NON-MOTORIZED FACILITIES CAPACITY AND LEVEL OF SERVICE AT INTERSECTIONS IN A CONNECTED AND AUTONOMOUS VEHICLES ENVIRONMENT

by

Yifan Wang

A thesis submitted to the Faculty of the University of Delaware in partial fulfillment
of the requirements for the degree of Master of Civil Engineering

Spring 2019

NON-MOTORIZED FACILITIES CAPACITY AND LEVEL OF SERVICE AT INTERSECTIONS IN A CONNECTED AND AUTONOMOUS VEHICLES ENVIRONMENT

by

Yifan Wang

Approved: ______________________________
Ardeshir Faghri, Ph.D.
Professor in charge of thesis on behalf of the Advisory Committee

Approved: ______________________________
Sue McNeil, Ph.D.
Chair of the Department of Civil and Environmental Engineering

Approved: ______________________________
Levi T. Thompson, Ph.D.
Dean of the College of Engineering

Approved: ______________________________
Douglas J. Doren, Ph.D.
Interim Vice Provost for Graduate and Professional Education

ACKNOWLEDGMENTS

Foremost, I would like to express my sincere gratitude to my advisor: Ardeshir Faghri. Not only for his tremendous academic support, but also for giving me so many opportunities to research. This thesis would not be completed without his support and guidance. He helped me in all the time of research and writing of this thesis with patience, motivation, and enthusiasm.

I would also like to thank Ming Li, for his encouragement and support for this thesis and my research. And I would also like to thank to the faculties who help me to complete this thesis.

Finally, I must express my gratitude to my parents, my brother and my sister, for their love, unfailing support, and always be my side. Without my family, I cannot be here. I would also like to acknowledge my friends during my master's period, for their continuous encouragement and company.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

The current trend that Connected and Autonomous Vehicles (CAVs) will be a major focus of transportation and the automotive industry and be widely used in future traffic system analysis is inevitable. Numerous studies have focused on the evaluation and potential development of CAVs technology. However, pedestrians and bicyclists, as two essential and important modes of the road users have seen little to no coverage. In response to the need for analyzing the impact of CAVs on non-motorized transportation, this thesis develops a new model for the evaluation of the Level Of Service (LOS) for pedestrians in a CAVs environment based on the Highway Capacity Manual (HCM). The HCM provides a methodology to assess the level of service of pedestrians and bicyclists on different types of intersections in urban areas.

Five scenarios were created for simulation via VISSIM software that correspond to the different proportions of the CAVs and different signal systems in a typical traffic environment. Meanwhile, the Surrogate Safety Assessment Model (SSAM) was selected for analyzing the safety performance of the five scenarios. Through computing and analyzing the results of simulation and SSAM, the last part of this thesis concentrates on developing a new model for evaluating pedestrians' LOS in urban areas based on HCM suitable for CAVs environments. The most important goal and results of this study are, for engineers and/or policymakers, to have a tool to conduct a comparison of capacity and LOS regarding the impact of CAVs on pedestrians during the process of a transportation system transition to CAVs.

Chapter 1

INTRODUCTION

1.1 Motivation

The automotive industry was born for more than 100 years age. In recent years, with the rapid development of science and technology, the intelligent process of the automotive field has ushered a period of rapid development. At this stage, the technology of active safety has matured, and part or all of the intelligent assisted driving technologies have been applied to existing passenger cars on a large scale. Assisted driving techniques include electronic stability systems, active braking systems, and lane departure and retention systems. However, the advancement in technology still cannot eliminate the occurrence of traffic accidents. Traffic accidents caused by drivers' mistakes still account for more than 93% of all accidents (Papadoulis, 2019). At present, vehicles are fully controlled by drivers: receiving information, making decisions, and finally taking action go through sophisticated process of perception and reaction to react different road hazards. The existing passive/active safety technologies for vehicles still cannot meet the requirements of current goal of having zero casualties and even zero accidents.

With the advancements of sensor technologies, information technologies, and vehicle control technologies, the automation of control of vehicles has attracted much attention. The intelligent traffic form with autonomous technologies have become an essential part of tackling some serious traffic safety, efficiency and convenience issues. Major car companies, Internet companies, universities and research institutes have successively launched prototype or concept models of CAVs. According to recent statistics (Kockelman, 2017), Audi, BMW, Mercedes-Benz, Volvo, and other car companies, as well as internet companies such as Baidu, WAYMO, and public transportation companies like Uber, have already developed autonomous prototypes on the road test and deploy the intelligent automotive market. At the same time, the driverless test area for CAVs is gradually improving, United States Detroit M-city, China's Shanghai Nice-city, and Chongqing's i-Vista are some examples. Governments are also promoting autonomous technologies, such as the state of California allowing for the application of CAVs on the road. Beijing, China, recently opened some paths for driverless automobile testing. Shanghai also allows autonomous vehicles to drive on partially open roads, further promoting the technological development of connected and autonomous vehicles.

