSUN, a microsimulation software, to evaluate the effect of ACC and CACC vehicles. New driver behavior models were developed and integrated into AIMSUN. It is found that CACC could increase road capacity to 4,000 vph, while ACC has no significant impact on road capacity.

2.3.2.5 Bierstedt et al.'s research work

Bierstedt et al. (2014) analyzed the effects of ACC vehicles on road capacity using VISSIM. The freeway scenario consists of basic, merge, and diverge segments. The default car following model in VISSIM, the Wiedemann model, was modified to better represent ACC systems. Two driving behavior were simulated by changing the headways and acceleration rates in the Wiedemann model, including aggressive and conservative driving. It is found that ACC vehicles have no impact to road capacity at a lower penetration level. The impact is still minor even the ACC penetration level gets up to 75%.

2.3.2.6 Auld et al.'s research work

Auld et al. (2017) employed POLARIS, an advanced traffic simulation software, to explore the influence of CAVs on road capacity. The analysis was conducted on different scenarios, including various market penetration levels, road capacity, and travel time values. It is concluded that VMT can be increased by 4% if road capacity is increased by 80%.

2.3.2.7 Lioris et al.'s research work

Lioris et al. (2017) examined the effect of CV platoons on road mobility with PointQ, a mesoscopic traffic simulation software. The traffic demand is assumed to be Poisson distribution. The simulation is conducted on a four-leg signalized intersection with fixed signal setting. The intersection capacity can get up to 4,800 vph if CV platooning has 0.75s headway at speed limit 45 mph. Compared to ACC, CACC vehicles can keep shorter headways. CV platoons are able to increase travel demand while not increase travel delay and travel time.

2.3.2.8 Arnaout and Arnaout's research work

Arnaout and Arnaout (2014) used F.A.S.T., a microscopic simulator, to examine the impact of CACC vehicles on freeway. The car following model is developed in Java. A mixed traffic environment on a four-lane freeway with a total length of 6km is defined, including cars and trucks. The results showed that CACC has no significant impact at a lower penetration rate. The impact can be observed when CACC penetration rate gets up to 40% or more.

2.3.2.9 Arnaout and Bowling's research work

Arnaout and Bowling (2011) examined the effects of CACC vehicles on highway performance with microscopic traffic simulation tool. The analysis is conducted on a freeway segment with an on-ramp with a total length of 6 km. The on-ramp traffic volume is set to be 500 vph. It is found that CACC vehicles have better performance in peak hours especially when CACC vehicles have more than 40% penetration rate. If the average traffic speed and flow rate are increased, the CACC vehicles will have more impact.

2.3.2.10 Olia et al.'s research work

Olia et al. (2017) simulated CAVs and AVs using a microscopic traffic simulator, PARAMICS, to evaluate their effects on highway capacity. The simulation scenario was a freeway segment with an on-ramp. User defined car following model and lane changing model are developed for CAVs. It is found that CACC vehicles can increase the freeway capacity up to 6,450 vph. The increase became significant when CACC vehicles are more than 30% in the traffic. ACC vehicles can only increase the capacity up to 2,238 vph.

2.3.2.11 Monteil et al.'s research work

Monteil et al. (2014) evaluated V2V cooperation using both analytical and simulation methods. User defined car following model and lane changing model are developed. A calibration process was first conducted for selected model parameters. During the calibration, the trajectory of the object vehicle was calculated every 15 minutes. With the calibrated models, simulation can be conducted with realistic data. The results showed that V2V cooperation can increase traffic safety and the homogeneity of traffic flow.

In summary, simulation based models are capable of evaluating the impacts of CAV technologies on freeway capacity. A variety of simulation-based freeway analysis studies have been conducted to achieve this goal. Table 2.3 exhibits a summary of the simulation based freeway analysis studies summarized in this section.

Table 2.3 Summary of Simulation Based Freeway Analysis Studies

No.	Author, Year	Vehicle Type	Tool	Project Purpose	Capacity Impact
1	Atkins, 2016	CAV	VISSIM	Traffic flow capacity	Decrease 40%
2	Shelton et al., 2016	CAV	Multi-resolution model	Urban roadway network	4,000 vph
3	Hartmann et al., 2017	AV	VISSIM	Freeway capacity	Decrease 7%
4	Shladover et al., 2012	ACC, CACC	AIMSUN	Lane capacity	CACC 4,000 vph
5	Bierstedt et al., 2014	ACC	VISSIM	Freeway capacity	Minor
6	Auld et al., 2017	CAV	POLARIS	Travel behavior	80% increase in capacity can increase 4% VMT
7	Lioris et al., 2017	CV	PointQ	Four-legged intersection	4,800 vph
8	Arnaout and Arnaout, 2014	CACC	F.A.S.T.	U-shaped four-lane freeway	Large improvement with high penetration rate

9	Arnaout and Bowling, 2011	CACC	-	Traffic performance	Highly increase
10	Olia et al., 2017	CAV	PARAMICS	Highway capacity	6,450 vph for CACC, 2,046 to 2,238 for ACC
11	Monteil et al., 2014	CV	-	Traffic flow	Increase traffic flow homogeneity

2.3.3 Survey Based Methods

2.3.3.1 Willke et al.'s research work

Willke et al. (2009) performed an extensive survey of inter-vehicle communication applications. The authors pointed out that effective inter-vehicle communication is able to reduce the cost and complexity of roadside infrastructure. Also, this technology can improve traffic safety and roadway capacity.

2.3.3.2 Mahmassani et al.'s research work

Mahmassani et al. (2012) created an application named Intelligent Network Flow Optimization (INFLO), which is transformative with high priority by USDOT. This application assessed wireless communication technologies, such as CACC, dynamic speed information, and queue alert. Traffic congestion at bottlenecks, such as weaving area, can be released by vehicle communication. As a result, roadway safety can be improved at those specific areas.

2.3.3.3 Cregger's research work

Cregger (2015) summarized the development of CAVs around the world and identified importation features contributing to the development. The information was collected through different ways, including print materials, interviews, and web search. The results showed that CAV technology is developed rapidly in many countries, such as the United States and Japan. In the United States, efforts were made on roadside infrastructure. In Japan, DSRC technology starts to benefit drivers on road.

2.3.3.4 Kockelman et al.'s research work

Kockelman et al. (2016) used two surveys to estimate the adoption of CAV technologies in the future. The survey questions include the vehicle possession number, attitude to new technology, future vehicle purchase possibility, and so on. national survey investigated each respondent's current household vehicle inventory, their technology adoption, future vehicle transaction decisions, and so on. Econometric models were used to analyze the survey results. The authors believed that with more familiarity with CAV technologies, the potential behavior are apt to change rapidly.

2.3.3.5 Schoettle and Sivak's research work

Schoettle and Sivak (2014) conducted a survey examining the attitude of public towards CAV technology. The survey results showed that people are willing to benefit from the new technology. But they are concerning about the safety since they cannot trust the technology completely.

In summary, survey based method is capable of evaluating the public attitude towards the CAV technologies. A variety of survey-based freeway analysis studies have been conducted to achieve this goal. Table 2.4 exhibits the survey based freeway analysis studies summarized in this section.

Table 2.4 Summary of Survey Based CAV Studies

No.	Author, Year	Content	Object	Findings
1	Willke et al., 2009	Inter-vehicle communication	-	Decrease 40%
2	Mahmassani et al., 2012	Wireless connectivity	-	Harmonize traffic flow and reduce the impending shockwaves
3	Cregger, 2015	CAV	Interview, electronic searches, print materials	Identify best practices to strengthen CAV programs
4	Kockelman et al., 2016	CAV	National survey, Texas survey	Potential behavior are apt to change rapidly
5	Schoettle and Sivak, 2014	AC	US, UK, Australia	High level of concern about security

2.4 Intersection Efficiency Analysis Methods

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

2.4.1 Trajectory Optimization Based Methods

2.4.1.1 Yu et al.'s research work

Yu et al. (2019) optimized CAV trajectories with a mixed-integer linear programming (MILP) model. Both the car following model and the lane changing model were optimized. All vehicle trajectories were considered at each intersection. Traffic signal is not needed since CAVs have coordinate maneuvers. The average delay under the

CAV-based control was from 1.1 to 3.9 seconds. And the delay under the signal control was from 27 to 116.9 seconds.

2.4.1.2 Liu et al.'s research work

Liu et al. (2019) proposed a strategy for CAVs at the unsignalized intersections. To ensure safety, CAVs are organized with different priorities by communicating with the organization center. CAVs can choose the optimized speed when passing through the intersection. The calculation is conducted through MATLAB and the simulation is conducted in SUMO. It is concluded that the proposed algorithm can successfully decrease traffic delay by more than 10%. The intersection capacity can be increased by as much as 20%.

2.4.1.3 Mirheli et al.'s research work

Mirheli et al. (2019) developed mixed-integer non-linear programs (MINLPs) to help CAVs pass through intersections. The programs provide CAVs a conflict free environment when passing through the intersection. It is concluded that the proposed programs can reduce travel time by 43%-70%. And the intersection capacity can be increased by 116% compared to signal controlled intersection. Also, the average vehicle speed can be increased by 400%.

2.4.1.4 Stebbins et al.'s research work

Stebbins et al. (2017) proposed a vehicle trajectory advice algorithm for CAVs passing through the intersections. The algorithm can provide vehicle an optimal trajectory for CAVs to follow. The travel delay can be reduced by 50% compared to signal controlled intersection. And vehicle stop time can be reduced to 0 with the help of the proposed algorithm.

2.4.1.5 Yao et al.'s research work

Yao et al. (2018) proposed a Variable Speed Limits with Location Optimization (IVSL-LC) method to smooth vehicle trajectory at intersections. Dynamic speed limits are assigned to CAVs based on real time traffic volume and signal timing through V2I technology. With the help of the proposed method, CAVs can pass through the intersection without stopping. As a result, intersection efficiency can be improved and fuel consumption can be reduced.

2.4.1.6 He et al.'s research work

He et al. (2015) proposed a constrained optimization model for CAVs on signalized intersections. By considering vehicle queue length and signal timing, an optimal speed is calculated for each individual vehicle. The proposed model was proved to increase intersection efficiency successfully.

2.4.1.7 Wei et al.'s research work

Wei et al. (2017) proposed dynamic and integer programming models to optimize vehicle trajectories. Newell's car following model is used to simulate vehicle driving behavior. The models can improve safety and increase throughput at the intersections efficiently by controlling real time vehicle trajectories.

2.4.1.8 Abbas and Chong's research work

Abbas and Chong (2013) employed Neuro-Fuzzy Actor-Critic Reinforcement Learning network to control vehicle trajectory. It is concluded that both machine learning method and regression models can predict vehicle trajectories. But machine learning method has less prediction errors and can reproduce vehicle trajectories which regression models cannot.

2.4.1.9 Guler et al.'s research work

Guler et al. (2014) proposed a vehicle discharging strategy at signalized intersections. Optimal sequences were assigned to each vehicle to minimize total travel delay. The results showed that at low travel demand, AVs can decrease the total travel delay by 7%. In comparison, CVs can decrease total travel delay by 60%.

2.4.1.10 Yang et al.'s research work

Yang et al. (2016) proposed a branch and bound method to optimize vehicle trajectory at intersections. The optimal discharge sequence can be calculated by the method based on current vehicle position information. It was found that this algorithm can reduce total travel delay and vehicle stops by up to 50%.

2.4.1.11 Lazar et al.'s research work

Lazar et al. (2018) employed vehicle platooning strategy for CAVs at intersections. The platoon was first generated at the stop line while signal is red. When signal turns to green, vehicles in the platoon will accelerate simultaneously. Vehicle platoon guarantee vehicles to keep a minimum headway in which way roadway capacity can be improved successfully.

In summary, trajectory optimization methods are capable of increasing intersection mobility, reducing vehicle emissions, and reducing traffic delay. A variety of trajectory optimization based intersection mobility analysis studies considering CAV technologies have been performed to achieve this goal. Table 2.5 exhibits a summary of the trajectory optimization based intersection analysis studies summarized in this section.

Table 2.5 Summary of the Trajectory Optimization Based Intersection Analysis Studies

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

11	Lazar et al., 2018	Cooperative adaptive cruise control	-	Generates shorter following gaps

2.4.2 Signal Optimization Based Methods

Traffic signal optimization plays an important role in transportation management. The goal of traffic signal optimization is to minimize travel delay and maximize intersection throughput. Several representative studies of signal optimization based methods are summarized.

2.4.2.1 He et al.'s research work

He et al. (2012) used a mixed-integer linear program to calculate optimal signal plan based on the current traffic condition. The algorithm will first identify existing queue information and generate all vehicle platoons approaching the intersection. VISSIM is used to conduct the simulation and the results showed that total travel delay can be reduced effectively.

2.4.2.2 Priemer and Friedrich's research work

Priemer and Friedrich (2009) proposed a decentralized adaptive signal optimization method through V2I technology. This is a dynamic program which can provide optimal signal phases every 5 seconds. The simulation is conducted in AIMSUN, a microscopic traffic simulator, under a mixed traffic environment. It was found that average travel delay can be reduced by 24% and traffic speed can be increased by 5%.

2.4.2.3 Feng et al.'s research work

Feng et al. (2015) proposed an adaptive signal phase allocation program to minimize total travel delay and queue length at intersections. The simulation is conducted in VISSIM under various market penetration rates of CAVs. The proposed algorithm can reduce travel delay by as much as 16%.

2.4.2.4 Datesh et al.'s research work

Datesh et al. (2011) developed an IntelliGreen Algorithm (IGA) to control traffic signals using K-means clustering. The performance of IGA is compared with traditional intersection in VISSIM. It is concluded that IGA can improve intersection mobility and traffic sustainability effectively and efficiently.

2.4.2.5 Qi and Hu's research work

Qi and Hu (2019) proposed a Monte Carlo Tree Search-based model to optimize traffic signals. At each time step, the proposed model will choose the best signal phase sequences. The model was compared with Synchro and the results showed that it has better performance at both saturate and unsaturated traffic flow.

2.4.2.6 Li and Sun's research work

Li and Sun (2019) used a cell mapping method to optimize signal timing and lane assignment. The simulation scenario is developed in a conflict free environment considering pedestrian. It was concluded that the proposed optimization method can improve intersection mobility effectively.

2.4.2.7 Chow et al.'s research work

Chow et al. (2019) proposed a kinematic wave model to generate decentralized solution for signal optimization. The simulation scenario was selected from a roadway segment in London. The results showed that the network-wide delay under high demand scenarios can be improved by up to 59.6 veh-h.

In summary, signal optimization based methods are capable of improving the intersection mobility considering the impacts of CAV technologies. A variety of signalized optimization based intersection analysis studies have been conducted to achieve this goal. Table 2.6 exhibits a summary of the signal optimization based intersection analysis studies summarized in this section.

Table 2.6 Summary of the Signal Optimization Based Intersection Analysis Studies

No.	Author, Year	Model	Object	Findings
1	He et al., 2012	Platoon-based mathematical formulation	Optimal signal plans	Reduce delay under both non-saturated and oversaturated traffic conditions
2	Priemer and Friedrich, 2009	Dynamic programming and complete enumeration	Decentralized adaptive traffic signal control	Reduce average delay by up to 24 %
3	Feng et al., 2015	Real time adaptive signal phase allocation	Optimal phase sequence	Reduce delay by as much as 16%
4	Datesh et al., 2011	IntelliGreen Algorithm	Improve efficacy of traffic signals	Achieve system-wide benefits at lower computational costs
5	Qi and Hu, 2019	Monte Carlo Tree Search-based model	Intersection optimization	Better than Synchro
6	Li and Sun, 2019	Multi-objective optimization method	Optimal signal setting	Effective in controlling the traffic at the intersection
7	Chow et al., 2019	Hamilton-Jacobi formulation of kinematic wave model	Optimal signal control framework	Improve the network-wide delay by up to 59.6 veh-h

2.4.3 Integrated Optimization Methods

2.4.3.1 Guo et al.'s research work

Guo et al. (2019) present a dynamic program with shooting heuristic (DP-SH) to optimize signal timing as well as vehicle trajectories. The simulation scenario considered a mixed traffic environment including CAVs and regular vehicles. Numerical results showed that the proposed program can reduce travel time and fuel consumption by 36% and 31%, respectively. The impact is observed even at a low penetration level of CAVs.

2.4.3.2 Yu et al.'s research work

Yu et al. (2018) developed a mixed integer linear programming (MILP) model to find the optimal vehicle trajectory and signal timing at the intersections. A mixed traffic environment including CAVs and human driven vehicles is considered. The objective function is to minimize total travel delay and vehicle emissions at the intersection. The proposed algorithm can help CAVs pass through the intersection without stopping. As a result, no queue will generate at the stop line. It is found that intersection capacity, total travel delay, and vehicle emissions were all improved significantly.

2.4.3.3 Feng et al.'s research work

Feng et al. (2018) proposed a two-stage optimization program for intersection optimization. The first stage is to optimize the signal timing and the second stage is to optimize vehicle trajectory. The objective function is aim to minimize total travel delay and vehicle emissions. The proposed program can reduce vehicle delay by as much as 24%. And vehicle emission can be reduced by 14%.

2.4.3.4 Li et al.'s research work

Li et al. (2014) present a joint control algorithm for both vehicle trajectory and signal phases. Vehicle will be assigned an optimized path through V2I communication between vehicle and signal controller. The proposed algorithm was compared with traditional signalized intersection under different traffic volumes. It was found that total travel delay can be reduced by 37% and intersection throughput can be increased by 20%.

In summary, with the rapid development of V2I technology, CAVs can communicate with signal controller efficiently and effectively. The optimization of vehicle trajectory and signal timing can be done simultaneously. Thus, better intersection mobility can be expected. Table 2.7 exhibits a summary of the integrated optimization based intersection analysis studies summarized in this section.

Table 2.7 Summary of the Integrated Optimization Based Intersection Analysis Studies

No.	Author, Year	Model	Object	Findings
1	Guo et al., 2019	Dynamic programming with shooting heuristic	Near-optimal intersection and trajectory control	Reduce travel time by 36%
2	Yu et al., 2018	Mixed integer linear program	Optimize vehicle trajectories and traffic signals	Decrease of vehicle delays by up to 80%
3	Feng et al., 2018	Dynamic programming	Minimize vehicle delay	Reduce about 10% vehicle delay
4	Li et al., 2014	Rolling horizon scheme	Optimize vehicle paths and signal control	Increase throughput by 2.7–20.2%

2.5 Summary

A comprehensive literature review and synthesis of the current and historical research studies related to CAV technology, freeway capacity analysis, intersection mobility analysis methods, simulation scenarios, and parameters are summarized in the this chapter. This provides a solid preparation for future research with respect to model development and simulation scenario selection.

CHAPTER 3 DATA DESCRIPTION

3.1 Introduction

This chapter will describe the database used to collect necessary data in this research. The California Department of Transportation (Caltrans) Performance Measurement System (PeMS) is used as the source to develop and calibrate the microsimulation software and determine the potential freeway segments as well.

The following sections are structured as follows. Section 3.2 introduces information about the Caltrans Performance Measurement System. Section 3.3 details potential freeway segments with necessary data related to the select freeway segments. Finally, section 3.4 summarizes this chapter.

3.2 The Caltrans Performance Measurement System

In this chapter, the Caltrans Performance Measurement System is used to select potential freeway segments. The PeMS is briefly present in this section.

3.2.1 Introduction to PeMS

PeMS is a statewide system in California since 1999. There are over 35,000 detectors which can report real-time traffic data every 30 seconds. Users are able to access the PeMS database via a standard internet browser with no charge generated.

PeMS is a web-based database providing historical traffic data in different aspects, such as speed, flow, capacity, and delay. By using PeMS, researchers can conduct research with the comprehensive information on selected freeway segments, identify congestion bottlenecks, evaluate freeway performance, and make better decisions on freeway operation.

A consolidated real-time traffic dataset can be collected by PeMS. The raw data sent to PeMS are from the following sources (PeMS 2001):

- "Traffic Detector and Census Stations
- Weight-In-Motion Sensors
- California Highway Patrol Incident Data
- The Caltrans Photolog
- Arterial Detector data and Timing Plans
- Transit data such as routes and schedules, Automated Vehicle Location and Automated Passenger Count data"

3.2.2 PeMS Data Sources

Data are collected and sent to PeMS by sensors and detector stations. The inductive loops are the most common detection devices used by PeMS. The inductive loops are installed at specific locations on the freeways, with a controller in a cabinet at the roadside recording the data. The inductive loops collect traffic flow and vehicle occupancy data and then send the information to PeMS through the controller every 30 seconds.

There are also other data sets that can provide information to the PeMS database. The detector configuration information is provided by the Caltrans Districts.

3.2.3 Functionality of PeMS

Users can query traffic data from PeMS to conduct analyses. PeMS provides users information on required freeway segment. Several freeway performance data can also be obtained, such as traffic volume, vehicle speed, travel delay, and so on. With the assistance of PeMS, users can conduct traffic analysis using analytical or simulation method. The PeMS data can be used as an input to the simulation models for research projects and other transportation planning objectives. Users can also use PeMS data for model calibration so that more accurate results can be achieved under the real-world traffic condition. Below are some examples of what PeMS can do (PeMS 2001):

- “Export data in different formats including Excel file, CSV text file, HTML tables, and plots.
- Integrate with current internet-based mapping tools, such as Google Maps and Google Earth.
- Compute basic freeway performance measures, such as flow, speed, truck volume, delay, and Level of Service.
- Compute advanced freeway performance measures, such as VMT ratio and VHT ratio.
- Conduct special freeway system analyses.
- Provide users with incident information.
- Identify freeway bottlenecks, recurrent or non-recurrent congestion through a special algorithm.
- Produce summary reports of different variables.”

3.3 Potential Freeway Segments

Three different freeway segments are selected through the PeMS database as potential simulation scenarios. To identify the impact of CAV technology under different freeway scenarios, the selected freeway segments contain a mix of configurations, such as on-ramp, off-ramp, and weaving area. All three freeway segments are selected around the City of Los Angeles, a large population area. These sites are selected because their preexisting congestion issues during the peak hour, as well as the fact that they are the major interstate freeways with high traffic volumes. According to the literature review in Chapter 2, each selected freeway segment has a length of around 3 miles. Table 3.1 summarizes the length of the simulation scenarios in previous studies. The following sections will describe each freeway segment in detail.

Table 3.1 Summary of the Length of Simulation Scenarios in Previous Studies

Authors	Length of Scenarios
Atkins (2016)	1 km Single-lane link
Atkins (2016)	1 km Multi-lane link
Bierstedt, J. et al. (2014)	3.2 mi Mix of merge, diverge and weaving area
Arnaout, G., and Bowling, S. (2011)	6 km
Olia et al. (2017)	20 km Two-lane with an on-ramp
Kesting et al. (2008)	13 km
Shelton (2016)	12 mi Corridor
Fernandes and Nunes (2010)	5 km
Arnaout and Arnaout (2014)	6 km U-shaped four-lane freeway
Fernandes and Nunes (2015)	4 km

3.3.1 I10 EB Postmile 7.36 – 10.08

The first freeway segment is a mainline segment of I-10 freeway eastbound in the west of downtown LA. It has a total length of 2.72 miles including three weaving sections with distances of 2,700 ft, 2,200 ft, and 2,800 ft, respectively. Figure 3.1 shows where the freeway segment is located. The selected freeway segment is inside the blue square. Table 3.2 shows the roadway information provided by the vehicle detector station VDS 717022.

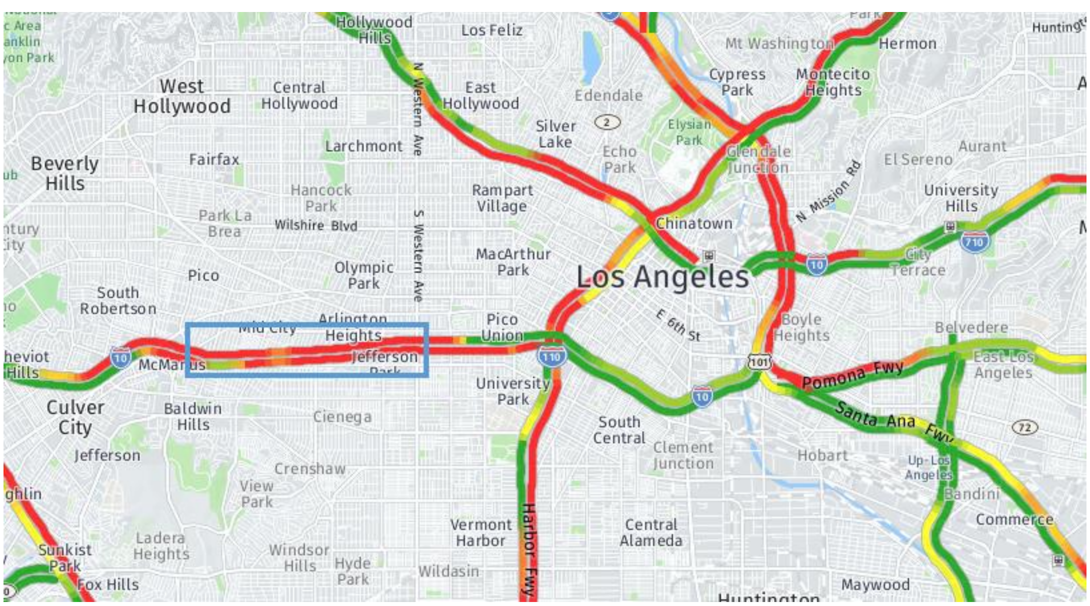

Figure 3.1 Freeway Segment at I-10 EB

Table 3.2 Roadway Information Provided by VDS 717022

Roadway Information	
Road Width	60 ft
Lane Width	12.0 ft
Inner Shoulder Width	10 ft
Inner Shoulder Treated Width	10 ft
Outer Shoulder Width	10 ft
Outer Shoulder Treated Width	10 ft
Inner Median Width	22 ft
Terrain	Flat
Population	Urbanized
Barrier	Concrete Barrier
Surface	Concrete

Figure 3.2 shows the daily traffic flow collected by VDS 717022 on Monday 02/19/2018.

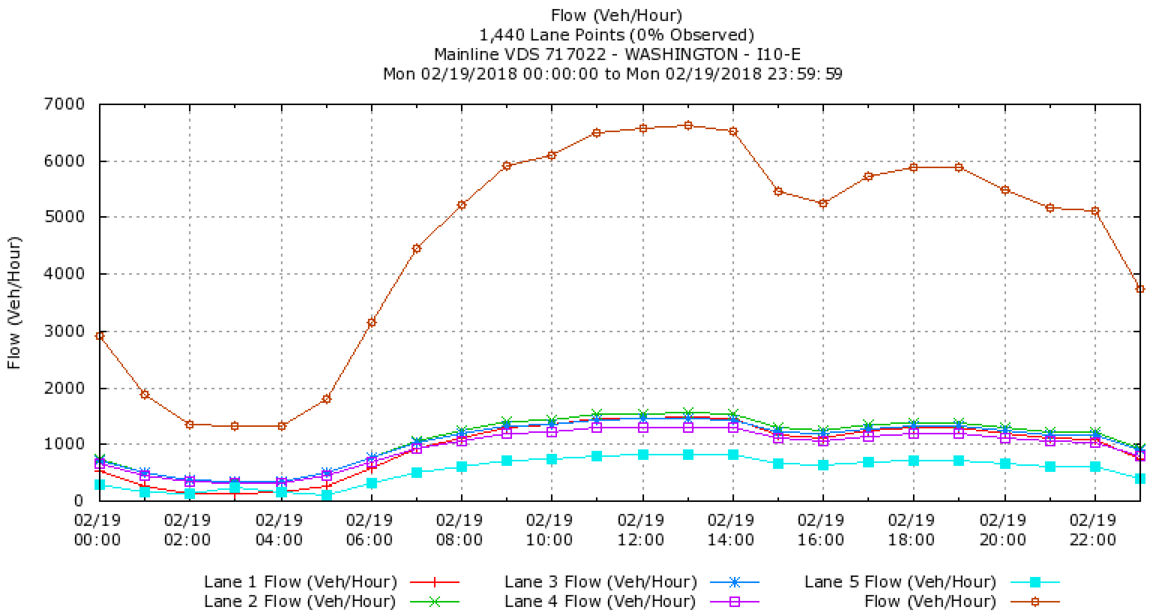

Figure 3.2 Daily Traffic Flow Example at VDS 717022

Figure 3.3 shows the daily traffic speed collected by VDS 717022 on Monday 02/19/2018.

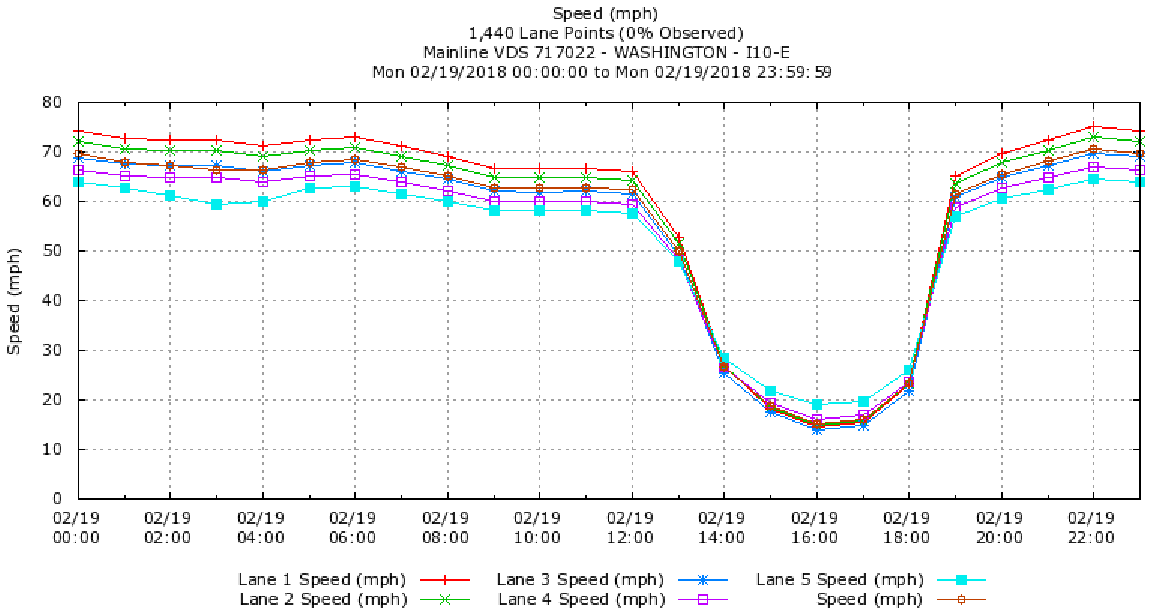

Figure 3.3 Daily Traffic Speed Example at VDS 717022

3.3.2 I-110 North Bound Postmile 15.03 – 17.90

The second freeway segment is a mainline segment of I-110 freeway northbound in the south of downtown LA. It has a total length of 2.87 miles including four weaving sections with distances of 2,900 ft, 1,500 ft, 650 ft, and 550 ft, correspondingly. Figure 3.4 shows the location of the freeway segment. Figure 3.5 provides a detailed configuration of the freeway segment. Table 3.3 shows the roadway information provided by the vehicle detector station VDS 763384.

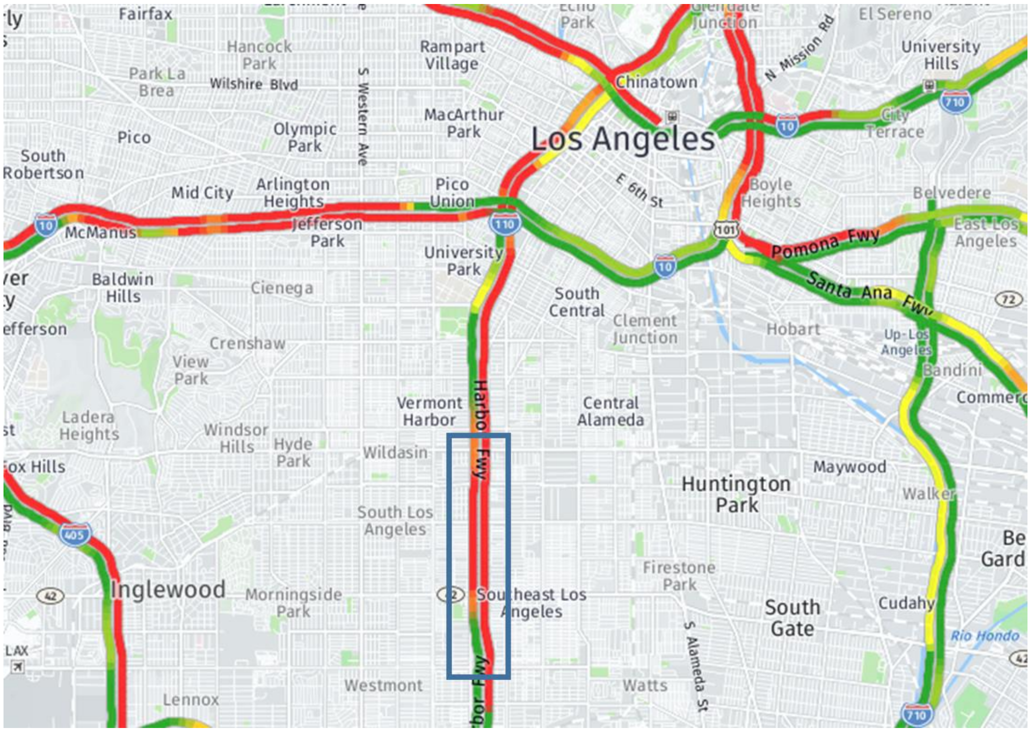

Figure 3.4 Freeway Segment at I-110 NB

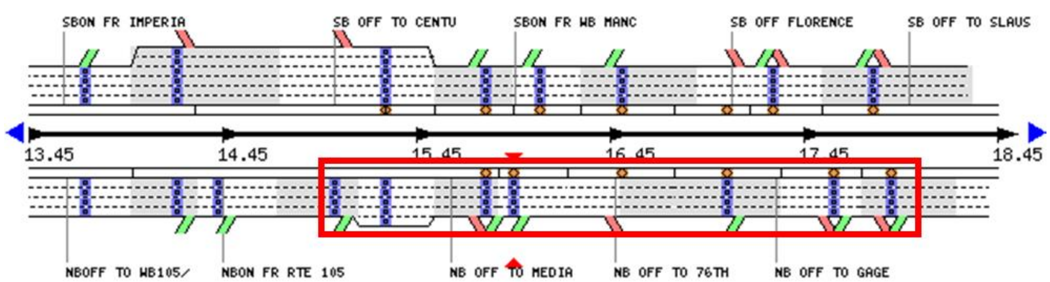

Figure 3.5 Configuration of Freeway Segment at I-110 NB

Table 3.3 Roadway Information Provided by VDS 763384

Roadway Information	
Road Width	48 ft
Lane Width	12.0 ft
Inner Shoulder Width	7 ft
Inner Shoulder Treated Width	7 ft
Outer Shoulder Width	10 ft
Outer Shoulder Treated Width	10 ft
Inner Median Width	16 ft
Terrain	Flat
Population	Urbanized
Barrier	Concrete Barrier w/Glare Screen

Surface	Concrete

Figure 3.6 shows the daily traffic flow collected by VDS 763384 on Monday 02/19/2018.

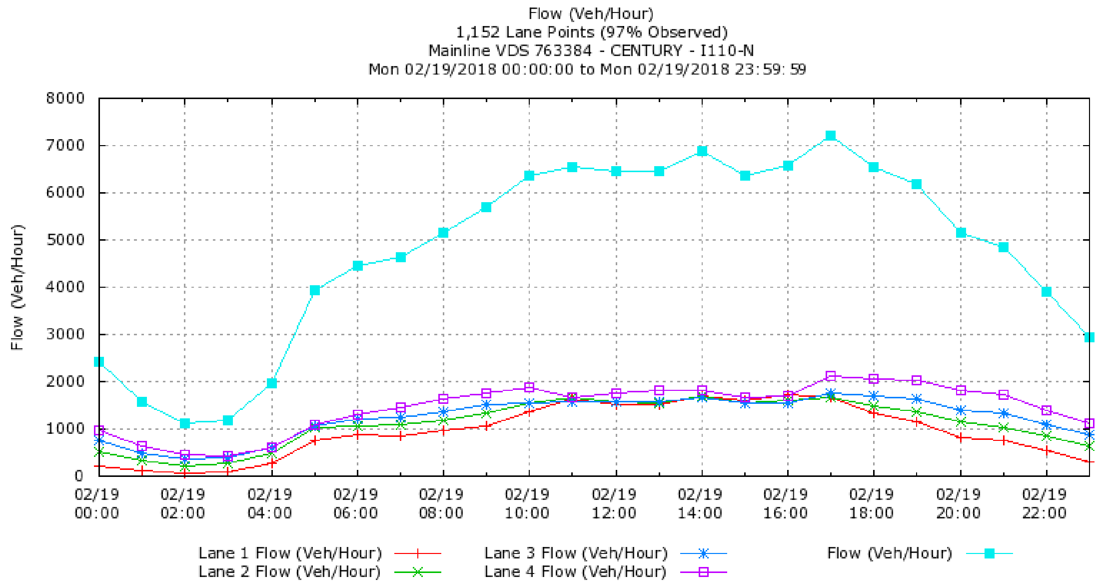

Figure 3.6 Daily Traffic Flow Example at VDS 763384

Figure 3.7 shows the daily traffic speed collected by VDS 763384 on Monday 02/19/2018.

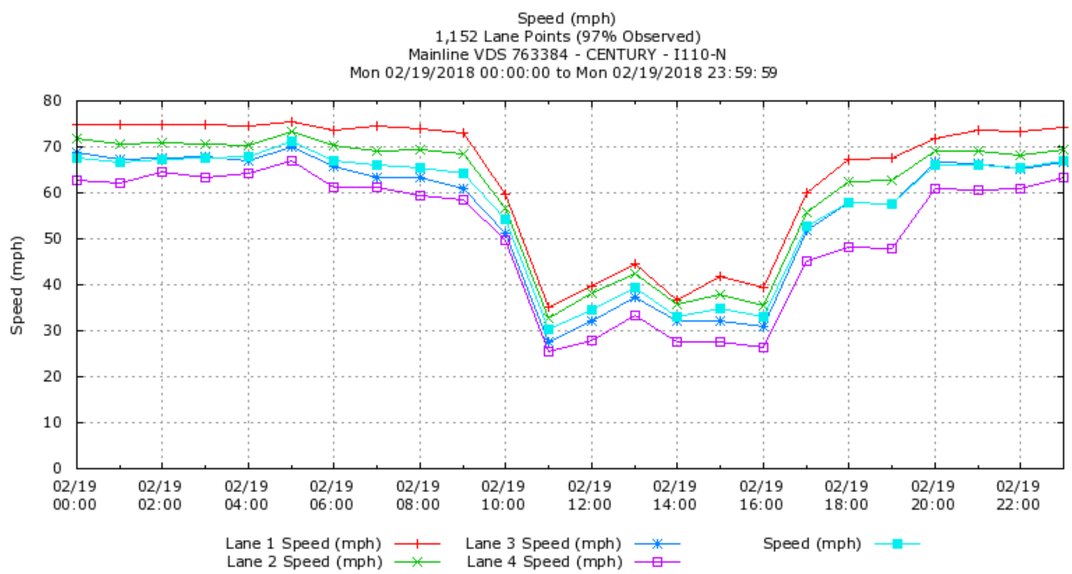

Figure 3.7 Daily Traffic Speed Example at VDS 763384

3.3.3 I-405 South Bound Postmile 69.87 – 66.22

The third freeway segment is a mainline segment of I-405 freeway southbound in the northwest of downtown LA. It has a total length of 3.65 miles including three on-ramp and off-ramp pairs with distances of 5,700 ft, 3,100 ft, and 5,100 ft, respectively. Also, this freeway segment has a lane drop from six lanes to four lanes. Figure 3.8 shows the location of the freeway segment. Figure 3.9 provides a detailed configuration of the freeway segment. Table 3.4 shows the roadway information provided by the vehicle detector station VDS 737529.