The emergence of CAVs also caused discussion of coexistence issues with other road users: conventional vehicles and non-motorized traffic. Pedestrians and bicyclists are a powerful indicator of the social and economic health and safety of a community. A high level of pedestrian and bicycle activity in a community is often associated with more robust economies and healthier, more socially-cohesive populations, while a lack of pedestrian and bicycle activity on roadways can be an indicator that personal security and safety needs are not being met or that destinations cannot be accessed on foot or by bike. However, the number of cars has increased year by year, and the transportation space for walking and bicycles has been eroded, and the travel environment has deteriorated. Encouraging and promoting a high LOS for pedestrians and bicyclists is a critical strategy for improving fitness, cleaner air and sustainability. Motor vehicles generate numerous amounts of air pollution. In fact, according to the US Environmental Protection Agency, transportation is the cause of nearly 80% of carbon monoxide emissions and 55% of nitrogen oxide emissions. The commuters using bicycles to work will avoid 2,000 miles of driving and (in the US) about 2,000 pounds of carbon dioxide per year. Moreover, it is equivalent to an average American carbon footprint reduction of nearly 5% (Gardner, 2010).

However, pedestrians and bicyclists are in a weak position on traffic safety issues in the urban transportation system and are more vulnerable to traffic accidents (Sherony & Zhang, 2015). In America, from 2000 to 2013, a research shows a total of 768,285 injury crashes and 50,147 fatal crashes were pedestrian related from 2000 to 2013, which accounted for 3.4% of total injury crashes and 11.5% of total fatal crashes respectively. For bicyclist crashes, 597,733 of all the injury crashes (2.6%) and 7,940 of all of the fatal crashes (1.8%) were bicyclist related (Sherony & Zhang, 2015). Furthermore, at present, most transportation regulations tend to be dominated by mobile traffic modes, and pedestrians and bicyclists as a secondary traffic system, thus losing the equality between the non-motorized and the motorized road users.

Furthermore, the new technologies such as, "Smart driving technologies," refer to telematics, sensing, and automation-based technologies and technology packages equipped on CAVs. Some barriers existed in applying the intelligent driving technologies on the development and implementation of CAVs, especially for mixed traffic environments including pedestrians, bicyclists, manual driving cars, and CAVs. Although it has tremendous potential to improve vehicle safety, congestion, travel costs, and freight movement, it does have its limitations. These limitations include safety cost, liability, insurance and policy. Table 1 shows the potential safety implications for CAVs for pedestrians and bicyclists (Sandt & Owens, 2017). A literature search conducted and recently shows 432 United States and international articles related to autonomous vehicle issues which identified fewer than 20 that discussed pedestrian or bicycle topics, either briefly or in depth (Sandt & Owens, 2017). The impact of CAVs on non-motorized transportation specially for bicycles and pedestrians need to be study and quantified. Also, it is essential to harmoniously accommodate all of road users during the different stages of and the transition process of the traffic system.

Table 1 Potential crash implications for CAVs, non-motorized crashes.

	CAV Market Penetration			
	0%	**10%**	**50%**	**90%**
# Crashes	436,975	405,168	248,213	70,450
# Injuries	224,930	208,569	127,794	36,289
# Fatalities	2,905	2,669	1,588	412
Economic Costs ($M)	$17,932	$16,593	$10,100	$2,814
Comprehensive Costs ($M)	$76,158	$70,389	$42,695	$11,770
Lives Saved	-	236	1,317	2,493
Economic Savings ($M)		$1,339	$7,832	$15,118
Comprehensive Savings ($M)	-	$5,769	$33,463	$64,388

Source: (Kockelman, 2017)

1.2 Problem Statement

There is no doubt that CAVs will bring changes to the existing transportation system and many studies have discussed the benefits and the possible challenges. As mentioned above, pedestrians and bicyclists as a vital part of the transportation system, have not seen their fair share of coverage in the current literature.

Most of these articles only describe the impact of CAVs on facilities and safety aspects in a very general way. These effects need to be quantified so that people could more intuitively perceive the influence of CAVs on pedestrians. Also, every technology needs an adaptation process from entering the market to integrating into society, not to mention the CAVs which will completely change the way people travel. The application of CAVs is a gradual process, and correspondingly, the new methods should reflect this process.

Due to the complexity of CAVs and the transition of technology, there are many uncertainties that surround the impact of CAVs on pedestrians in urban areas. This will affect the future implementation of CAVs and as a result need detailed studies and research.

1.3 Purpose and Objectives

This thesis established a method to quantify the impact of CAVs on pedestrians. The objectives can be summarized as follow:

- Identifying the factors that most influence the assessment of LOS of pedestrians on the urban intersections
- Building five scenarios to reflect the gradual process of the application of CAVs.
- Using SSAM software to analyze the safety performance between pedestrians and vehicles.
- Developing a new model for evaluating the pedestrian level of service (PLOS) on the urban intersections.
- Comparing the differents in capacity and LOS between the future and the current traffic environments.

1.4 Scope

The impact of CAVs on non-motorized transportation is both dynamic and complex. Non-motorized transportation includes pedestrians, bicycles, other small-wheeled transport (skates, skateboards, push scooters and hand carts) and wheelchairs. This thesis concentrates on only pedestrians.

The automated levels of autonomous vehicles in current technology are different. Their environmental awareness, location determination, sensor fusion, route plan, behavioral decision making, motion planning, and advanced control algorithms, as well as deep reinforcement learning, end-to-end driverless devices are not uniform. However, currently, there is a highly accepted CAVs classification system from Society of Automotive Engineers (SAE): there are six levels of autonomous vehicles from Level 0 to Level 5 (Level 0 suggest entirely human driving, and Level 5 indicate completely autonomous in any environment). All the autonomous vehicles mentioned in the simulation are in Level 5. The PTV Vissim is chosen as a simulation software. The motion characteristics and their interaction with human-driven vehicles, connected vehicles, and connected and autonomous vehicles were described in Chapter 6. The analysis of the impact of CAVs in this study focuses on the intersection in the urban areas.

1.5 Overview of Approach

Four different parts are included in this study. The first part contains a guided tour of HCM describing the LOS evaluation methods of pedestrians and bicyclists on signalized intersections in urban areas. The analysis of this method is worth mentioning since it guides the model developing within CAVs. For the process of calculating the pedestrian level of service (PLOS), this part describes in detail the variables, definitions, and formulas. Besides, the relative contribution of each variable and a comprehensive sensitivity analysis are also described. The final goal of this part is learning ideas from the existing methods and discover the factors which affect the final results of the level of service.

The second part concentrates on the five scenarios and making logical assumptions respectively. The broad application of CAVs need a run-in period, and in order to analyze the impact of driverless vehicles on non-motorized traffic comprehensively, five scenarios are established that corresponding to different ratios of CAVs in the transportation system (0%, 25%, 50%, 75%, and 100%). The proportion of the CAVs as the fundamental factors provide the platform to make reasonable assumptions about the different parameters in different aspects including traffic characteristics, geometric design, signal control, and coordinate methods.

The third part introduces the SSAM software and uses this software to perform safety analysis on the simulation results from VISSIM. Through the prediction of pedestrian and vehicle conflicts, the safety of users in different scenarios is analyzed. Through the simulation analysis of VISSIM and SSAM software, the fourth part establishes a model to evaluate the pedestrian service level, which is suitable for the road network in a CAVs environment. The main parameters used in the model are the time of pedestrian delay, the traffic volume, and speed of the CAVs, the traffic volume and speed of the traditional vehicle, the road width of the intersection sidewalk, and the number of conflicts between pedestrians and vehicles.

The final part will summarize and analyze the new model. The thesis sets a control group which has different pedestrian volume in the same scenario. The newly developed regression model is tested by the control group.