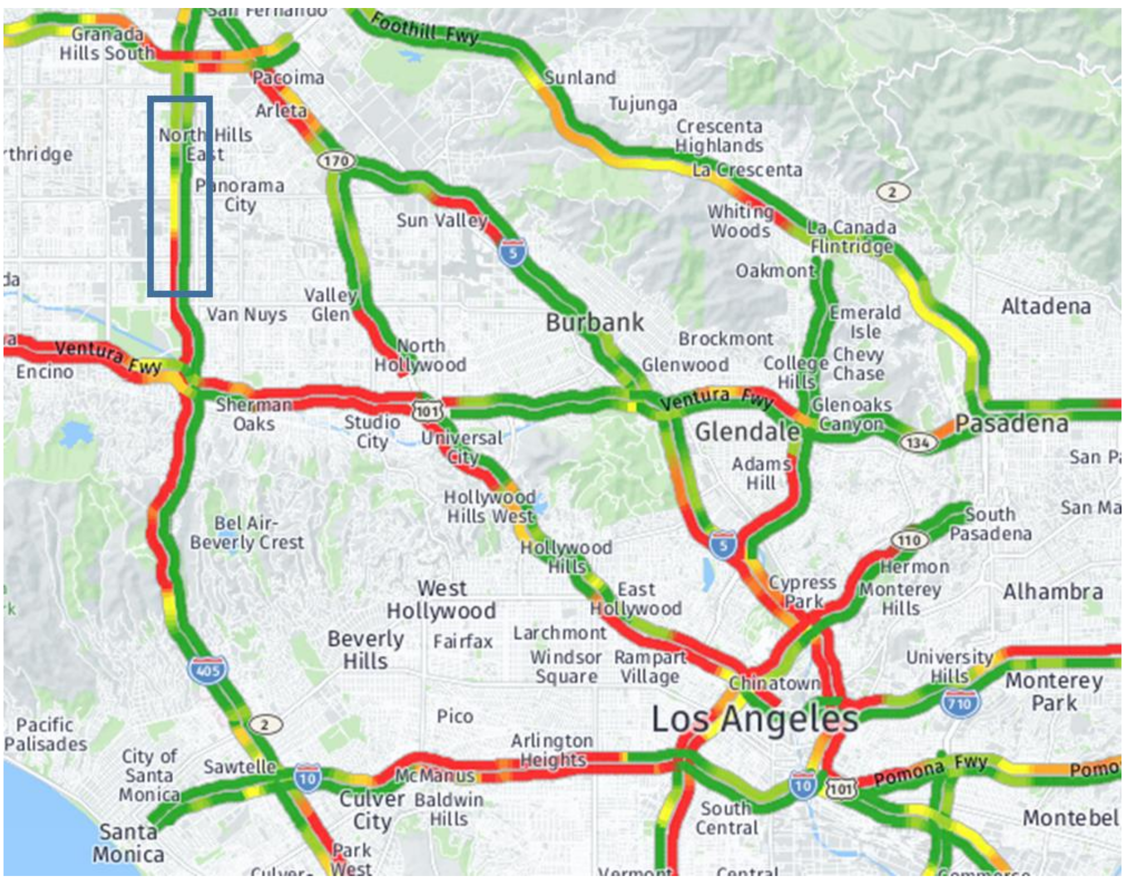

Figure 3.8 Freeway Segment at I-405 SB

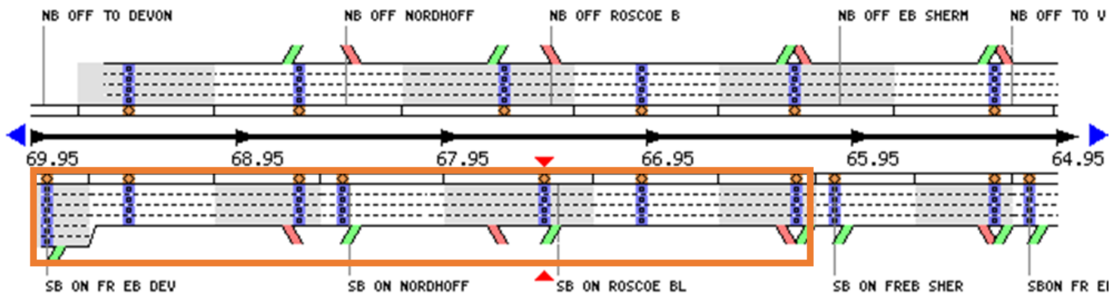

Figure 3.9 Configuration of Freeway Segment at I-405 SB

Table 3.4 Roadway Information Provided by VDS 737529

Roadway Information	
Road Width	56 ft
Lane Width	11.2 ft
Inner Shoulder Width	1 ft
Inner Shoulder Treated Width	1 ft
Outer Shoulder Width	0 ft
Outer Shoulder Treated Width	0 ft
Inner Median Width	6 ft
Terrain	Flat
Population	Urbanized
Barrier	Concrete Barrier
Surface	Bridge Deck

Figure 3.10 shows the daily traffic flow collected by VDS 737529 on Monday 02/19/2018.

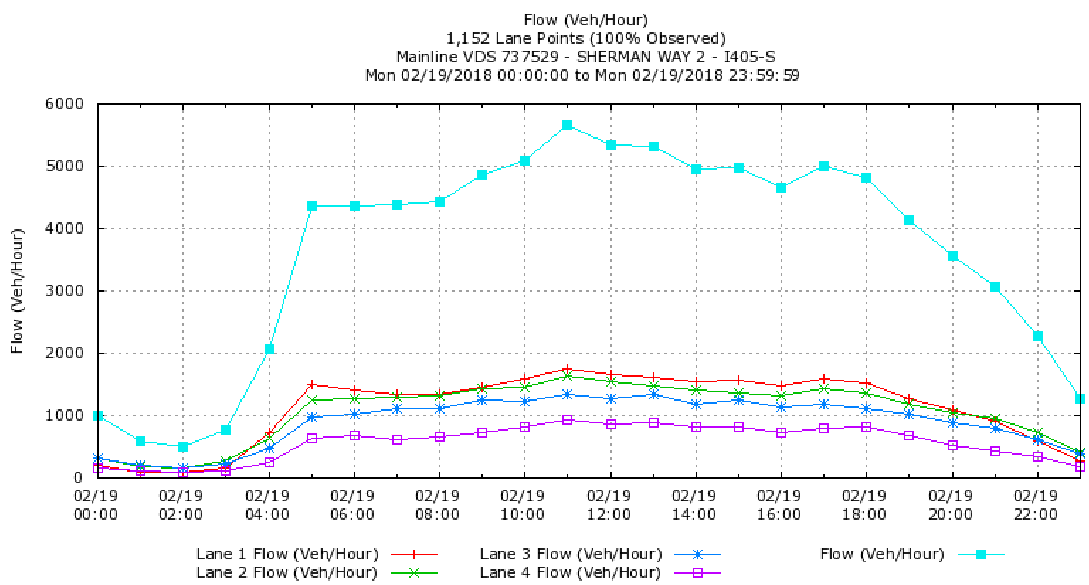

Figure 3.10 Daily Traffic Flow Example at VDS 737529

Figure 3.11 shows the daily traffic speed collected by VDS 737529 on Monday 02/19/2018.

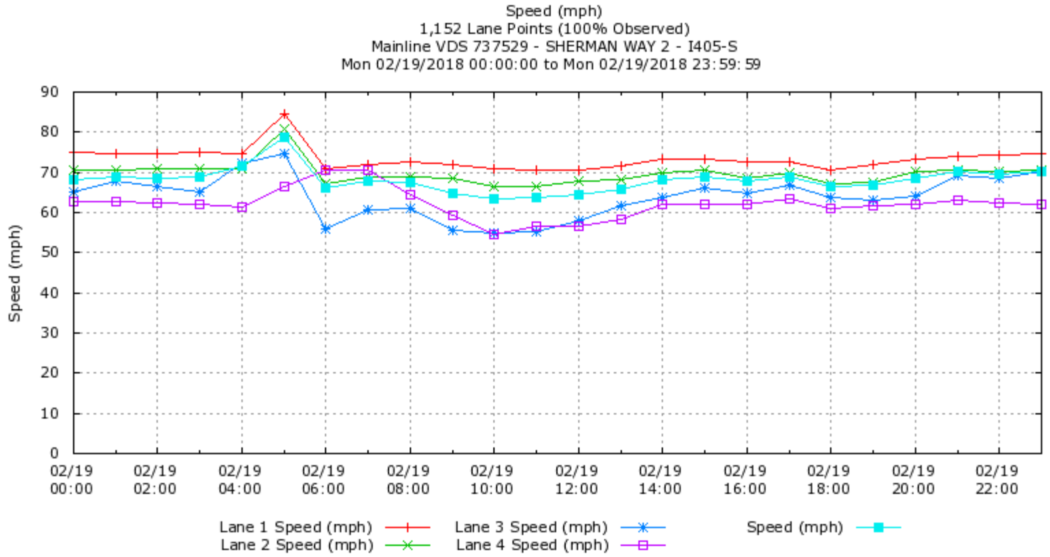

Figure 3.11 Daily Traffic Speed Example at VDS 737529

3.4 Summary

PeMS provides real-time traffic data across the state of California. A comprehensive introduction to PeMS has been presented in the preceding section. After examining the PeMS database, three freeway segments have been selected as potential simulation scenarios. The selected freeway segments contain a mix of merging, diverging, and weaving area. There are vehicle detector stations before and after each merging, diverging, and weaving area. The basic information about the selected freeway segments is discussed and traffic speed and flow data from three vehicle detector stations are shown as an example of the necessary data related to the selected freeway segments. This is a basic preparation for simulating freeway capacity with CAV technologies in the future tasks.

CHAPTER 4 CALIBRATION OF THE MICROSIMULATION SOFTWARE

4.1 Introduction

Microscopic simulation models are widely used in transportation analysis. Compared to field testing, simulation provides a safer, faster, and costless environment for researchers. However, in order to obtain reliable results through simulation, the default parameters in the simulation model should be calibrated. The calibration procedure aims to minimize the differences between the simulated and the observed data. This chapter presents the calibration process for the simulation model built in VISSIM by a case study from a freeway segment selected from PeMS. VISSIM allows users to input other values for the parameters. To obtain a better match between the simulated and observed data, a proper calibration of the VISSIM parameters needs to be conducted. Genetic Algorithm (GA) is employed to find the optimal solutions for the optimization function.

This chapter is structured as follows. Section 4.2 summarizes the study site selected through PeMS for conducting the calibration procedure. Section 4.3 describes the objective function used in the calibration including proper performance measures. Section 4.4 introduces the GA process and section 4.5 presents the set of parameters in VISSIM being calibrated. Section 4.6 shows the calibration results. Finally, section 4.7 summarizes this chapter.

4.2 Study Site

As an example, the study site used for the conduct of case study in this paper is a basic freeway segment that is selected through the PeMS database. The freeway segment is a portion of the I-405 freeway located in the city of Los Angles, California, as shown in Figure 4.1 (within the rectangular area). This freeway stretch is a four-lane basic freeway segment with a total length of 2100 ft. The study period spans 1 hour of the a.m. peak, from 7:00 to 8:00 a.m. on May 16th, 2018, and the field traffic data (i.e. flow and speed) are aggregated into 5-min counts. Table 4.1 shows the traffic flow and speed in each lane during a 5-min interval. And the right two columns show the total traffic flow and the average traffic speed of four lanes.

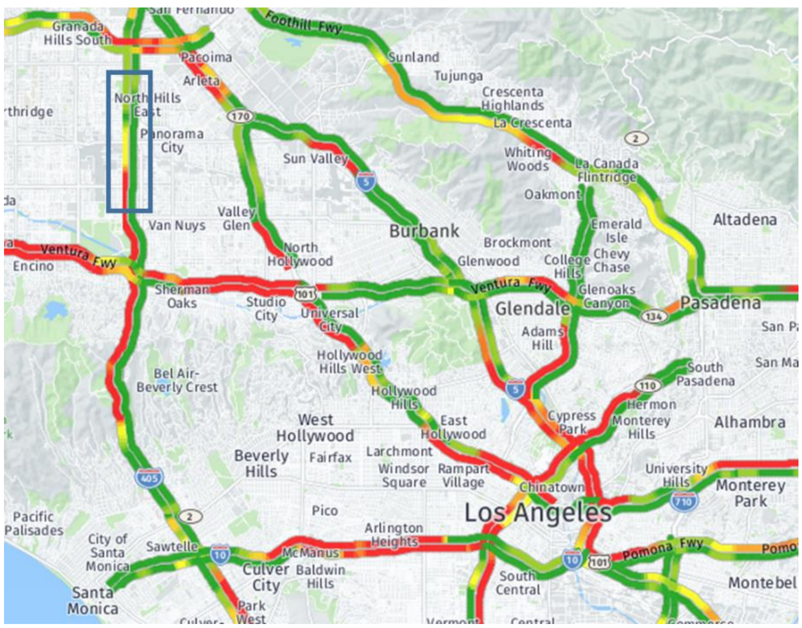

Figure 4.1 Map of the Study Site at I-405 from the PeMS

Table 4.1 Traffic Flow and Speed throughout the Study Period

Time	**Lane 1 Flow (Veh/5 Mins)**	**Lane 1 Speed (mph)**	**Lane 2 Flow (Veh/5 Mins)**	**Lane 2 Speed (mph)**	**Lane 3 Flow (Veh/5 Mins)**	**Lane 3 Speed (mph)**	**Lane 4 Flow (Veh/5 Mins)**	**Lane 4 Speed (mph)**	**Flow (Veh/5 Mins)**	**Speed (mph)**
7:00	98	73.70	114	67.60	113	60.10	75	57.00	400	65.00
7:05	132	73.20	134	68.00	116	57.80	77	55.60	459	64.80
7:10	116	73.00	122	66.50	120	56.00	85	52.70	443	62.70
7:15	122	71.90	141	66.00	136	57.30	92	56.60	491	63.30

7:20	135	69.60	153	65.30	133	56.30	116	54.30	537	61.80
7:25	139	69.50	158	65.10	132	55.20	114	53.80	543	61.40
7:30	131	70.00	148	64.80	150	56.20	110	55.40	539	61.80
7:35	154	69.90	155	64.40	142	56.80	113	54.10	564	61.90
7:40	150	71.00	142	63.90	135	54.80	113	52.80	540	61.30
7:45	146	68.60	159	62.90	140	54.70	127	52.10	572	60.00
7:50	136	70.30	152	64.50	155	52.80	111	50.80	554	59.90
7:55	136	70.90	145	66.10	152	56.10	115	53.80	548	61.90

4.3 Objective Function

In order to minimize the discrepancy between observed and simulated traffic data, the parameters of the microscopic traffic simulation model should be calibrated for the existing human driven vehicles. In this regard, the general optimization framework is formulated as follows.

$$min\, f(\boldsymbol{V}^{obs}, \boldsymbol{V}^{sim}) \tag{4.1}$$

Subject to the constraints:

$$\boldsymbol{l}_{x_i} \leq \boldsymbol{x}_i \leq \boldsymbol{u}_{x_i}, i = 1 \dots n, \tag{4.2}$$

Where

$\boldsymbol{x}_i$= the model parameters to be calibrated.

$f(.)$= objective function.

$\boldsymbol{V}^{obs}, \boldsymbol{V}^{sim}$= observed and simulated value of model parameters being calibrated.

$\boldsymbol{l}_{x_i}, \boldsymbol{u}_{x_i}$= the respective lower and upper bounds of model parameter $\boldsymbol{x}_i$.

n = number of variables.

In this study, the objective function uses the Mean Absolute Normalized Error (MANE), which is provided by the following equation. The objective function aims to minimize the differences between simulated and observed traffic flow and speed data:

$$Minimize MANE(\boldsymbol{q}, \boldsymbol{v}) = \frac{1}{N}\sum_{i=1}^{N}(\frac{|\boldsymbol{q}_{obs,i}-\boldsymbol{q}_{sim,i}|}{\boldsymbol{q}_{obs,i}} + \frac{|\boldsymbol{v}_{obs,i}-\boldsymbol{v}_{sim,i}|}{\boldsymbol{v}_{obs,i}} \qquad (4.3)$$

Where

$\boldsymbol{q}_{obs,i}, \boldsymbol{q}_{sim,i}$= observed and simulated traffic flow for a given time period i.

$\boldsymbol{v}_{obs,i}, \boldsymbol{v}_{sim,i}$= observed and simulated traffic speed for a given time period i.

N = total number of observations.

4.4 Genetic Algorithm

Genetic Algorithm is available to achieve near-global optima during the calibration procedure of the microscopic traffic simulation model. The GA is an inspiration of biological evolution process with selection, crossover and mutation as its three steps. The GA starts from a random population set. For each generation, the better solutions have higher probabilities to be selected and used to generate new populations after crossover and mutation within the selected solutions. In this study, the population size is set to be 10, and the crossover and mutation rate are set to be 0.8 and 0.2, respectively. The max generation number is 20. The GA-based calibration is conducted through MATLAB. A population of binary chromosomes is generated randomly at the very beginning and each represents a feasible solution. Then the chromosomes are decoded to relative model parameters and passed onto the VISSIM for simulation. The objective function value is calculated based on the simulated traffic flow and speed data. The calibration process will not stop until the maximum number of generation is reached or the stopping criterion is met. Figure 4.2 shows the GA calibration process.