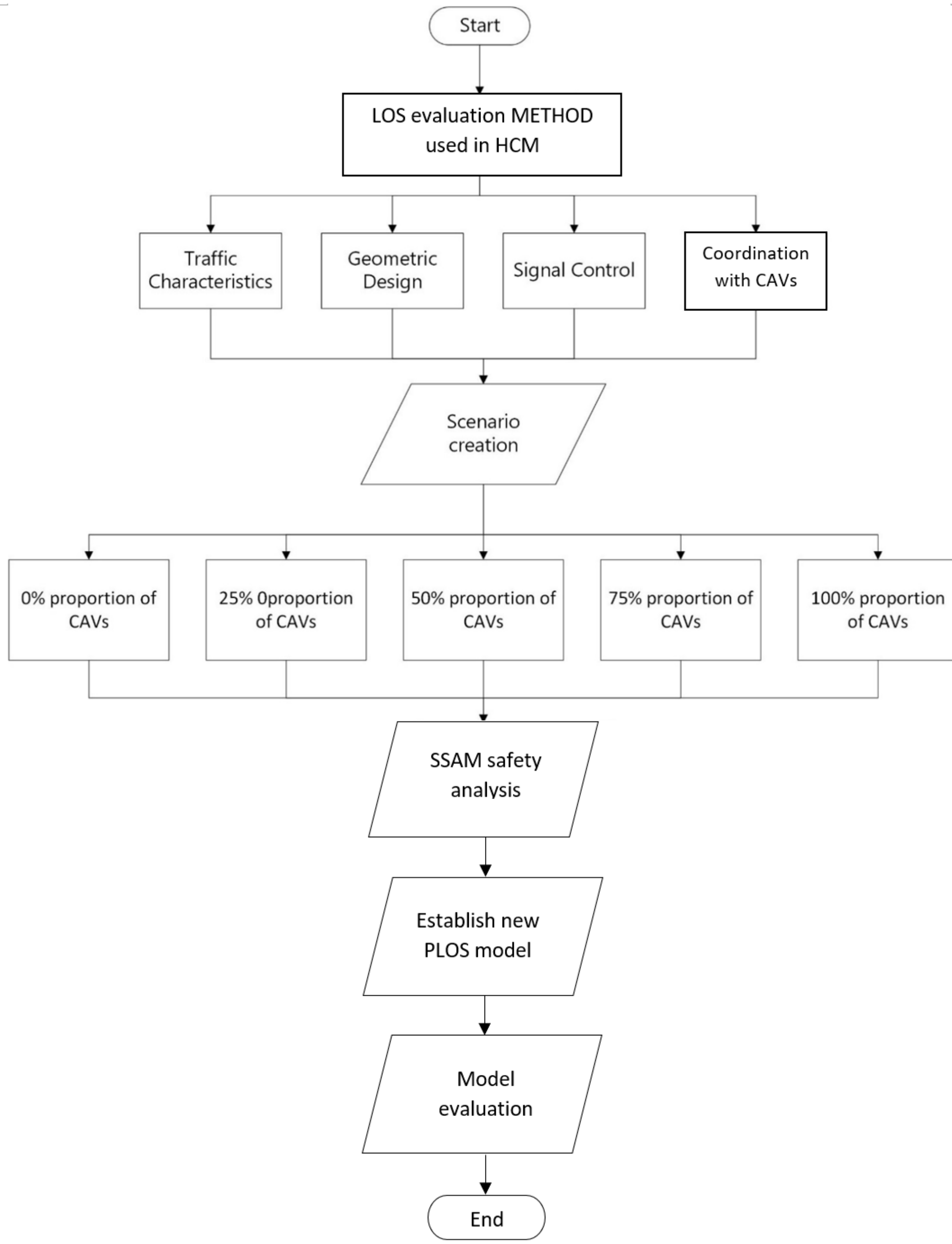


Figure 1 The general flow chart of the methodology

1.6 Organization of the Thesis

This thesis includes seven chapters.

Chapter one is the introduction to the research for explaining the motivation and the problem that would be solved chapter 1, also includes the scope and objectives which contain what outcomes and results this thesis will obtain.

Chapter two describes the comprehensive definition of CAVs and a brief overview about the most up to date international progress of CAVs.

Chapter three presents the issues related to CAVs. Seven aspects are explained in this chapter: the obstacles on the technical development; safety hazards about CAVs; regulation and policy situation in different countries; economical changes caused by CAVs; privacy and cyber-security issues; people's acceptance about CAVs and the liability and insurance problems.

Chapter four describes the methodology related to this thesis: the non-motorized traffic LOS evaluation system in different concentrations and the coordination algorithm of CAVs in urban areas.

Chapter five presents the guidelines from Highway Capacity Manual (HCM) regarding pedestrians and bicyclists LOS evaluation methods in urban intersections.

Chapter six describes the simulation process via VISSIM and the establishment of the pedestrians LOS evaluation model in urban areas. Also include is the calibration and validation of the model. During the model developmental process, the SSAM software is selected as an important tool for analyzing the safety of each scenario.

Chapter seven summarizes the entire work effort and results obtained in the thesis.

Chapter 2

MOST UP TO DATE ADVANCES RELATED TO CAVS

From the past few decades, the concept of CAVs gradually has turned from imagination to reality due to several technical breakthroughs: computers, artificial intelligence, and robotic control to name a few. Also, CAVs have attracted worldwide attention among academia, the automobile industry, and governments. There is no uniform expression on the definition of CAVs. In the first part of this chapter, a throughout definition of CAVs from different sources it presented. The second part, concentrates on the most up to date international progress on CAVs. The last part of this chapter describes the performance and characteristics of CAVS in different roadway environments.

2.1 What Are CAVs?

Before discussing the CAVs, the concept of Automated Driving System (ADS) and Advanced Driver Assistant System (ADAS) need to be understood. In the ADS system, it has more than a warning function. It also has a property on planning and controlling the driving assistance system to autonomous driving ADAS uses a variety of sensors installed in the vehicles to receive information in its immediate surroundings: collecting data, identifying static or dynamic objects, detecting and tracking static vehicles, and combining information to the navigation map data. After calculation and analysis from ADAS, drivers can receive alerts in advance when in an emergency. On this account, ADAS increases the driving comfort and safety of the car effectively. For the latest ADAS technology, the system could actively intervene, for example, activating the automatic braking system.

The automation grades of CAVs are divided into six levels: level 0 to level5. Table 2 shows the definition of these six levels (Sandt & Owens, 2017). The ADAS system refers to the function of the Level 0 to Level 2, and the ADS system refers to the function of the Level 3 to Level 5.

Table 2 The automated level of CAVs.

Level 0	No automation
Level 1	Automated systems can sometimes assist the human in some parts of the driving task
Level 2	Partially automated systems can conduct some driving tasks while human monitors and performs other driving tasks
Level 3	Conditionally automated systems can conduct some driving tasks in some conditions, but the human driver must be ready to take back control
Level 4	Highly automated can conduct all driving tasks in some conditions without human control
Level 5	Fully automated systems can perform all driving tasks, under all conditions in which human could drive

Also, some terminologies related to CAVs need to be describe.

- DDT: the operation required to control the vehicle in road traffic, except for the navigation route planning operation.

- MRC: current driving mission cannot continue when the vehicle enters a state that reduces the risk of collision.
- DDT fallback: when the system cannot continue to complete DDT due to fault and scene changes, and then causes the system occupant to take over DDT, may enter MRC.
- ODD: environment, geography, time, traffic, road and other conditions defined when designing a function for autonomous driving.
- OEDR: detection and response of targets and events.

All ADS system can be divided into three segments: perception, decision making, and execution. The perception segment is composed of various types of sensors. Each sensor has its areas of expertise and inherent shortcomings. For example, the camera can classify the target well and determine the lateral position of the target but cannot accurately measure the distance and speed of the target. Moreover, it is susceptible to severe weather: haze and heavy rain. The characteristics of the millimeter wave radar are just the opposite. Thus, many driving automation systems combine the information obtained by different types of sensors to improve the perceiving performance of the system.

The decision-making process depends on the control unit which is equivalent to a computer. This unit selects the optimal operation through various possible actions after receiving the information obtained by the sensor. And then it sends an instruction to the execution system.

The execution system is responsible for controlling the vehicle for acceleration, deceleration, and steering. The acceleration data is sent by the control unit to the engine controller. Some systems may use the motor controller to send a torque request or acceleration request. The deceleration behavior takes place when the control unit sends a deceleration request to the Electronic Stability Program (ESP) or an electronic brake system. For steering commands, the EPS system sends a steering torque or steering angle request to the control unit.

2.1.1 Connected vehicles

The vision of connected vehicles indicates that the vehicle will provide the driver with useful information to help the driver make decisions. It should be noted that the vehicle itself does not make any decisions but communicates with the outside world to obtain valuable information. Formerly, this technology represented. communication between vehicles. Now it usually extends to the Internet of Vehicles. The Internet of Vehicles enables real-time networking between vehicles and roads, vehicles and vehicles, vehicles and people, and vehicles and the environment. It is a network system for active, intelligent monitoring, scheduling, and management of all the components of the system. The Internet of Vehicles collects the information from the sensing device (sensing layer) mounted on the vehicle and realizes the interconnection of drivers, the pedestrians, the car networking platform, and the urban network through the network sharing (network layer). Thereby achieving intelligent, safe driving, enjoying technologies and living services (application layer).

For sensing layer, vehicles on the road exchange information with each other through short-range wireless communication and this communication is called Vehicle to Vehicle communication (V2V). Vehicles could also connect to the basic communication units directly located on the roadside. Common roadside units have base stations and hotspots on both sides of the road or at intersections. And these static communication nodes are often deployed in the infrastructures: street lights, traffic signs, and traffic lights to name a few.

The Internet of Vehicles is the foundation for smart city. In the last few decades, United States has shifted the strategy of intelligent transportation to vehicle coordination technologies and began research on integrated transportation coordination methods, vehicle safety issues, V2V technologies, and vehicle sensing devices. The main projects are the Intelligent Vehicle Program (IVI), Vehicle-Infrastructure Integration Project (VII), Commercial Vehicle Safety Program.

The program of Vehicle Infrastructure Integration VII (Vehicle Infrastructure Integration) is dedicated to the use of wireless communication technology to make driving vehicles more closely connected to the surroundings. Through this program to improve the safety of the transportation system. The main participants of the program Include the US Department of Transportation, the California Department of Transportation, Daimler, Ford and General Motors for testing the communication capabilities of cars and roadside base stations

In the VII system, the OnBoard Unit (OBU) uploads the information collected by various sensors placed on the vehicle (such as the speed of the vehicle, position information, and so forth) to the Roadside Unit (RSU). At the same time, it also accepts real-time status information of surrounding vehicles transmitted by the roadside unit and various types of traffic service information (traffic status information and road environment information). The vehicle unit and the roadside unit are connected by Dedicated Short Range Communications (DSRC).

Facing infrastructure operators and car manufacturers when promoting VII systems, The Department of Transportation promoted the development of the

IntelliDrive project by establishing a single uniform standard. In the IntelliDrive project, in order to promote mobile communication technologies, WiMAX, a satellite company, established an open communication platform to provide seamless communication services for vehicles. IntelliDrive's services focus on driving safety and providing action strategies for mixed traffic and supplying dynamic, continuous service for drivers. That means the IntelliDrive project connects travelers, management centers, and vehicles with a broad range of wireless mobile communications and a fixed backbone cable network to complete information interaction.

Wingcast system launched by Ford and Qualcomm, connect the vehicles to form a car portal. The vehicles in the system are equipped with a voice operating system capable of assisting safe driving. Two hundred voice commands can operate, and the detailed process of executing the relevant commands is displayed on the screen in real time. The driver understands the condition of the vehicle through multiple cameras installed in the vehicle. Besides, the “Traffic View" subsystem in the vehicles can automatically alarm and request rescue when in an emergency.

2.1.2 Autonomous vehicles

The autonomous vehicles utilize an onboard sensor to sense the state of the vehicle itself and the surrounding environment and controls the speed and steering of the vehicle by automatically manipulating from actuator. The decision making is based on the path, vehicle position, and obstacle information obtained by the perception devices. It is a comprehensive intelligent system integrating navigation, environmental awareness, control and decision-making, and interaction.

The autonomous vehicles currently under research and development usually have their own independent human-computer interaction models, different sensing devices and algorithms. There is no unified interactive platform in existing today. Autonomous vehicles today are still in a relatively closed system and do not have a connection to the Internet of Vehicles.

2.1.3 Connected and Autonomous Vehicles

The Internet of Vehicles is the base that supports infrastructures for the development of CAVs and smart cities. It is also a necessary prerequisite for intelligent transportation. The whole process consists of vehicle position, speed and route information, driver information, road congestion, accident information, and various multimedia applications. It contains the essential information elements, realms and implements networked interactivity control through big data and cloud computing. Autonomous driving, in turn, promotes the continuous improvement and maturity of the Internet of Vehicles technologies. It can be said that the two promote each other and develop interactively and to form a true CAVs environment.