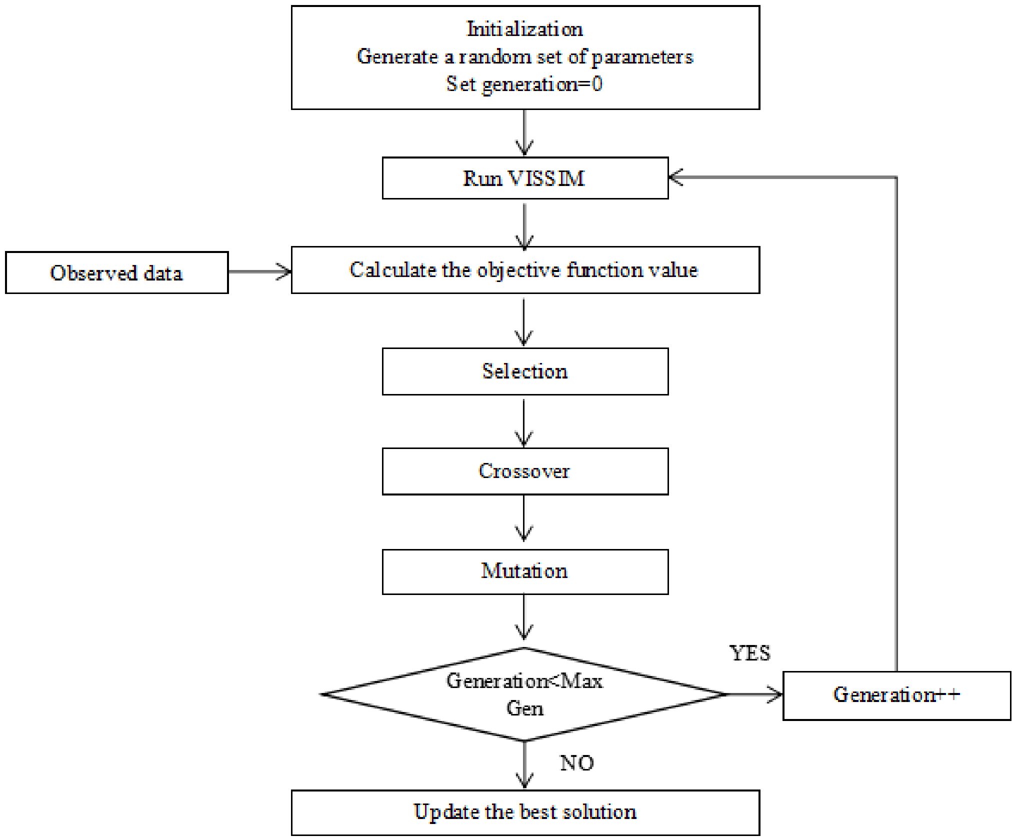

Figure 4.2 GA Calibration Process

4.5 VISSIM Calibration Parameters

VISSIM uses the Wiedemann's car following model to capture the physical and human components of vehicles (PTV 2015). As the Wiedemann model stated, a vehicle has four driving modes: free driving, approaching, following and braking. The model has ten unique parameters (i.e. $CC0, CC1, \dots, CC9$) representing the car following characteristics. $CC0$ (standstill distance) is the desired distance between two stopped vehicles. $CC1$ (headway time) represents the travel time between two consecutive vehicles. Thus, at a given speed v, the safety distance *dx_safe* is defined as follows:

$$dx\_safe = CC0 + CC1 \times v \tag{4.4}$$

Other than *CC0* and *CC1*, *CC2-CC5*, and *CC7* can also significantly impact the simulation results (Lownes and Machemehl, 2006). So, in this study, $CC0$-*CC5*, and $CC7$ are calibrated.

4.6 Calibration Results

The calibrated value of $CC0$ is 2.20 ft compared to the default value of 4.92 ft. And the optimized value of $CC1$ calibrated by the GA is 1.20 seconds compared to the default value of 0.90 seconds. Figure 4.3 presents the GA objective function MANE values during the optimization period. The y-axis represents the minimum objective function value up to every generation and the x-axis denotes the number of generations. Table 4.2 shows all the calibration results for the car following model parameters.

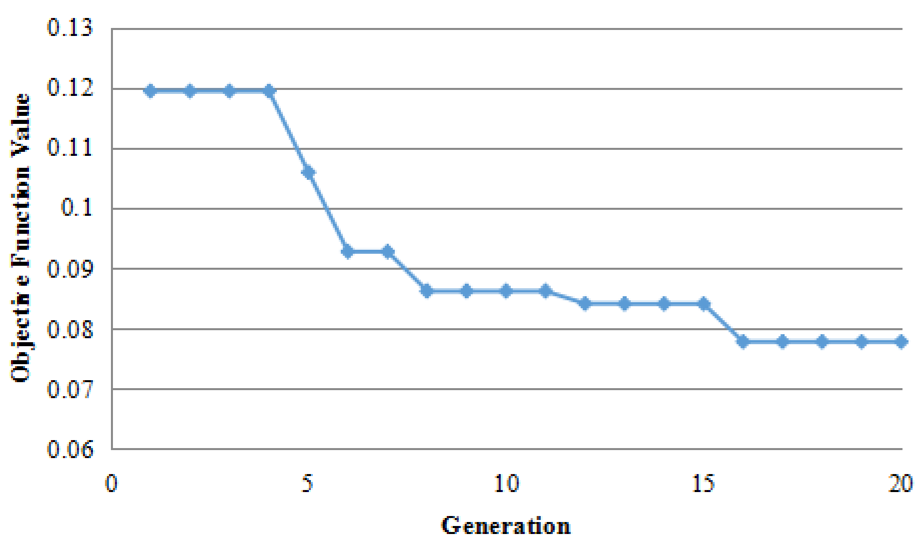

Figure 4.3 GA Objective Function Value vs. Generation

Table 4.2 Calibration Results of the Car Following Model Parameters

Parameter	**Default Value**	**Calibrated Value**
CC0-Standstill distance (ft)	4.92	2.12
CC1-Headway time (gap between vehicles) (seconds)	0.9	1.2
CC2-Car-following distance/following variation (ft)	13.12	11
CC3 - Threshold for entering following (seconds)	-8	-13
CC4 - Negative following threshold (ft/s)	-0.35	-0.8
CC5 - Positive following threshold (ft/s)	0.35	1.3
CC7 - Oscillation during acceleration (ft/s^2)	0.82	1.5

4.7 Summary

This chapter presents the calibration procedure of the microscopic simulation model. The GA is adopted to find optimized values of calibrated parameters which can reduce the differences between field and simulated data. It should be mentioned that only local optimal solutions can be obtained due to the inherent characteristics of GA and limited generations. It is noted that, with more generations, the solution can be further improved to approach closer to global optimal.

CHAPTER 5 IMPACT OF CAV ON FREEWAY CAPACITY

5.1 Introduction

This chapter discusses the numerical results of the simulation. An External Driver Behavior Model (EDBM) is employed to simulate the CAVs and AVs. Four different freeway scenarios are finally selected according to the results of Chapter 3. The impacts of CAVs and AVs on the freeway segments are evaluated under different penetration level of CAVs and AVs.

The chapter is structured as follows. Section 5.2 presents the External Driver Behavior Model. Section 5.3 shows the numerical results of the analysis conducted on the four selected freeway segments. Finally, section 5.4 summarizes this chapter.

5.2 External Driver Behavior Model

VISSIM cannot simulate operations of CAVs with its internal driver behavior model. However, VISSIM provides the option to replace the internal model with an External Driver Behavior Model (EDBM), which is a fully user-defined driving behavior model for CAVs. The EDBM is implemented as a C++ Dynamic Link Library (DLL) plug-in, which contains specific algorithms for CAVs. These algorithms can determine the next step maneuver (i.e. acceleration, lane change) for each affected vehicle. During each simulation time step, VISSIM calls the DLL file to determine the behavior of the vehicle by passing the current state of the vehicle and its surroundings to the DLL and retrieving the updated state calculated by the DLL.

The EMDB model is developed in C++ and needs to be compiled to generate a DLL file. The DLL file can be implemented as a V2V communication device, wherein the leading vehicle informs the following vehicle of its location, speed and acceleration. The following vehicle can change its speed quickly to avoid rear-end collisions. The algorithm continuously adjusts the acceleration rates by measuring the headways between vehicles to keep short headways. The headway between CAVs is set as 0.6 s and the headway between CAVs/AVs and AVs or regular vehicle is set to be 0.9 s. Headway for regular vehicles followingeach other and CAVs/AVs is set to be 0.9s also.

5.3 Numerical Results

Based on the potential freeway segments identified from Chapter 3, four freeway segments are finally selected from PeMS to conduct the analysis. The selected freeway segments represent four different freeway scenarios including basic freeway segment, on-ramp, off-ramp, and weaving segment. The impacts of CAVs and AVs on each freeway segment are examined under different CAV/AV penetration levels. The numerical results are presented in detail in the following sections.

5.3.1 Basic Freeway Segment

The basic freeway segment is obtained from a portion of the I-405 freeway identified in Chapter 3, as shown in Figure 5.1 (in red). The study period is the peak hour from 7:00 to 8:00 a.m. on May 16th, 2018. The traffic flow data are collected from PeMS and used as input in the simulation. This freeway segment stretch is a four-lane basic freeway segment with a total length of 2500 ft.

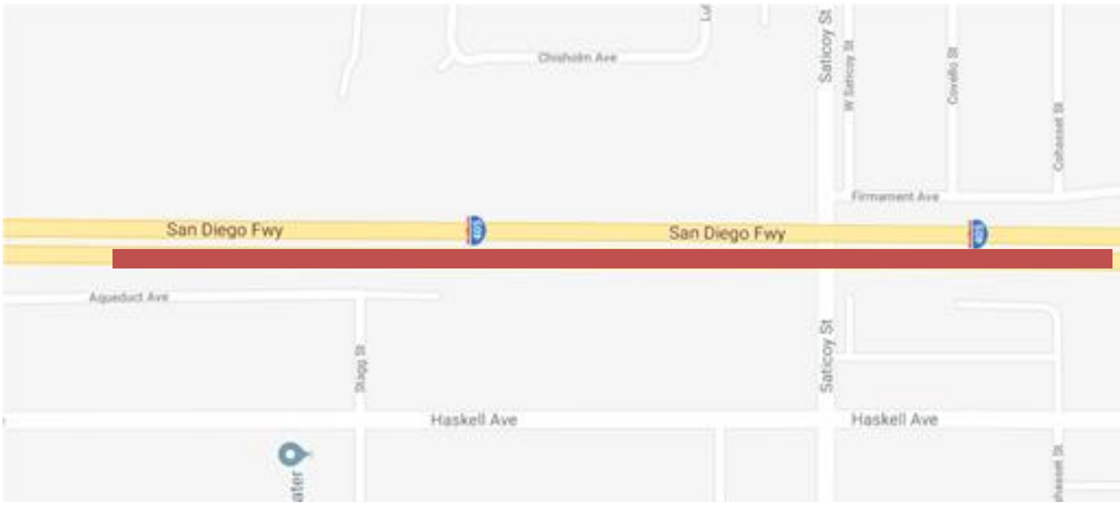

Figure 5.1 Location of the Basic Freeway Segment

The freeway capacity for different penetration level of CAVs and AVs are shown in Table 5.1. The speed limit on the tested freeway segment is 104 km/h (65 mph). Figure 5.2 plots the tendency of the capacity change with different penetration level of CAVs and AVs. And the simulations are also conducted under other three speed limits, which are 80 km/h, 90 km/h, and 120 km/h, respectively. The results are shown in Table 5.2, Table 5.3, and Table 5.4, respectively.

Table 5.1 Capacity Analysis on Basic Freeway Segment under Speed Limit 104 km/h

Basic Freeway Segment with Speed Limit 104 km/h							
		AV					
		0%	20%	40%	60%	80%	100%
CAV	0%	2160	2209	2305	2371	2472	2537
	20%	1798	2092	2272	2464	2699	
	40%	2603	3067	3472	3705		
	60%	3902	3838	3856			
	80%	3927	3929				
	100%	3980					

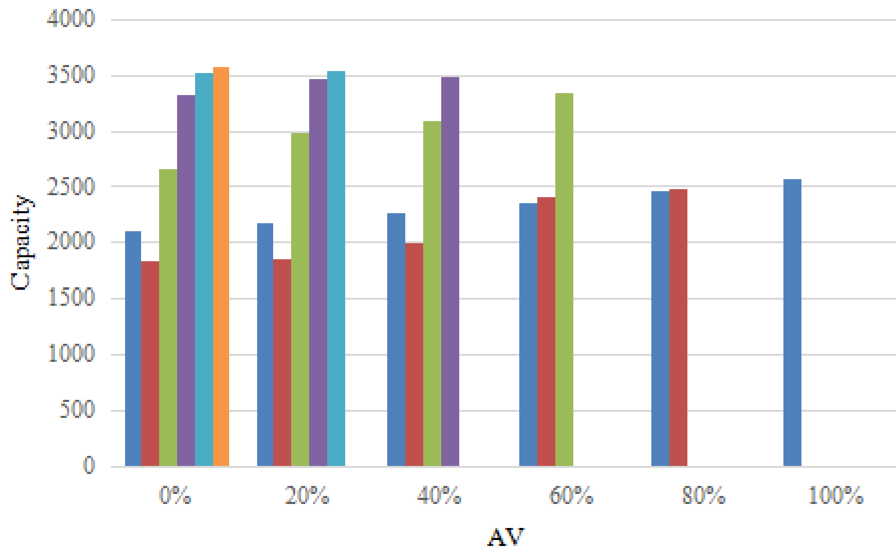

Figure 5.2 The Capacity Tendency on Basic Freeway Segment under Speed Limit 104 km/h

Table 5.2 Capacity Analysis on Basic Freeway Segment under Speed Limit 80 km/h

Basic Freeway Segment with Speed Limit 80 km/h							
		AV					
		0%	20%	40%	60%	80%	100%
CAV	0%	2105	2173	2269	2363	2472	2567
	20%	1840	1850	2007	2416	2482	
	40%	2668	2985	3090	3336		
	60%	3314	3459	3479			
	80%	3526	3530				
	100%	3575					

Table 5.3 Capacity Analysis on Basic Freeway Segment under Speed Limit 90 km/h

Basic Freeway Segment with Speed Limit 90 km/h							
		AV					
		0%	20%	40%	60%	80%	100%
CAV	0%	2134	2211	2289	2378	2469	2576
	20%	1745	2075	2085	2402	2498	
	40%	2666	2827	3296	3543		
	60%	3716	3747	3750			
	80%	3806	3813				
	100%	3854					

Table 5.4 Capacity Analysis on Basic Freeway Segment under Speed Limit 120 km/h

Basic Freeway Segment with Speed Limit 120 km/h							
		AV					
		0%	20%	40%	60%	80%	100%
CAV	0%	2162	2234	2321	2382	2454	2566
	20%	1895	2130	2289	2537	2829	
	40%	2674	2942	3438	3712		
	60%	4117	4234	4214			
	80%	4297	4300				
	100%	4345					

The all-manual case can be seen as a base case with a nominal capacity around 2,200 vehicles per hour per lane (vphpl). With 100% penetration level of CAVs, freeway capacity can be increased by 101%, 84.3%, 80.6%, and 69.8% under speed limits of 120 km/h, 104 km/h, 90 km/h, and 80 km/h, respectively. With 100% penetration level of AVs, freeway capacity can be increased by 18.7%, 17.5%, 20.7%, and 21.9% under speed limits of 120 km/h, 104 km/h, 90 km/h, and 80 km/h, respectively.

5.3.2 On-ramp Freeway Segment

The on-ramp freeway segment is obtained from a portion of the I-405 freeway identified in Chapter 3, as shown in Figure 5.3 (in red). The study period is the peak hour from 7:00 to 8:00 a.m. on May 16th, 2018. The traffic flow data are collected from PeMS and used as input in the simulation. This freeway segment stretch is a four-lane freeway segment with an on-ramp with a total length of 2000 ft.

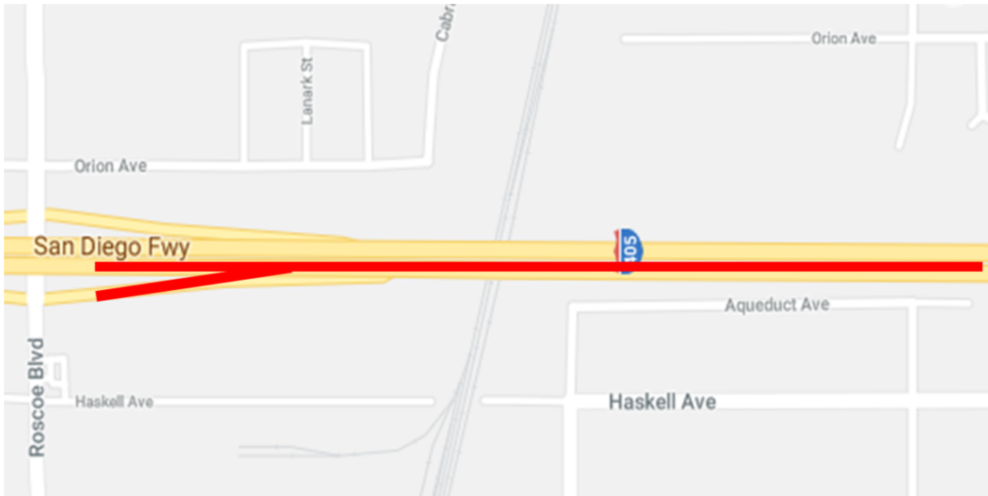

Figure 5.3 Location of the On-ramp Freeway Segment

The freeway capacity before and after the on-ramp for different penetration level of CAVs and AVs are shown in Table 5.5. Figure 5.4 plots the tendency of the capacity change before the on-ramp with different penetration level of CAVs and AVs. Figure 5.5 plots the tendency of the capacity changes after the on-ramp with different penetration level of CAVs and AVs. The simulations are also conducted under other three speed limits, which are 80 km/h, 90 km/h, and 120 km/h, respectively. The capacity results before and after the on-ramp are shown in Table 5.6, Table 5.7, and Table 5.8, respectively.