2.2 International Progress

At the beginning of the 1970s, research institutions and companies in the United States began studying connected and autonomous vehicles technologies. The core processing method about CAVs was adopted gradually: the computer receives the sensor information and distributes it to the control unit for processing for vehicle control. This method completed by the 4,585 kilometers road test, starting in Pittsburgh, reaching the end of San Diego and crossing the continental United States. The test included highways, complicated urban roads, unstructured ordinary roads, and harsh weather conditions such as various weather conditions. For the sensing devices, based on the Navlab series developed by Carnegie Mellon University, the sensors include differential GPS, laser radars, cameras, and inertial navigation systems.

Many companies spend much time on designing more powerful sensors and writing more intelligent decision algorithms. At present, semi-automatic driving system is installed in Daimler's Mercedes-Benz S-Class and E-Class sedan; the self-driving trucks of the same company has already begun testing on the highway in 2015. Also, this company plans to make autopilot trucks officially on the road in 2020. The automated level of new Audi A8 is in Level 3, which is also the highest level of automated driving that can be achieved in all the vehicles that could have mass production. However, Waymo, Uber, and Baidu engage in research with Level 4 autonomous driving technology directly. The perception segment they mainly used is Laser-based, supplemented by vision, plus sensors and high-precision electronic maps with redundant functions on the vehicles. Laser radar, which provides exceptionally high precision and robust sensing information, makes it possible for CAVs to handle extreme conditions. Waymo has already brought the self-service to the public via smartphone. It provides the online CAVs-hailing service in the Metro Phoenix area.

2.3 CAVs in Different Types of Roads

Highways are continuous flow facilities, and urban roads usually consists of intermittent flow facilities. The main difference is if there have import or export conflicts in the continuous flow facility. Therefore, from the algorithm level of autonomous driving, the information input required by the continuous flow facility (highway) theory is more straightforward (only feedback is needed for the same traffic flow, there is no sudden insertion of the opposite/lateral vehicle), The output is more straightforward (only lane-based acceleration/deceleration and lane change are required). In reality, there are more unstable non-motor vehicle traffic in the urban roads, and the unprotected phase of the suburban intersection (the green light is simultaneously released straight and left, and the left-turn driver and the direct-going driver need to compete for the priority.) Such problems will lead to further difficulties in the implementation of autopilot algorithms in urban roads.

2.3.1 CAVs in urban areas

If humans no longer need to spend time driving a vehicle when they pass, what happens to the city is unpredictable. This phenomenon means that cities now need to start thinking about how to integrate autonomous vehicles into their plans. In the future, traffic planners believe that motorways can become narrower. Moreover, there will be more space on the main road for walking and cycling where it used to be parking meter places since people do not need to park vehicles. CAVs may not even have exclusive dedicated space. The shared mobility with the Internet of Vehicles can make CAVs switch to different services at different times of the day.

Many low-level CAVs could support freeway and suburban roads driving, but the automotive technology for urban roads is still limited, especially for the area with difficult traffic conditions. Compared with other roads, urban roads are more complex, with a large number of vehicles and complex types. There are vast differences in speeds between different sections, non-motorized traffic flows, and road intersections. Therefore, the primary challenge of urban environments to driverless cars, is a technical challenge.

On the hardware side, it is whether the relevant sensors can be judged and operated accurately. At present, the most significant technical difficulty is perception.

Tesla’s earlier traffic accident was caused by a problem with the perception system. It uses Mobileye technology, which is more active on the highway and is difficult to apply to cities. Another point is that the cost will be directly related to the sales price of the vehicle. It is said that the laser radar currently used by Google's CAVs are sold for as much as $80,000, so there are still many difficulties to overcome in order to achieve mass production.

In terms of software, the program algorithm can accurately identify various problems encountered in the urban environment and make a correct judgment. Based on ensuring the accuracy of sensor data, driverless cars need to make accurate predictions and judgments on the data. In addition to the essential logic judgment, more is needed in the processing of the emergency situations, in addition to the program needs to have sufficient stability and speed. It also needs to be updated a regular and have an computer algorithm for the way humans think.

Finally, CAVs are closely related to human life in urban environments. The ethical issues that arise when dealing with hazard avoidance still need to be further explored. For example, in the face of animal life and vehicle losses, how to choose to avoid, according to the degree of loss, still need a more in-depth discussion.

2.3.2 CAVs in highways and rural areas

In this environment, the roads have better structural conditions and traffic signs, and it is technically easier to achieve full-automatic driving of the vehicle. At the same time, the driver can be free for a long distance. Such technologies as ACC (Adaptive Cruise System), FCW (Front Collision Warning System), and LDW (Drive Departure Warning System) are relatively mature and widely used in many medium and high-end production vehicles.

2.4 Chapter Summary

This chapter discusses the definition and the latest developments in driverless vehicles.

First, it details the definition of driverless vehicles, the classification of autonomous driving, and the specialized equipment and technology involved. There are many controversies about the definition of connected and autonomous vehicles and car networking. Some scholars believe that connected and autonomous vehicles include the Internet of Vehicles. Some experts believe that the Internet of Vehicles and connected and autonomous vehicles are independent of each other, which means that they can all develop independently. By comparison, the two concepts are distinguished and summarized in this chapter.

Second, this chapter discusses the progress of driverless vehicles worldwide. The level of development varies from country to country, with the United States, China, Europe and Japan taking the lead. These countries encourage the development of connected and autonomous vehicles technology and have measures to promote communication between government and companies. At the same time, the focus of many companies in the world is different. Some companies focus on CAVs which walk in Level 2 and Level 3, and some companies directly study Level 4 and Level 5, such as Audi, Tesla, and Google.

The last part explains that there is a difference between connected and autonomous vehicles running on different class of roads. Because of the single environment, connected and autonomous vehicles in highways usually have lower technical requirements than in urban areas. The platoon is one of the most critical concepts in CAVs. It can significantly expand the advantages of CAVs. At the same time, several difficulties are in the application of CAVs on urban roads, especially in dealing with the relationship between people and vehicles.

Chapter 3

ISSUES RELATED TO CAVS

In the past few decades, CAVs have achieved important breakthroughs in all aspects. At the same time, new issues and problems have emerged. In particular, the occurrence of multiple accidents involving CAVs have caused more thoughtful and objective discussions about the impact of CAVs. This chapter describes the challenges and obstacles faced by CAVs from six aspects: technologies, safety issues, regulation and policy, economy, privacy and cyber-security, and people’s acceptance.

3.1 Technology

CAVs related technologies can be divided into the following three parts: sensor, sensor fusion and localization, motion planning and decision making. Sensor devices help CAVs identify the surroundings of the vehicles, pedestrians, signal lights, and road signs. After delivering the information, vehicles should know whether to move forward or stop. The related technologies are computer vision and machine learning. With the popularity of deep learning technology, the perception process with sensor devices has made significant progress in recent years, and therefore, the accuracy of the identification of other road users and facilities has a subversive improvement. This technology provides a foundation for the safe driving of CAVs. However, currently, sensors still cannot identify small-scale road signs and pedestrians’ movements. The difficulties lie in the identification of the behavior of pedestrians and predictability of their intentions, especially for the gestures.

For the second part of sensor fusion and localization, whether laser, sonar or radar sensors, the signals transmitted have massive noise and uncertainties. How to filter this useless information and carry out the 3D restoration of the objective world are the main problems. The commonly used methods for localization are Particle Filter and Kalman Filter. In the early years, autonomous vehicles mainly used radar or sonar as sensors. Nowadays, a new system named LIDAR became a trend. This system utilizes light for detection and ranging (equipped with laser beams to illuminate at different times and spaces to get information). This system has the advantages of high penetration rates, high-speed perceptions, and high accuracy. However, LIDAR systems respond to a high price. For the mass production of CAVs with LIDAR system, cost is a hindrance.

Motion learning and decision making is the core part of CAVs. This step takes place after the sensor fusion part. The primary goal of this step is making the right judgments and drawing up plans in uncertain and dynamic environments. Several obstacles existed during this part. First, it has enormous computational complexities for motion learning and decision making. The computation space has grown exponentially. Second, many uncertain factors affect conclusions. Moreover, the results of the entire motion planning and the searching are continually changing with information.

In addition, the concept of the Internet of Vehicles related to CAVs also has technology obstacles. Among the Internet of Vehicles, the communication mode of Vehicle to Vehicle(V2V) is flexible and convenient and does not require coordination and control of basic communication facilities. That makes V2V to have good scalability. However, due to the faster moving speed of the vehicle, the distance of the work zone varies significantly with time. As the result, the network connectivity between the vehicles reduced significantly. When dealing with a low traffic density, vehicles will be isolated. On the contrary, a high traffic density will lower the transmission efficiency and accuracy of network data.

The communication mode of Vehicle to Roadside(V2R) requires roadside fixed communication unit for support. That makes the scalability of the network lower. Therefore, this communication mode is preferred in applying in urban traffic environments which need abundant hotspots and the base station signals.

3.2 Safety

According to the technology challenges describing in the last part, all aspects of driverless vehicles require more research and development. Each part of the technical upgrade can greatly improve the safety of the CAVs. At the same time, it will accelerate the process of launching the driverless car into the application. For now, CAVs still need time for improvements. Table 3 elaborates the timeline on the implementation of CAVs technology developments. In these predictions, the maturity of most technologies will be completed by 2020. But some core technologies require more time. In fact, during the testing phase, there have been many driverless car accidents in the world and increased the public concerns about the safety of CAVs.

Table 3 Forecast of Technology Development Timeline.

#	Technology	Mainstream Adoption	Barriers
1	Forward Collision Warning	2015-2020	Reliability
2	Blind Spot Monitoring	2015-2020	Cost
3	Lane Departure Recognition	2015-2020	Infrastructure
4	Traffic Sign Recognition	2015-2025	Cost
5	Left Turn Assist	2015-2025	Cost, Infrastructure
6	Adaptive Headlight	2015-2020	None
7	Adaptive Cruise Control	2015-2020	Cost
8	Cooperative Adaptive Cruise Control	2015-2025	Standard, Cyber-security
9	Automatic Emergency Braking	2015-2025	Cost
10	Lane Keeping	2015-2020	Infrastructure
11	Electric Stability Control	2010-2011	None; mandated by NHTSA since 2011
12	Parental Control	2015-2020	None
13	Traffic Jam Assist	2015-2020	Cost
14	High-Speed Automation	2015-2025	Reliability
15	Automated Assistance in Roadwork and Congestion	2015-2025	Infrastructure, Reliability
16	On-Highway Platooning	2015-2020	Infrastructure, Cost
17	Automated Operation for Military	Unknow	Unknown
18	Driverless Car	2015-2030	Regulation, Liability, Cost, Cyber-security, Infrastructure
19	Emergency Stopping Assistance	2015-2025	Liability
20	Auto-Valet Parking	2015-2025	Infrastructure