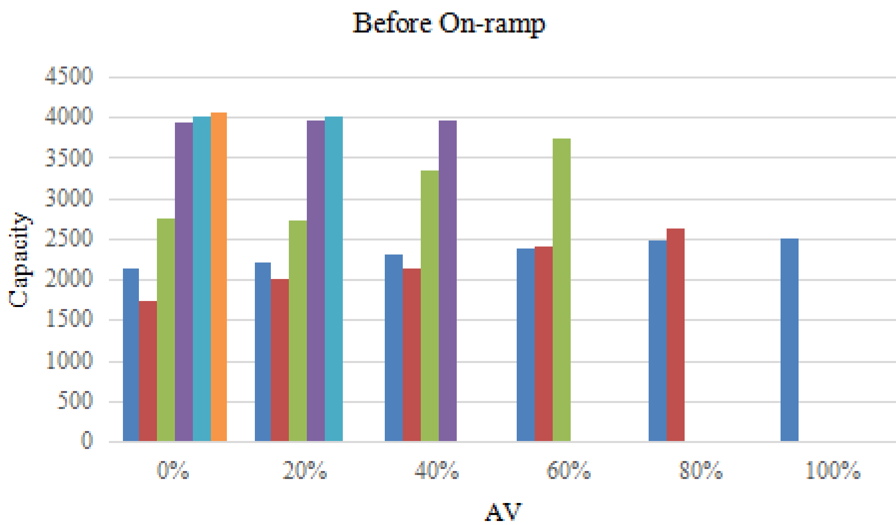

Figure 5.4 The Capacity Tendency before On-ramp under Speed Limit 104 km/h

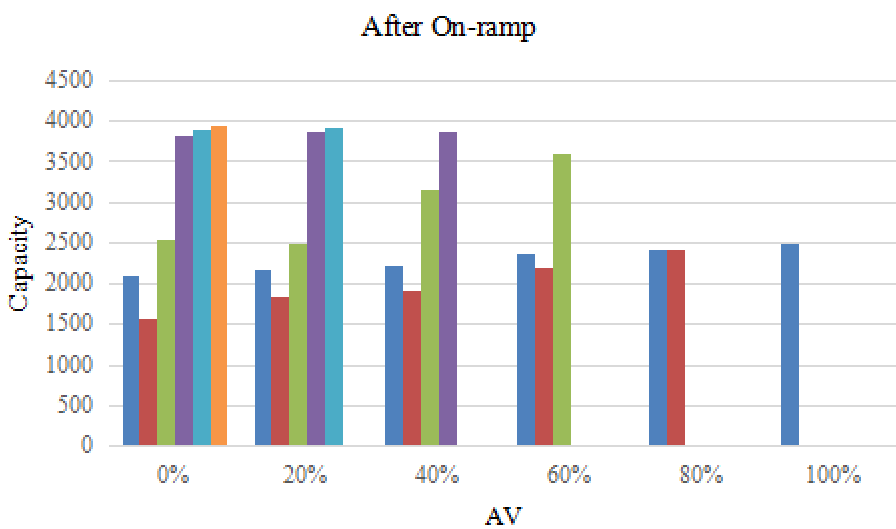

Figure 5.5 The Capacity Tendency after On-ramp under Speed Limit 104 km/h

Table 5.5 Capacity Analysis on Freeway On-ramp Segment under Speed Limit 104 km/h

Freeway On-ramp Segment with Speed Limit 104 km/h							
Before On-ramp		AV					
		0%	20%	40%	60%	80%	100%
CAV	0%	2131	2214	2310	2394	2493	2511
	20%	1752	2028	2149	2421	2635	
	40%	2746	2744	3361	3751		
	60%	3948	3980	3981			
	80%	4008	4025				

	100%	4058					
After On-ramp		AV					
		0%	20%	40%	60%	80%	100%
CAV	0%	2089	2175	2220	2357	2404	2476
	20%	1582	1847	1925	2195	2418	
	40%	2524	2490	3142	3587		
	60%	3823	3874	3882			
	80%	3902	3924				
	100%	3947					

Table 5.6 Capacity Analysis on Freeway On-ramp Segment under Speed Limit 80 km/h

Freeway On-ramp Segment with Speed Limit 80 km/h							
Before On-ramp		AV					
		0%	20%	40%	60%	80%	100%
CAV	0%	2121	2176	2270	2357	2444	2497
	20%	1652	1920	2268	2286	2619	
	40%	2643	3147	3244	3402		
	60%	3499	3491	3531			
	80%	3559	3574				
	100%	3611					
After On-ramp		AV					
		0%	20%	40%	60%	80%	100%
CAV	0%	2048	2104	2195	2292	2385	2438
	20%	1447	1700	2042	2071	2413	
	40%	2460	2950	3014	3242		
	60%	3377	3350	3418			
	80%	3441	3451				
	100%	3487					

Table 5.7 Capacity Analysis on Freeway On-ramp Segment under Speed Limit 90 km/h

Freeway On-ramp Segment with Speed Limit 90 km/h							
Before On-ramp		AV					
		0%	20%	40%	60%	80%	100%
CAV	0%	2127	2207	2302	2404	2482	2515
	20%	1872	2004	2042	2377	2457	
	40%	2705	3094	3425	3609		
	60%	3791	3810	3816			
	80%	3840	3859				
	100%	3887					
After On-ramp		AV					
		0%	20%	40%	60%	80%	100%

CAV	0%	2096	2157	2266	2333	2409	2463
	20%	1701	1809	1846	2191	2246	
	40%	2462	2922	3221	3417		
	60%	3676	3697	3706			
	80%	3731	3750				
	100%	3777					

Table 5.8 Capacity Analysis on Freeway On-ramp Segment under Speed Limit 120 km/h

Freeway On-ramp Segment with Speed Limit 120 km/h							
Before On-ramp		AV					
		0%	20%	40%	60%	80%	100%
CAV	0%	2140	2221	2332	2434	2480	2534
	20%	1876	2067	2172	2487	2716	
	40%	2689	3083	3442	3746		
	60%	4108	4246	4290			
	80%	4327	4337				
	100%	4370					
After On-ramp		AV					
		0%	20%	40%	60%	80%	100%
CAV	0%	2132	2197	2287	2369	2418	2506
	20%	1685	1841	1937	2284	2517	
	40%	2474	2877	3245	3529		
	60%	3940	4120	4189			
	80%	4224	4244				
	100%	4272					

With 100% penetration level of CAVs, freeway capacity before on-ramp can be increased by 104%, 90.4%, 82.7%, and 70.2% under speed limits of 120 km/h, 104 km/h, 90 km/h, and 80 km/h, respectively. And with 100% penetration level of CAVs, freeway capacity after on-ramp can be increased by 100%, 88.9%, 80.2%, and 70.3% under speed limits of 120 km/h, 104 km/h, 90 km/h, and 80 km/h, respectively.

With 100% penetration level of AVs, freeway capacity before on-ramp can be increased by 18.4%, 17.8%, 18.2%, and 17.7% under speed limits of 120 km/h, 104 km/h, 90 km/h, and 80 km/h, respectively. And with 100% penetration level of AVs, freeway capacity after on-ramp can be increased by 17.5%, 18.5%, 17.5%, and 19.0% under speed limits of 120 km/h, 104 km/h, 90 km/h, and 80 km/h, respectively.

5.3.3 Off-ramp Freeway Segment

The off-ramp freeway segment is obtained from a portion of the I-405 freeway identified in Chapter 3, as shown in Figure 5.6 (in red). The study period is the peak hour from 7:00 to 8:00 a.m. on May 16th, 2018. The traffic flow data are collected from PeMS and used as input in the simulation. This freeway segment stretch is a four-lane freeway segment with an off-ramp with a total length of 2000 ft.

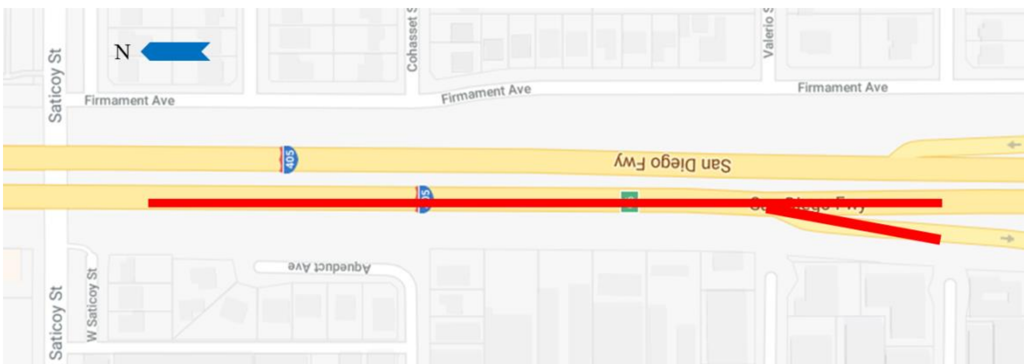

Figure 5.6 Location of the Off-ramp Freeway Segment

The freeway capacity before and after the off-ramp for different penetration level of CAVs and AVs are shown in Table 5.9. Figure 5.7 plots the tendency of the capacity change before the off-ramp with different penetration level of CAVs and AVs. Figure 5.8 plots the tendency of the capacity change after the off-ramp with different penetration level of CAVs and AVs. The speed limit on the tested freeway segment is 104 km/h (65 mph). And the simulations are also conducted under other three speed limits, which are 80 km/h, 90 km/h, and 120 km/h, respectively. The results before and after the on-ramp are shown in Table 5.10, Table 5.11, and Table 5.12, respectively.

Table 5.9 Capacity Analysis on Freeway Off-ramp Segment under Speed Limit 104 km/h

Freeway Off-ramp Segment with Speed Limit 104 km/h							
Before Off-ramp		AV					
		0%	20%	40%	60%	80%	100%
CAV	0%	2003	1963	2164	2396	2303	2473
	20%	1681	1798	1892	1856	2160	
	40%	2133	2332	2739	3065		
	60%	3666	3894	4002			
	80%	4034	4044				
	100%	4086					
After Off-ramp		AV					
		0%	20%	40%	60%	80%	100%
CAV	0%	1706	1717	1785	2087	2040	2235
	20%	1264	1474	1506	1409	1707	
	40%	1738	1800	2202	2545		
	60%	3172	3377	3685			
	80%	3750	3749				
	100%	3791					

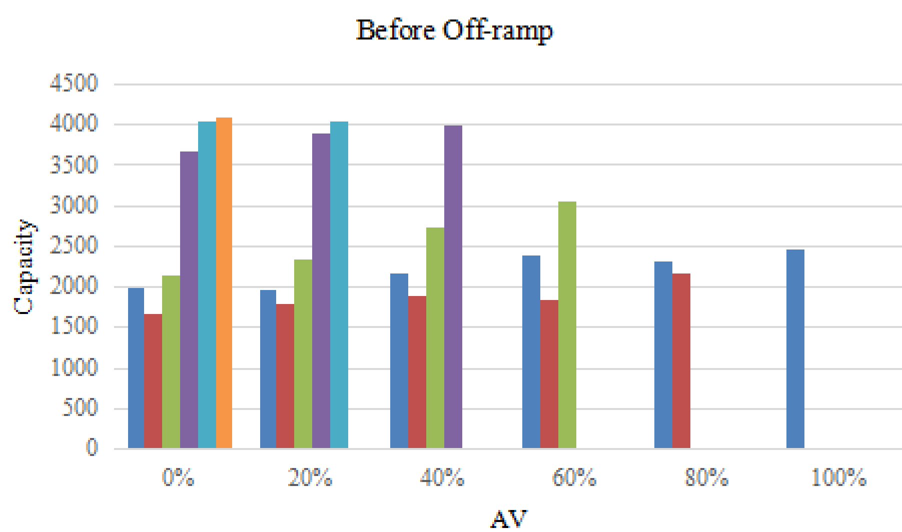

Figure 5.7 The Capacity Tendency before Off-ramp under Speed Limit 104 km/h

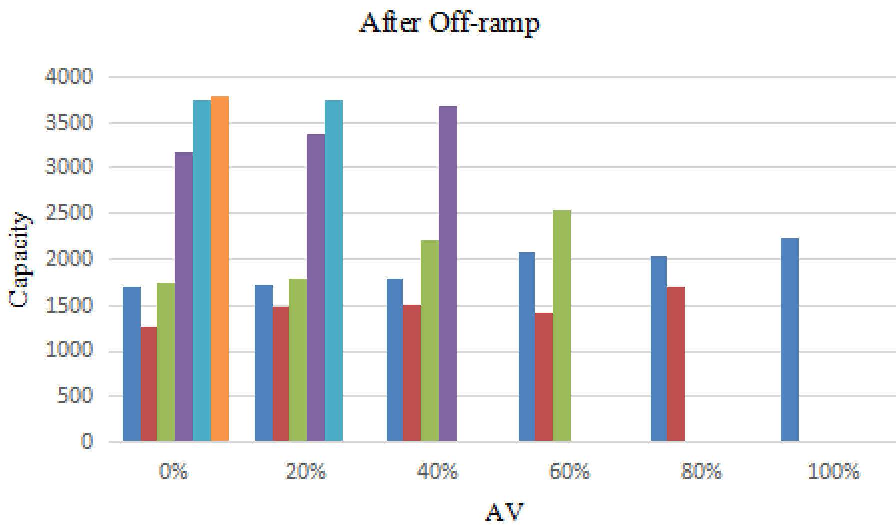

Figure 5.8 The Capacity Tendency after Off-ramp under Speed Limit 104 km/h

Table 5.10 Capacity Analysis on Freeway Off-ramp Segment under Speed Limit 80 km/h

Freeway Off-ramp Segment with Speed Limit 80 km/h							
Before Off-ramp		AV					
		0%	20%	40%	60%	80%	100%
CAV	0%	1843	1930	1894	2012	2025	2116
	20%	1749	1749	1799	2053	2219	
	40%	2223	2372	2455	2856		
	60%	3427	3419	3498			
	80%	3546	3558				
	100%	3596					
After Off-ramp		AV					
		0%	20%	40%	60%	80%	100%
CAV	0%	1537	1554	1572	1698	1605	1826
	20%	1343	1430	1421	1544	1723	
	40%	1782	1845	2052	2308		
	60%	2940	2873	3066			
	80%	3256	3266				
	100%	3317					

Table 5.11 Capacity Analysis on Freeway Off-ramp Segment under Speed Limit 90 km/h

Freeway Off-ramp Segment with Speed Limit 90 km/h							
Before Off-ramp		AV					
		0%	20%	40%	60%	80%	100%
CAV	0%	1907	1934	2030	2120	2235	2204
	20%	1757	1879	1872	1915	2375	
	40%	2248	2501	2634	2887		
	60%	3511	3762	3796			
	80%	3817	3837				
	100%	3873					
After Off-ramp		AV					
		0%	20%	40%	60%	80%	100%
CAV	0%	1552	1663	1730	1848	1846	1814
	20%	1372	1491	1428	1555	1892	
	40%	1798	1974	2202	2297		
	60%	2995	3343	3478			
	80%	3526	3536				
	100%	3603					

Table 5.12 Capacity Analysis on Freeway Off-ramp Segment under Speed Limit 120 km/h

Freeway Off-ramp Segment with Speed Limit 120 km/h							
Before Off-ramp		AV					
		0%	20%	40%	60%	80%	100%
CAV	0%	2035	2227	2085	1907	2176	2538
	20%	1748	1882	1851	1984	2211	
	40%	2249	2411	2534	2856		
	60%	3363	4104	4267			
	80%	4295	4322				
	100%	4352					
After Off-ramp		AV					
		0%	20%	40%	60%	80%	100%
CAV	0%	1728	1866	1808	1648	1835	2315
	20%	1337	1479	1423	1560	1702	
	40%	1819	1996	1935	2348		
	60%	2923	3622	3953			
	80%	4023	4034				
	100%	4088					

With 100% penetration level of CAVs, freeway capacity before off-ramp can be increased by 114%, 104%, 103%, and 95.1% under speed limits of 120 km/h, 104 km/h, 90 km/h, and 80 km/h, respectively. And with 100% penetration level of CAVs, freeway capacity after off-ramp can be increased by 137%, 122%, 132%, and 116% under speed limits of 120 km/h, 104 km/h, 90 km/h, and 80 km/h, respectively.

With 100% penetration level of AVs, freeway capacity before off-ramp can be increased by 24.7%, 23.5%, 15.6%, and 14.8% under speed limits of 120 km/h, 104 km/h, 90 km/h, and 80 km/h, respectively. And with 100% penetration level of AVs, freeway capacity after off-ramp can be increased by 34.0%, 31%, 16.9%, and 18.8% under speed limits of 120 km/h, 104 km/h, 90 km/h, and 80 km/h, respectively.

5.3.4 Weaving Freeway Segment

The weaving freeway segment is selected from the I-110 freeway identified in Chapter 3, as shown in Figure 5.9 (in red). The study period is the peak hour from 7:00 to 8:00 a.m. on May 16th, 2018. The traffic flow data are collected from PeMS and used as input in the simulation. This freeway segment stretch is a four-lane freeway segment with a weaving area with a total length of 2000 ft. The weaving area has a total length of 700 ft.

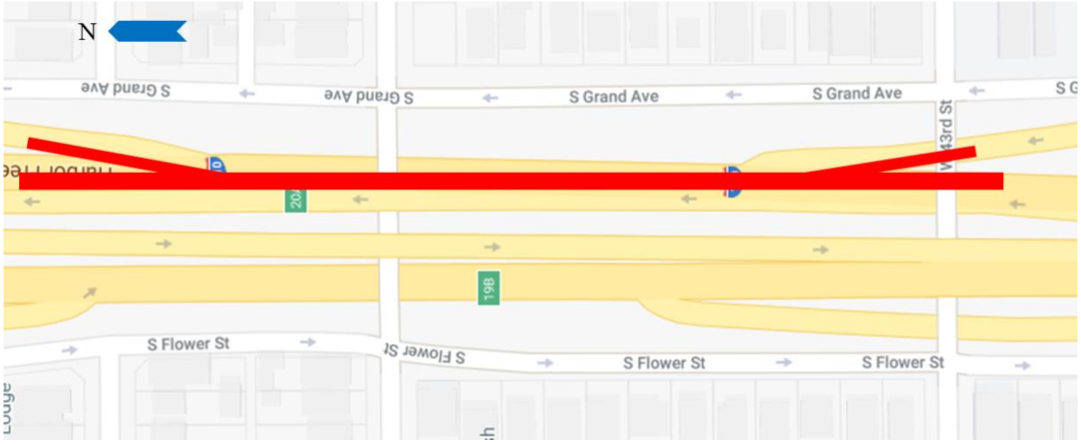

Figure 5.9 Location of the Weaving Freeway Segment

The freeway capacity before and after the weaving area for different penetration level of CAVs and AVs are shown in Table 5.13. Figure 5.10 plots the tendency of the capacity change before the weaving area with different penetration level of CAVs and AVs. And Figure 5.11 plots the tendency of the capacity change after the weaving area with different penetration level of CAVs and AVs. The speed limit on the tested freeway segment is 104 km/h (65 mph). And the simulations are also conducted under other three speed limits, which are 80 km/h, 90 km/h, and 120 km/h, respectively. The results before and after the weaving area are shown in Table 5.14, Table 5.15, and Table 5.16, respectively.

Table 5.13 Capacity Analysis on Freeway Weaving Segment under Speed Limit 104 km/h

Freeway Weaving Segment with Speed Limit 104 km/h							
Before Weaving Area		AV					
		0%	20%	40%	60%	80%	100%
CAV	0%	1674	1699	1757	1843	1955	1858
	20%	1586	1803	1828	1980	1961	
	40%	2390	2237	2465	3076		
	60%	3674	3719	3921			
	80%	3961	3981				
	100%	4019					
After Weaving Area		AV					

		0%	20%	40%	60%	80%	100%
CAV	0%	1565	1572	1680	1721	1807	1728
	20%	1396	1616	1637	1750	1739	
	40%	2107	1968	2214	2786		
	60%	3349	3379	3575			
	80%	3632	3646				
	100%	3682					

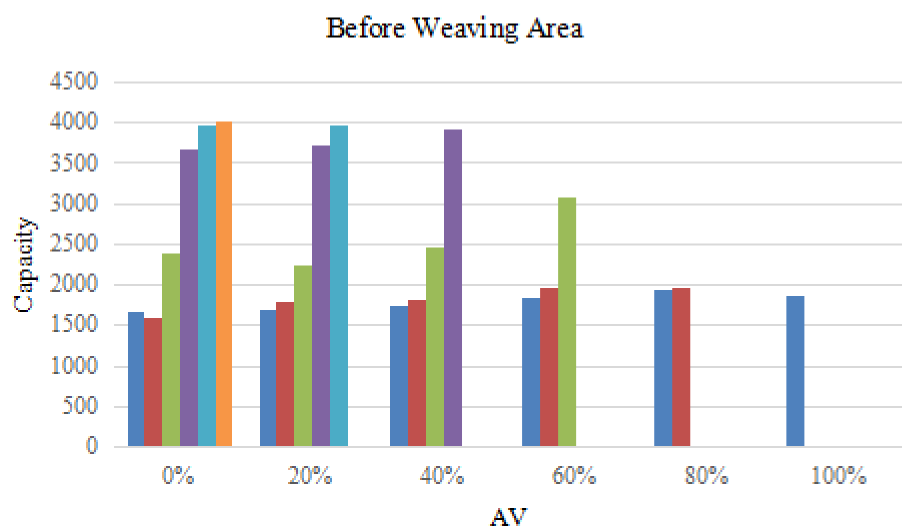

Figure 5.10 The Capacity Tendency before Weaving Area under Speed Limit 104 km/h

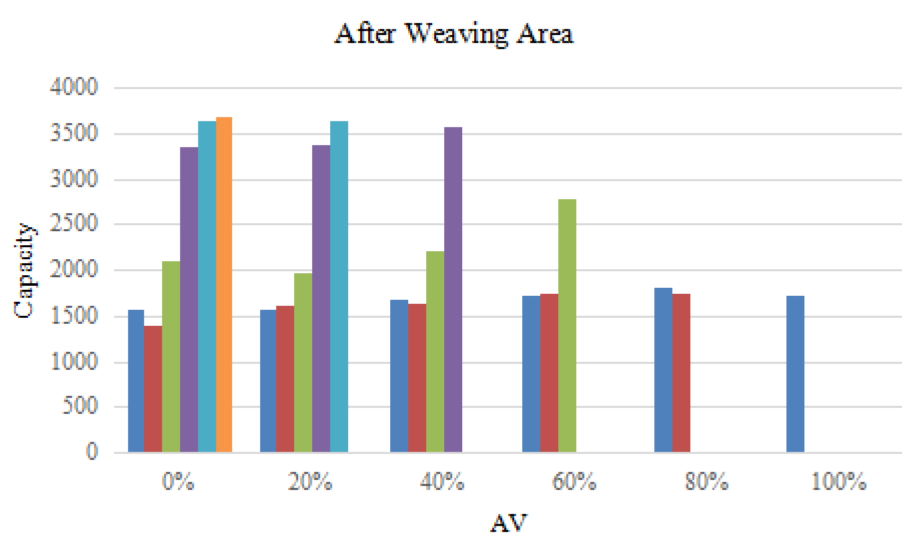

Figure 5.11 The Capacity Tendency after Weaving Area under Speed Limit 104 km/h

Table 5.14 Capacity Analysis on Freeway Weaving Segment under Speed Limit 80 km/h

Freeway Weaving Segment with Speed Limit 80 km/h							
Before Weaving Area		AV					
		0%	20%	40%	60%	80%	100%
CAV	0%	1630	1642	1760	1889	1892	1925
	20%	1475	1722	1937	1642	1905	
	40%	2084	2410	2682	2776		
	60%	3346	3339	3394			
	80%	3444	3453				
	100%	3496					
After Weaving Area		AV					
		0%	20%	40%	60%	80%	100%
CAV	0%	1508	1538	1640	1759	1740	1767
	20%	1319	1530	1702	1520	1712	
	40%	1873	2189	2414	2471		
	60%	3027	3009	3104			
	80%	3141	3154				
	100%	3179					

Table 5.15 Capacity Analysis on Freeway Weaving Segment under Speed Limit 90 km/h

Freeway Weaving Segment with Speed Limit 90 km/h							
Before Weaving Area		AV					
		0%	20%	40%	60%	80%	100%
CAV	0%	1619	1595	1800	1842	1802	1876
	20%	1634	1685	1832	1951	2134	
	40%	2299	2378	2540	2745		
	60%	3542	3581	3698			
	80%	3715	3737				
	100%	3776					
After Weaving Area		AV					
		0%	20%	40%	60%	80%	100%
CAV	0%	1518	1477	1662	1711	1676	1726
	20%	1448	1504	1635	1746	1867	
	40%	2034	2128	2248	2439		
	60%	3208	3238	3355			
	80%	3397	3409				
	100%	3454					

Table 5.16 Capacity Analysis on Freeway Weaving Segment under Speed Limit 120 km/h

Freeway Weaving Segment with Speed Limit 120 km/h							
Before Weaving Area		AV					
		0%	20%	40%	60%	80%	100%
CAV	0%	1702	1798	1771	1837	1922	1939
	20%	1705	1800	1791	1828	1947	
	40%	2330	2542	2755	2881		
	60%	3565	3722	4106			
	80%	4187	4200				
	100%	4245					
After Weaving Area		AV					
		0%	20%	40%	60%	80%	100%
CAV	0%	1591	1683	1623	1730	1756	1811
	20%	1535	1588	1540	1626	1746	
	40%	2053	2255	2446	2596		
	60%	3250	3346	3728			
	80%	3858	3877				
	100%	3907					

With 100% penetration level of CAVs, freeway capacity before weaving area can be increased by 149%, 140%, 133%, and 114% under speed limits of 120 km/h, 104 km/h, 90 km/h, and 80 km/h, respectively. And with 100% penetration level of CAVs, freeway capacity after weaving area can be increased by 146%, 135%, 128%, and 111% under speed limits of 120 km/h, 104 km/h, 90 km/h, and 80 km/h, respectively.

With 100% penetration level of AVs, freeway capacity before weaving area can be increased by 13.9%, 11.0%, 15.9%, and 18.1% under speed limits of 120 km/h, 104 km/h, 90 km/h, and 80 km/h, respectively. And with 100% penetration level of AVs, freeway capacity after weaving area can be increased by 13.8%, 10.4%, 13.7%, and 17.2% under speed limits of 120 km/h, 104 km/h, 90 km/h, and 80 km/h, respectively.

5.4 Summary

This chapter describes the numerical results of the capacity analysis under the selected freeway scenarios. The External Driver Behavior Model used to simulate CAV and AV is presented. For each scenario, the freeway capacities under different CAV and AV penetration rate and speed limits are evaluated. The freeway capacities before and after on-ramp, off-ramp, and weaving area are also compared. The numerical results show that CAVs are able to increase the freeway capacity under the four freeway scenarios. And the improvement of capacity increases if freeway speed limit gets higher. With 100% penetration level of CAVs, freeway capacity can be increased by over 100%. Compared to CAVs, there is no significant impact of AVs on freeway capacity. With 100% penetration level of AVs, freeway capacity can be increased by around 20%.

CHAPTER 6 TRAJECTORY OPTIMIZATION OF CAVs AT SIGNALIZED INTERSECTIONS

6.1 The Potential Signalized Intersection

6.1.1 Layout of the Potential Signalized Intersection

To better explore the influence of CAV technologies on the operation of signalized intersection(s), the potential intersection should have existing congestion problem with regular vehicles. Based on this criterion, the selected signalized intersection is located in the north of Charlotte, NC. It is a four-leg signalized intersection with two-way road in each direction. The westbound has three through lanes and two left turn lanes. The eastbound has three through lanes and two left turn lanes. The southbound has two through lanes, two left turn lanes, and one right turn lane. The northbound has two through lanes, two left turn lanes, and one right turn lane. The map of the selected signalized intersection is shown in Figure 6.1.

Figure 6.1 The Map of the Selected Signalized Intersection

6.1.2 Traffic Volumes of the Selected Intersection

The study period is the midday peak hour from 12:30p.m. to 1:30p.m. on April 3rd, 2018. The detail traffic volume information onthe study period is shown in Table 6.1.

Table 6.1 Traffic Volume of the Selected Signalized Intersection

Leg Direction	N. Tryon St Southbound					Harris Blvd Westbound				
Time	R	T	L	U	All	R	T	L	U	All
12:30 PM	66	80	94	0	240	65	328	49	11	453
12:45 PM	47	60	69	0	176	65	307	61	14	447
1:00 PM	54	84	92	0	230	59	277	60	10	406
1:15 PM	49	69	98	0	216	50	317	42	10	419
Total	216	293	353	0	862	239	1229	212	45	1725
% Approach	25.1	34.0	41.0	0	-	13.9	71.2	12.3	2.6	-
% Total	4.3	5.8	7.0	0	17.2	4.8	24.5	4.2	0.9	34.3

Leg Direction	N. Tryon St Northbound					Harris Blvd Eastbound				
Time	R	T	L	U	All	R	T	L	U	All
12:30 PM	48	83	84	15	230	51	276	27	1	355
12:45 PM	71	98	96	12	277	39	261	46	1	347
1:00 PM	76	107	82	11	276	40	234	36	6	316
1:15 PM	56	109	85	19	269	39	279	49	2	369
Total	251	397	347	57	1052	169	1050	158	10	1387
% Approach	23.9	37.7	33.0	5.4	-	12.2	75.7	11.4	0.7	-
% Total	5.0	7.9	6.9	1.1	20.9	3.4	20.9	3.1	0.2	27.6

6.1.3 Signal Plan

The cycle length of the selected intersection is 140s and there are eight movements in one cycle. Detailed time split for each movement can be seen in Table 6.2. The signal phasing is shown in Figure 6.2.

Table 6.2 Time Split for Each Movement

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

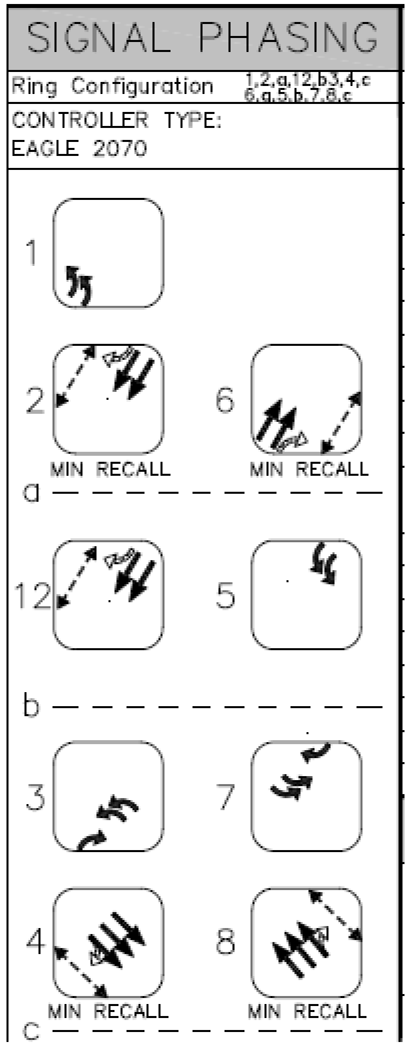

Figure 6.2 Signal phasing

6.2 Speed Advisory Strategy

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

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

$$0 \leq T_{GS} < T_{GE} \leq T \tag{6.1}$$

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

$$0 \leq t_c \leq T \tag{6.2}$$

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

$$t_{GS} = \begin{cases} T_{GS} - t_c, & 0 \leq t_c < T_{GS} \\ T + T_{GS} - t_c, & T_{GS} \leq t_c \leq T \end{cases} \tag{6.3}$$

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

$$t_{GE} = \begin{cases} T_{GE} - t_c, & 0 \leq t_c \leq T_{GE} \\ T + T_{GE} - t_c, & T_{GE} < t_c \leq T \end{cases} \tag{6.4}$$

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

$$v_{max} = \frac{D}{t_{GS}} \tag{6.5}$$

This speed ensures that CAVs arrive at green start. If vehicle speed is higher than v_{max}, the vehicle will arrive early and have to wait until next green starts. If vehicle speed is less than v_{max}, the vehicle will arrive after green starts, which will waste some green time thus reduce the intersection efficiency.

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

$$v_{min} = \frac{D}{t_{GE}} \tag{6.6}$$

This speed makes CAVs arrive at green end. CAVs should travel no less than v_{min} in order to arrive at green.

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

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

$$v_{os} = \begin{cases} \min(v_{max}, v_{SL}), & v_{min} > v_{SL} \\ v_{SL}, & v_{min} \leq v_{SL} \end{cases} \tag{6.7}$$

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

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

$$v_{os} = \min(v_{max}, v_{SL}) \tag{6.8}$$

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

6.3 Vehicle Driving Behavior

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

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

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

6.4 Numerical Results

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

6.4.1 Performance of the Strategy

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

The trajectory of regular vehicles is shown in Figure 6.3. According to the slope of the trajectory, one can see that regular vehicles keep a relative constant speed while approaching the intersection without any deceleration. If the signal is red, regular vehicles have to decelerate with a high rate when they are close to the stop line. As a result, queue will gradually form at the intersection. The speed of regular vehicles is shown in Figure 6.4. It can be seen that the speed decreases from free flow speed to zero in a short time. The acceleration rate of regular vehicles is shown in Figure 6.5. One can see that regular vehicles have unstable acceleration rate while approaching to the intersection ranging from -3 to 3 m/s^2.

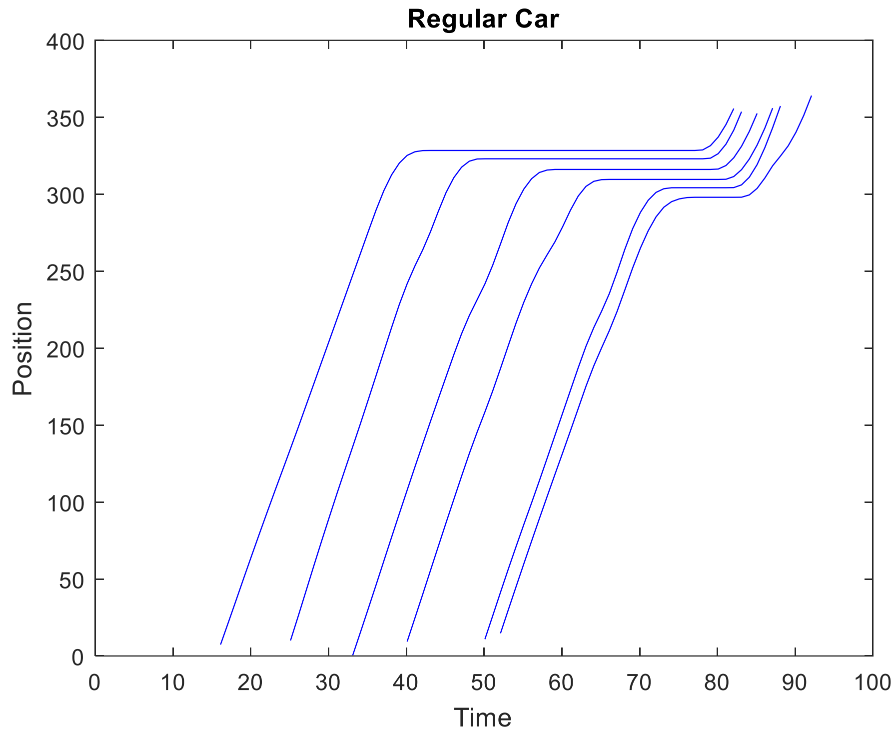

Figure 6.3 Trajectory of regular vehicles

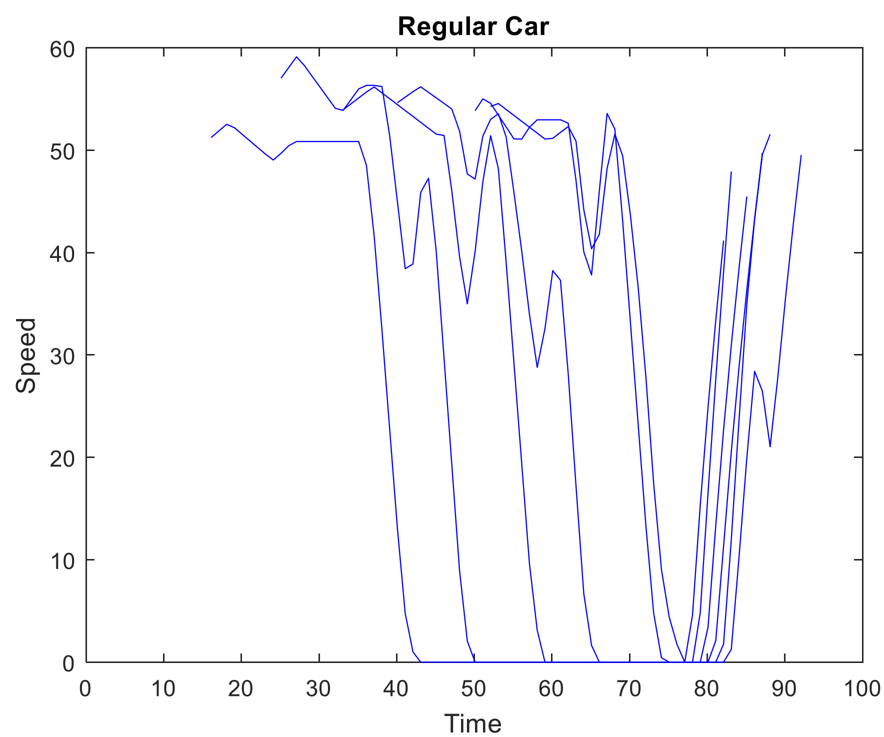

Figure 6.4 Speed of Regular Vehicles

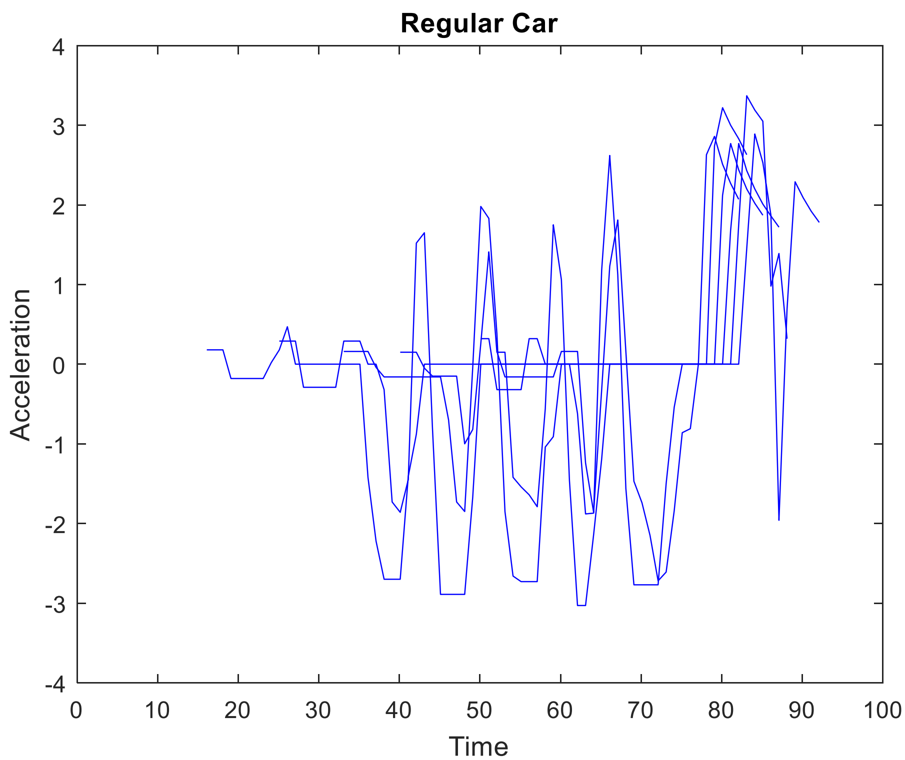

Figure 6.5 Acceleration Rate of Regular Vehicles

The trajectory of AVs is shown in Figure 6.6. The trajectory of AVs is similar to regular vehicles but smoother, which means that AVs keep a relatively constant speed and acceleration rate. This can be verified from Figure 6.7 and Figure 6.8, which are the speed and acceleration rate of AVs, respectively. It can be seen from Figure 6.8 that AVs have more stable acceleration rate while approaching to the intersection ranging from -3 to 0.5 m/s^2.

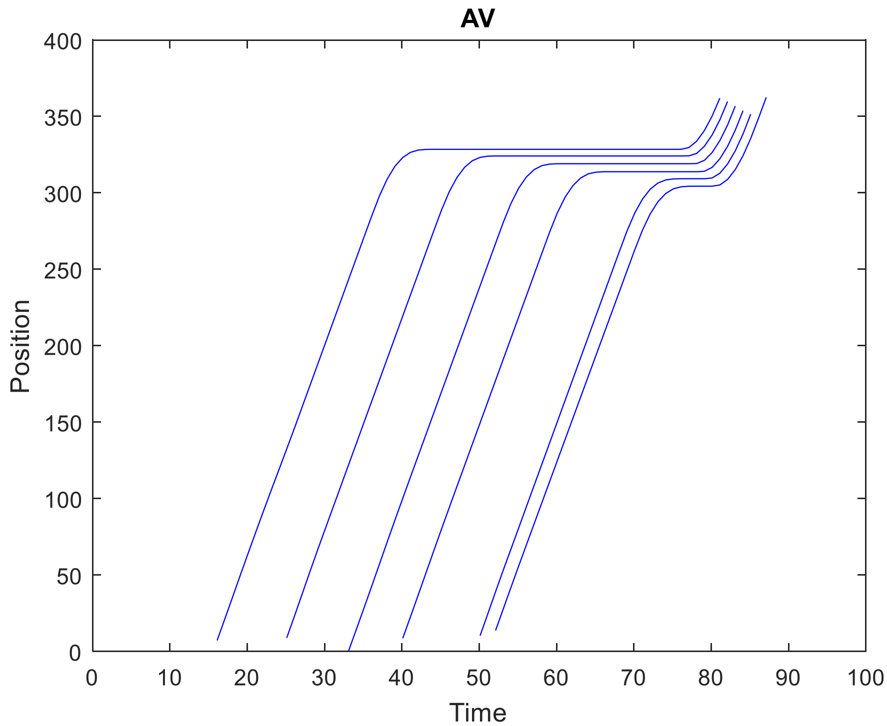

Figure 6.6 Trajectory of AVs

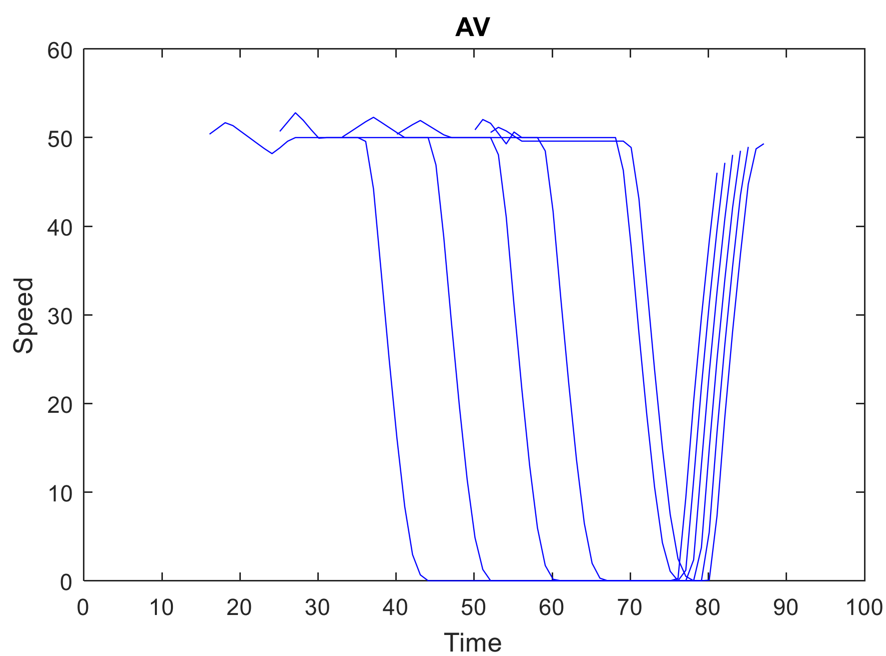

Figure 6.7 Speed of AVs

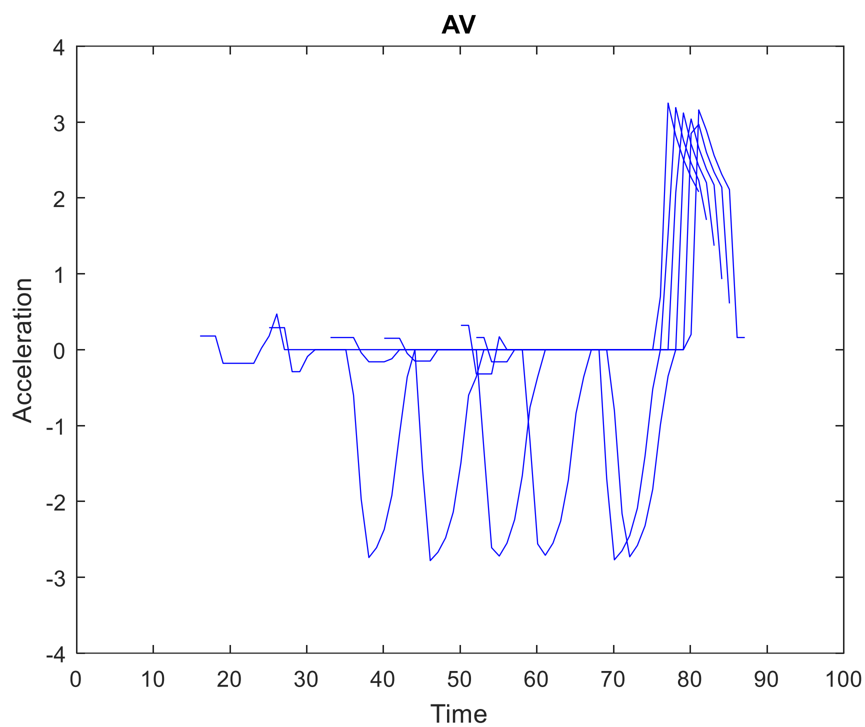

Figure 6.8 Acceleration Rate of AVs

The trajectory of CAVs is shown in Figure 6.9. According to the slope of the trajectory, one can see that CAVs can change their speed while approaching to the intersection. As a result, all CAVs can pass through the intersection at green without any stopping. The speed of CAVs is shown in Figure 6.10. It can be seen that CAVs start to decrease their speed earlier than the other two types of vehicles. And the minimum speed is around 10 m/s which means CAVs can pass the intersection without idling. The acceleration rate of CAVs is shown in Figure 6.11. One can see that CAVs have the most stable acceleration rate compared to AVs and regular vehicles while approaching to the intersection ranging from -1.5 to 1 m/s^2.

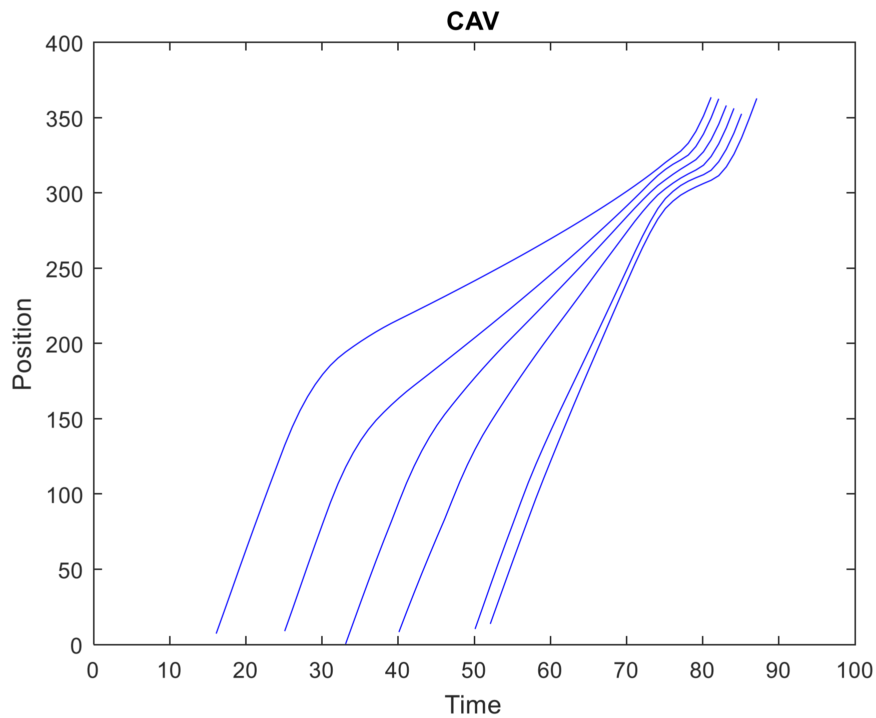

Figure 6.9 Trajectory of CAVs

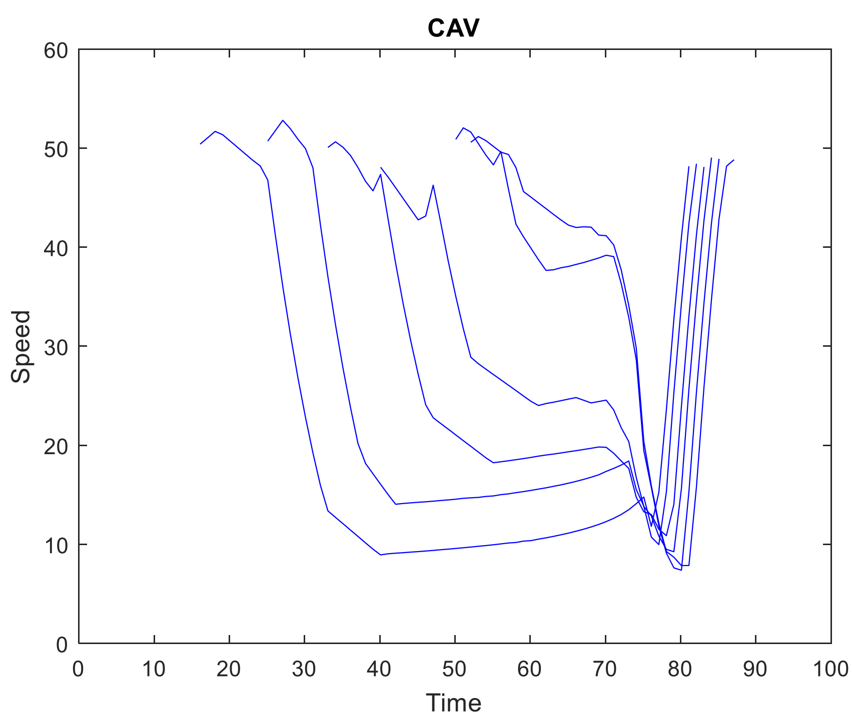

Figure 6.10 Speed of CAVs

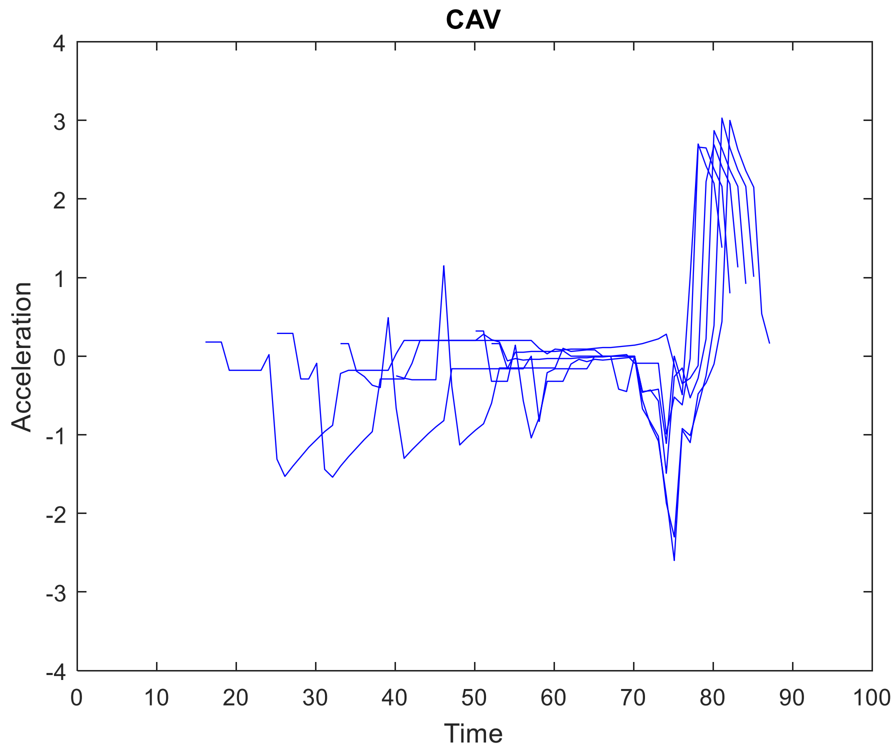

Figure 6.11 Acceleration Rateof CAVs

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

6.4.2 Performance of the Intersection

The intersection performance and vehicle emissions are recorded during the 60-min simulation with different combinations of CAVs, AVs, and regular vehicles. The travel delay for each penetration level of three vehicle type is shown in Table 6.3. The vehicle delay is the total travel delay of all vehicles passing through the intersection during the simulation. It can be seen that with only CAVs, AVs, or regular vehicles on road, the vehicle delay is 41.23s, 49.30s, and 76.43s, respectively. With 100% penetration rate of CAVs vehicle delay can be reduced by 46.06% compared to regular vehicles only. AVs can reduce vehicle delay by as much as 35.50% compared to regular vehicles only. So with V2I/I2V communications, CAVs can effectively improve the efficiency of signalized intersections.

Table 6.3 Traffic Delay under Different CAV Penetration Rates

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

The vehicle stop for each penetration level of three vehicle type is shown in Table 6.4. The vehicle stop is the number of vehicle stops per vehicle during the simulation. It can be seen that with only CAVs, AVs, or regular vehicles on road, the vehicle stop is 0.56, 0.75, and 1.36, respectively. With 100% penetration rate of CAVs, vehicle stop can be reduced by 58.82% compared to regular vehicles only. AVs can reduce vehicle stop by as much as 44.85% compared to regular vehicles only.

Table 6.4 Vehicle Stops under Different CAV Penetration Rates

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

The stopped delay for each penetration level of three vehicle type is shown in Table 6.5. The stopped delay is the stopped delay per vehicle during the simulation. It can be seen that with only CAVs, AVs, or regular vehicles on road, the stopped delay is 23.04s, 39.73s, and 63.02s, respectively. With 100% penetration rate of CAVs,stopped delay can be reduced by 63.44% compared to regular vehicles only. AVs can reduce stopped delay by as much as 36.96% compared to regular vehicles only.

Table 6.5 Stopped Delay under Different CAV Penetration Rates

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

The queue length for each penetration level of three vehicle type is shown in Table 6.6. It can be seen that with only CAVs, AVs, or regular vehicles on road, the queue length is 10.45m, 10.02m, and 23.88m, respectively. With 100% penetration rate of CAVs, the queue length can be reduced by 56.24% compared to regular vehicles only.

Table 6.6 Average Queue Length under Different CAV Penetration Rates

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

The maximum queue length for each penetration level of three vehicle type is shown in Table 6.7. It can be seen that with only CAVs, AVs, or regular vehicles on road, the maximum queue length is 186.76m, 138.90m, and 272.96m, respectively. With 100% penetration rate of CAVs, the maximum queue length can be reduced by 31.58% compared to regular vehicles only.

Table 6.7 Maximum Queue Length under Different CAV Penetration Rates

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

The CO emissions under all scenarios are shown in Table 6.8. The numbers reflect the quantity of carbon monoxide emitted by all vehicles passing the intersection during the simulation. As one can see from Table 6.8, with only CAVs, AVs, or regular vehicles on road, the CO emissions are 6594.78g, 7431.42g, and 9912.17g, respectively. CAVs can reduce CO emissions by as much as 33.47% compared to regular vehicles and 11.26% compared to AVs. As a result, CAVs can benefit the environment through V2I/I2V communications.

Table 6.8 CO Emissions under Different CAV Penetration Rates

CO Emissions (grams)		CAV				
		0%	25%	50%	75%	100%
AV	0%	9912.17	8725.95	8126.39	7187.46	6594.78
	25%	7928.60	8224.88	7465.15	6936.46	
	50%	7667.01	7794.19	7260.71		
	75%	7543.33	7589.18			
	100%	7431.42				

The NO_x emissions under all scenarios are shown in Table 6.9. The numbers reflect the quantity of nitrogen oxides emitted by all vehicles passing the intersection during the simulation. As one can see from Table 6.9, with only CAVs, AVs, or regular vehicles on road, the NO_x emissions are 1283.10g, 1445.89g, and 1928.55g, respectively.

Table 6.9 NO_x Emissions under Different CAV Penetration Rates

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

The VOC emissions under all scenarios are shown in Table 6.10. The numbers reflect the quantity of volatile organic compounds emitted by all vehicles passing the intersection during the simulation. As one can see from Table 6.10, with only CAVs, AVs, or regular vehicles on road, the VOC emissions are 1528.40g, 1722.30g, and 2297.24g, respectively.

Table 6.10 VOC Emissions under Different CAV Penetration Rates

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

100%	1722.30

The fuel consumptions under all scenarios are shown in Table 6.11. The numbers reflect the fuel consumptions by all vehicles passing the intersection during the simulation. As one can see from Table 6.11, with only CAVs, AVs, or regular vehicles on road, the fuel consumptions are 94.35 gallon, 106.32 gallon, and 141.80 gallon, respectively.

Table 6.11 Fuel Consumption under Different CAV Penetration Rates

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

6.5 Summary

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

CHAPTER 7 TRAJECTORY PREDICTION USING MACHINE LEARNING APPROACH

7.1 XGBoost algorithm

XGBoost is a prevalent boosting tree algorithm employed in industry because of its accuracy and high efficiency in predicting. In fact, XGBoost is developed from gradient boosting decision tree (GBDT) algorithm and employed in classification and regression problems with multiple decision trees (Xu et al., 2019). XGBoost can prevent over-fitting by normalizing the objective function. The details of the model are illustrated as follows.

A dataset is assumed as$D = \{(x_i, y_i)\}(i = 1,2, \dots, n)$, and the model has k trees. The model result $\widehat{y_i}$is expressed as:

$$\widehat{y_i} = \sum_{k=1}^{K} f_k(x_i), f_k \in F \tag{7.1}$$

where F is the hypothesis space, and $f(x)$ denotes a decision tree:

$$F = \{f(x) = \omega_{q(x)}\} \tag{7.2}$$

where $\omega_{q(x)}$ represents the score of each leaf node; $q(x)$ is the number of leafs.

When a new tree is developed to fit the residual errors of last tree, the predicted score for the *t*-th tree can be calculated as:

$$\widehat{y_i}^t = \widehat{y_i}^{t-1} + f_t(x) \tag{7.3}$$

The objective function is as follows:

$$J^{(t)} = \sum_{i=1}^{n} L(y_i, \widehat{y_i}) + \Omega(f_t) \tag{7.4}$$

where L is the loss function, Ω is a penalizing term, and:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} {\omega_j}^2 \tag{7.5}$$

where γ is a parameter represents the complexity of the leaf; Tdenotes the number of the leaves; λ is a parameter scaling the penalty; and $\omega$is the vector of scores on each leaf.

Unlike the general gradient boosting methods, the XGBoost employs the second-order Taylor expansion to the loss function. Formula (7.4) is then simplified as follows:

$$J^{(t)} = \sum_{i=1}^{n} \left[L(y_i, {\hat{y}_i}^{t-1}) + g_i f_t(x_i) + \frac{1}{2} h_i {f_t}^2(x_i) \right] + \Omega(f_t) \tag{7.6}$$

$$g_i = \frac{\partial L(y_i, {\hat{y}_i}^{t-1})}{\partial {\hat{y}_i}^{t-1}} \tag{7.7}$$

$$h_i = \frac{\partial^2 L(y_i, {\hat{y}_i}^{t-1})}{\partial {\hat{y}_i}^{t-1}} \tag{7.8}$$

Then, the final objective function can be generated as follows:

$$\begin{aligned} J^{(t)} &= \sum_{i=1}^{n} \left[g_i \omega_{q(x_i)} + \frac{1}{2} h_i \omega_{q(x_i)}^2) \right] + \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} {\omega_j}^2 \\ &= \sum_{j=1}^{T} \left[\left(\sum_{i \in I_j} g_i \right) \omega_j + \frac{1}{2} \left(\sum_{i \in I_j} h_i + \lambda \right) \omega_j^2 \right] + \gamma T \end{aligned} \tag{7.9}$$

where $I_j = \{i | q(x_i) = j\}$ is the set of data point indices belonged to the *j*-th leaf. Since the same score is assigned to all the data points on the same leaf, the index of the summation in the second line can be revised. The terms $g_i$and $h_i$denote the first and second derivativesof the loss function. Let $G_j = \sum_{i \in I_j} g_i$ and $H_j = \sum_{i \in I_j} h_i$, then the final objective function is changed to a quadratic function as follows:

$$J^{(t)} = \sum_{j=1}^{T} \left[G_j \omega_j + \frac{1}{2} \left(H_j + \lambda \right) \omega_j^2 \right] + \gamma T \tag{7.10}$$

Finally, the optimal solution of the optimized objective function can be generated:

$$\omega_j^* = -\frac{G_j}{H_j + \lambda} \tag{7.11}$$

$$J^* = -\frac{1}{2} \sum_{j=1}^{T} \frac{G_j^2}{H_j + \lambda} + \gamma T \tag{7.12}$$

7.2 Intelligent Driver Model

The Intelligent Driver Model (IDM) produces better realism than most of the deterministic car following models (Treiber et al. 2000). The fundamental of the IDM is to calculate the acceleration rate of the object vehicle by considering both the ratio of desired velocity versus actual velocity and the ratio of desired headway versus actual headway. The calculation of acceleration rate is expressed as follows:

$$a = a_m [1 - (\frac{v}{v_0})^{\delta} - (\frac{s^*(v, \Delta v)}{s})^2] \tag{7.13}$$

$$s^*(v, \Delta v) = s_0 + s_1 \sqrt{\frac{v}{v_0}} + vT + \frac{v \times \Delta v}{2\sqrt{a_m b}} \tag{7.14}$$

where

a = acceleration rate of the object vehicle;

a_m = maximum acceleration;

v = current velocity of the object vehicle;

v_0 = desired velocity;

δ = acceleration exponent;

$s^*(v, \Delta v)$ = desired minimum headway;

Δv = speed difference between the object vehicle and the leading vehicle;

s = current headway between the object vehicle and the leading vehicle;

s_0 = linear jam distance;

s_1 = non-linear jam distance;

T = desired headway;

b = comfortable deceleration.

Table 7.1 presents the values of all the parameters in the proposed IDM in this study.

Table 7.1 Values of Parameters in the IDM

Parameters	**Values**	**Parameters**	**Values**
a_m	0.73 m/s^2	s_1	3 m
v_0	29 m/s	T	0.6 s
δ	4	b	1.67 m/s^2
s_0	2 m		

7.3 Model comparison

Root mean square error (RMSE) and Mean absolute error (MAE) are employed to examine the performance of the proposed models.

RMSE calculates the average of square errors between predicted values and actual values:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{N}(y_i^* - y_i)^2} \tag{7.15}$$

Mean absolute error (MAE) is calculated by averaging the absolute errors between predicted values and actual values:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i^* - y_i| \tag{7.16}$$

where N is the number of data points; y_i^* and y_i represent the predicted and actual values.

7.4 Data and Features

7.4.1 Dataset

In this study, the Next Generation Simulation (NGSIM) dataset is used to train the proposed model. It is an open source of real vehicle trajectory data collected by the United States Federal Highway Administration (FHWA) in 2005. NGSIM dataset has been widely used in vehicle trajectory prediction (Tomar et al., 2010; Ding et al., 2013; Altché and Fortelle, 2017; Deo and Trivedi, 2018; Li et al., 2019). More specifically, this research considers a 15 minute interval of vehicle trajectories on the US101 highway. Since different vehicle type has different car following behavior, only passenger cars are involved in the analysis. The time period is between 7:50am and 8:05am, June 15th, 2005. In total, the selected dataset includes trajectories for 1,993 individual vehicles, recorded at 10 Hz. To examine the performance of the XGBoost model, 80% vehicles in the selected dataset are used as the training set and the rest 20% are used in the testing phase.

7.4.2 Feature Extraction

The NGSIM dataset provides vehicle speed, position, acceleration rate, and headway of each individual vehicle. In this study, the objective is to predict the acceleration rate for the object vehicle, which is the determining factor of vehicle trajectory. Under the CAV environment, the object vehicle can receive information from its leading vehicle. The acceleration rate of the object vehicle is then predicted according to the status of both the object vehicle and its leading vehicle. The following features are defined for predicting the acceleration rate for the object vehicle:

- Lateral position of the object vehicle x which is the lateral position of the vehicle based on the leftmost edge of the road
- Longitudinal position of the object vehicle$y$
- Speed of the object vehicle v
- Space headway between object vehicle and its leading vehiclesp
- Lateral position of the leading vehicle x_l
- Longitudinal position of the leading vehicle y_l
- Speed of the leading vehicle v_l
- Acceleration rate of the leading vehicle a_l

7.5 Results and Discussions

7.5.1 Performance of the models

In this study, RMSE and MAE are employed to evaluate the prediction accuracy of the XGBoost model and the IDM. Table 7.2 shows the RMSE and MAE values for the proposed models. As one can see from the table, the RMSE and MAE of the XGBoost model are 3.9953 and 2.6950, respectively, which are smaller than the errors of the IDM (i.e., 6.2748 and 4.7164). This illustrates the superiority of the XGBoost model in the prediction of vehicle trajectory.

Table 7.2 Comparison of the Two Models in Acceleration Rate Prediction

Algorithm	**RMSE**	**MAE**
XGBoost	3.9953	2.6950
IDM	6.2748	4.7164

Figure 7.1 shows the predicted and observed values in a predict horizon of 30 seconds. As can be seen in the figure, the XGBoost model can effectively predict the acceleration rate of the object vehicle. The prediction results of the IDM are inferior to

those of the XGBoost model. By comparing the prediction results, one can conclude that the XGBoost model is more reliable for vehicle trajectory prediction than the IDM.

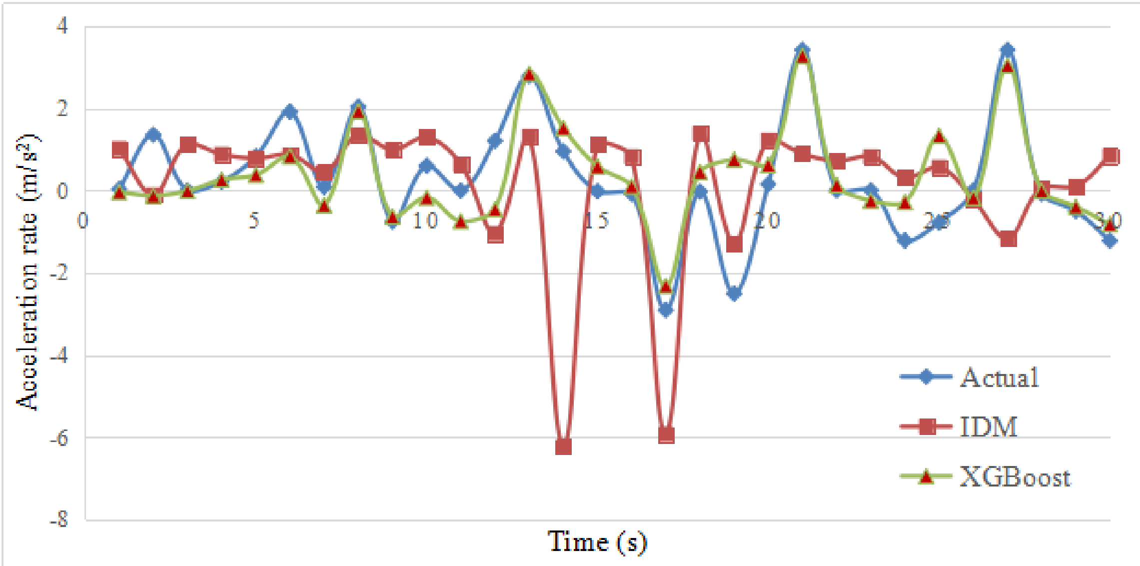

Figure 7.1 Comparison of the Predicted Results and the Actual Data

7.5.2 Feature Importance

To further explore the impact of each feature on the vehicle trajectory prediction, the relative importance of the eight input features in the XGBoost model is calculated. The feature importance is ranked based on the F score, which is a measurement of the frequency that a variable is selected for splitting. The feature will get higher score if it is used to make decisions in the decision trees more frequently. The importance ranking of the input features are displayed in Figure 7.2. It can be seen from the figure, the longitudinal position, lateral position, and the velocity of the object vehicle are the most important features to predict the vehicle trajectory.

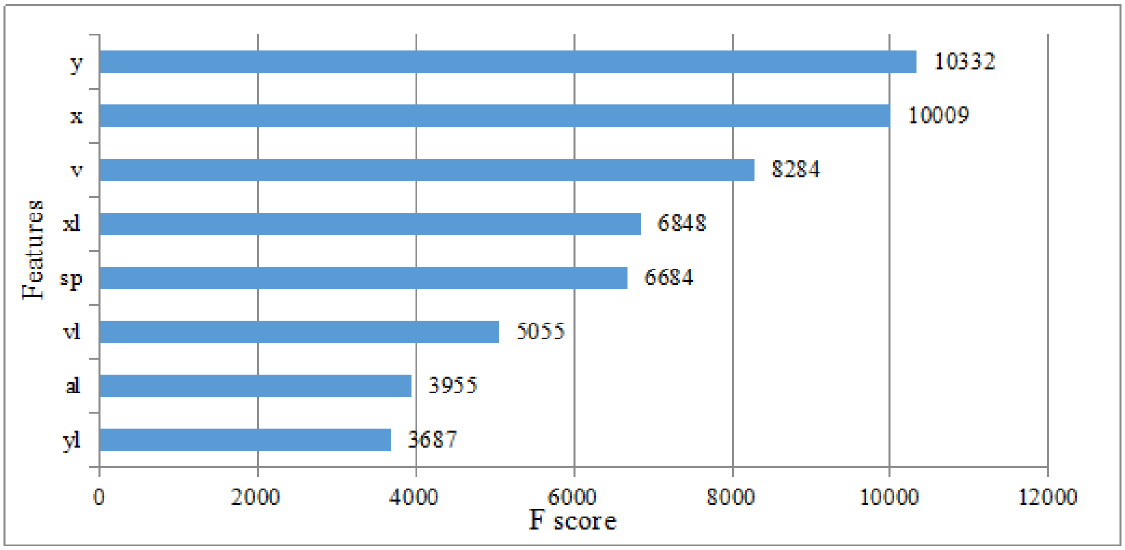

Figure 7.2 Feature Importance Ranking

7.6 Summary

In this research, the XGBoost model is developed in order to predict vehicle trajectories in a CAV environment. The predicted results are compared with the IDM, which is a traditional car following model. The NGSIM dataset is utilized to train and test the proposed XGBoost model. The predicted results show that the XGBoost model gets higher prediction accuracy than the IDM model. The longitudinal position of the object vehicle is the most important feature to predict the vehicle trajectory. The results of this research could help guide the machine learning approaches in the area of vehicle trajectory prediction.

CHAPTER 8 SUMMARY AND CONCLUSIONS

8.1 Introduction

Connected and autonomous vehicle (CAV) technologies are known as an effective way to improve roadway safety and mobility. As a combination technology of connected vehicle and autonomous vehicle, CAVs share real time information with each other, such as position, speed, and acceleration. CAV requires narrower lane width and shorter headway which will results in a higher roadway capacity. Also, CAVs enable the communication between vehicles and transportation infrastructures. The coordination operation among CAVs and the communication between CAVs and traffic signals will improve the throughput at signalized intersections and lead to a higher intersection capacity. The coordinated through or turning maneuvers of CAVs may eliminate crashes and reduce the total travel delay at the intersection.

Traffic signals are essential in urban traffic management. On the other hand, traffic signals increase travel time, gas emissions and fuel consumption of vehicles. Moreover, stop-and-go traffic increases the possibility of vehicle collisions and lead to economic cost in result. As the increasing travel demand in recent years, traditional signalized intersections are generating more delays as well as gas emissions. There is an urgent need to enhance intersection efficiency and the throughput mobility using the emerging CAV technologies.

By using VISSIM, a traffic microsimulation tool, four different freeway scenarios are chosen from PeMS. To obtain reliable results, selected parameters are calibrated in the car following model. Genetic algorithm is used to find the optimal solution of the objective function. After the calibration process, the simulation is conducted on freeway segments and intersections under a mixed traffic environment.

To better examine the impact of CAVs on the operation of freeway and signalized intersections, autonomous vehicles (AVs) are also involved in this study, so that a mixed traffic environment can be investigated including regular vehicles, AVs, and CAVs. Overall, the results of this study can help traffic engineers and stakeholders better understand how different market penetration levels of CAVs influence freeway capacity and traffic operation of signalized intersections.

8.2 Summary and Conclusions

Through a comprehensive literature review of the current CAV technologies, various methodological approaches to analyze highway capacity with or without CAVs are summarized. Simulation based method is widely used in CAV related studies. Compared to other approaches, simulation based method is imperative for practical decision making in transportation planning and operations. To conduct analysis using microsimulation models, potential scenarios need to be selected.

PeMS is used to select potential freeway segments. PeMS is a web-based database consists of historical traffic data in different aspects, such as speed, flow, capacity, and delay. By using PeMS, researchers can conduct research with the comprehensive information of selected freeway segments, make better decisions on freeway operation, identify congestion bottlenecks, and evaluate freeway performance. Three different freeway segments are selected through the PeMS database as potential simulation scenarios. In order to examine the impact of CAV technology on different freeway scenarios, the selected freeway segments contain a mix of configurations, such as on-ramp, off-ramp, and weaving area. The three freeway segments are all selected around the city of Los Angeles, a large population area. These sites are selected because their preexisting congestion issues during the peak hour, as well as they are the major interstate freeway with high traffic volumes. The traffic flow and speed data is collected from PeMS and used in the microsimulation model.

Microscopic simulation models are widely employed in transportation planning and operation analysis. Compared to field testing, simulation provides a safer, faster, and costless environment for researchers. However, in order to obtain reliable results through simulation, the model parameters have to be calibrated. The calibration procedure can minimize the differences between the simulated and observed data. Genetic Algorithm is available to achieve near-global optima during the calibration procedure of the microscopic traffic simulation model. The GA is an inspiration of biological evolution process with selection, crossover and mutation as its three steps. The GA starts from a random population set. For each generation, the better solutions have higher probabilities to be selected and used to generate new populations after crossover and mutation within the selected solutions. In this study, the population size is set to be 10, and the crossover and mutation rate are set to be 0.8 and 0.2, respectively. The max generation number is 10. The GA-based calibration is conducted through MATLAB. A population of binary chromosomes is generated randomly at the very beginning and each represents a feasible solution. Then the chromosomes are decoded to relative model parameters and passed onto the VISSIM for simulation. The objective function value is calculated based on the simulated traffic flow and speed data. The calibration process will not stop until the maximum number of generation is reached or the stopping criterion is achieved.

VISSIM uses the Wiedemann's car following model to capture the physical and human components of vehicles. As the Wiedemann model stated, a vehicle has four driving modes: free driving, approaching, following and braking. The model has ten unique parameters (i.e. $CC0, CC1, \dots, CC9$) representing the car following characteristics. The optimized value of $CC0$ calibrated by the GA is 7.75 ft compared to the default value of 4.92 ft. And the optimized value of $CC1$ calibrated by the GA is 1.14 seconds compared to the default value of 0.90 seconds.

VISSIM cannot simulate operations of connected and autonomous vehicles with its internal driver model. However, VISSIM provides the option to replace the internal model by an External Driver Behavior Model (EDBM), which is a fully user-defined driving behavior model for connected and autonomous vehicles. The EDBM is implemented as a C++ Dynamic Link Library (DLL) plug-in, which contains specific algorithms for connected and autonomous vehicles. These algorithms can determine the next step maneuver (i.e. acceleration, lane change) for each affected vehicle. During each simulation time step, VISSIM calls the DLL file to determine the behavior of the vehicle by passing the current state of the vehicle and its surroundings to the DLL and retrieving the updated state calculated by the DLL.

The EMDB model is developed by the Open Source Application Development Portal (OSADP). The code is written in C++ and needs to be compiled to generate a DLL file. The DLL file can be implemented as a V2V communication device, wherein the leading vehicle informs the following vehicle if its location, speed and acceleration. The following vehicle can change its speed quickly to avoid rear-end collisions. The algorithm continuously adjusts the acceleration rates by measuring the headways between the leading vehicles and following vehicles to keep short headways. The headway between two connected and autonomous vehicles is set 0.9 s and the headway between connected and autonomous vehicle and regular vehicle is set 1.2 s.

For each scenario, the freeway capacity under different CAV penetration rate and speed limit is evaluated. And the freeway capacity before and after on-ramp, off-ramp, and weaving area is also compared. The numerical results show that CAVs can increase the freeway capacity under the four freeway scenarios. Also, CAVs can reduce the capacity drop before and after the on-ramp, off-ramp, and weaving area.

With the rapid development of CAV technologies, CAVs can share information with both other CAVs and infrastructures. Traffic signal control framework can be optimized to improve intersection mobility. In this study, three types of vehicles are considered in the network, which are regular vehicles, AVs, and CAVs. Only CAVs can receive the signal information and adjust their speed accordingly. The speed advisory strategy is developed and aims to help CAVs arrive at green without stopping. The speed advisory strategy for CAVs is written in Python. During each simulation time step, VISSIM calls the Python script to determine the optimal speed of the vehicle by passing the current state of the vehicle and signal information to the script and retrieving the updated state calculated by the script.

CAVs and AVs behave more deterministically than regular vehicles without stochastic value spreads. For acceleration and deceleration functions, the maximum and minimum values are identical to the median value of regular vehicles. Speed limit is 50 km/h. VISSIM’s default values for regular vehicles are stochastic and speed-dependent. The maximum and desired acceleration is uniformly distributed between 0.9 m/s2 and 3.3

m/s^2 with a median value of 2.0 m/s^2 at 50 km/h. The desired deceleration is distributed uniformly between -2.5m/s^2 and -3.0 m/s^2 with a median value of -2.8 m/s^2 at 50 km/h. The maximum deceleration is distributed uniformly between -6.0 m/s^2 and -8.0 m/s^2 with a median value of -7.0 m/s^2 at 50 km/h. The average headway is 0.5s for CAVs and AVs and 0.9s for regular vehicles.

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

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

To better predict the vehicle trajectories, the XGBoost model is developed to predict vehicle trajectories in CAV environment. The predicted results are compared with the IDM, which is a traditional car following model. The NGSIM dataset is used to train and test the XGBoost model. The predicted results prove that the XGBoost model gets higher prediction accuracy than the IDM model. The longitudinal position of the object vehicle is the most important feature to predict the vehicle trajectory. The results of this study could help guide the machine learning approaches in the area of vehicle trajectory prediction.

The case studies in this paper only focus on simple freeway segments or an isolated intersection. Future studies will focus on more complicated scenarios, such as freeways with multiple ramps and weaving sections, and arterial roadswith multiple intersections. A mixed traffic environment will be considered including both trucks and passenger cars. An advanced car following model considering lane change situations is another research direction. Future research efforts will also investigate other machine learning models to predict vehicle trajectory considering lane changing in different roadway scenarios.

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