Source: (Kockelman, 2017)

Several accidents that occurred in the US and China are listed in Table 4. This table only contains accidents which caused deaths. The cause of these accidents is largely related to the technical and design flaws. The reason for the accident in Florida, is the weakness of the objects recognition system. The accident in Ariana was caused by the detection system.

Table 4 The list of CAVs Fatalities

Data	Country	State	Automation Level	System manufacturer	Vehicle Type	Notes
01/20/2016	China	Hebei	L2	Tesla	Model S	Driver fatality
05/07/2016	USA	Florida	L3	Tesla	Model S	Driver fatality
03/18/2018	USA	Arizona	L4	Uber	Refitted Volvo	Pedestrian fatality
03/23/2018	USA	California	L3	Tesla	Model X	Driver fatality

Source: (Uber Puts First Self-Driving Car Back on the Road Since Death, 2018); (Boudette, 2016); (Green, 2018).

3.3 Regulation and Policy

At present, the United States, Germany, and other governments have already admitted the legal status of CAVs and allowed CAVs test in the existed transportation system by standardizing the road test (Saeed Asadi BagloeeMadjid Tavana, 2016). The innovation of regulation and policy has great significance to the development of CAVs. KPMG (a professional service company) released a report related to CAVs (Index, 2018), which proposed four indicators to measure the maturity of CAVs: policy and legislation; technology and innovation; infrastructure and consumer acceptance. Among them, the Netherlands, Singapore, the United States, Sweden, and the United Kingdom ranked in the top five.

As early as 2013, the US Highway Traffic Safety Administration issued the *Preliminary Opinions on the Autopilot Vehicle Control Policy* and developed standards for automatic driving tests to support the development and promotion of autonomous driving technologies. In September 2016, the US Department of Transportation issued the *Federal Automated Vehicles Policy* to provide a regulatory policy framework for autonomous driving safety deployments to guide effective use of technological change; in September 2017, an upgraded version of autonomous driving was released. The policy *Automated Driving Systems 2.0: A Vision for Safety* is not only regarded by the industry as a rulebook for the development of autonomous vehicles but also represents the federal government's attitude towards autonomous driving. In October 2018, the latest release of *Preparing for the Future of Transportation: Automated Vehicles 3.0* pointed out that the US Department of Transportation will work to eliminate policies and regulations that hinder the development of autonomous vehicles and support the inclusion of autonomous vehicles in the entire transportation system. In September 2017, the US House of Representatives unanimously passed the SELF DRIVE ACT, H.R.3388, which provided important support for the successful development, R&D, testing and security deployment of autonomous vehicles in the United States.

At the state level, some state governments in the United States also have their own policy bills that allow autopilot cars to be tested and launched. Nevada took the lead in launching autonomous vehicle legislation in 2011 to address road test problems with self-driving cars on the state highway. In September 2012, California introduced a more liberal auto-driving vehicle regulation, establishing a legislative concept of "promoting and safeguarding the safety of driverless vehicles" and striving to clear the way for the development of autonomous driving technology. Subsequently, more than a dozen states such as Florida, the District of Columbia, and Michigan issued dozens of traffic policies and regulations for self-driving cars to promote the development of the US autopilot technology and artificial intelligence industry.

In June 2017, Germany enacted the world's first law on automatic driving, *the Road Traffic Law Amendment*, which allows autonomous driving system to replace human-driven vehicles under certain conditions, and greatly promoting the CAVs in German road-testing progress. Moreover, Germany open the part of the A9 highway for automated driving technology testing. In addition, Germany also announced the world's first ethical standards for autonomous driving, providing a strong support for autonomous driving system design and ethics research.

Japan set CAVs as an important development strategy. In the *2017 Official ITS Conception and Route Map*, Japan has defined the promotion schedule for autonomous driving technology: automatic driving at the level 3 on the expressway, and automatic driving for trucks at the level 2, automatic driving at the level 4 in a specific area will be applied around 2020. CAVs at the level 4 of the highway will be accomplished by 2025.

3.4 Economy

CAVs will also change the existing economic market. Driverless car technology has changed the way that traditional car manufacturers used to be. It strengthens the communication between manufacturers and governments: whether governments need to give sufficient authority to car manufacturers for producing the peripheral products (infrastructures) of the CAVs. Governments will also face budgetary issues: in the development of driverless cars, whether large amounts of funds are needed to build roads that are exclusively for driverless cars. Not only that, most of the current studies related to CAVs are using clean energy, which has also impacted the fuel markets.

3.4.1 Fuel economy

Studies have proposed a standardized method for testing the fuel economy effects of CAVs when following another vehicle (Congress, 2016). The method consists of two steps and is applicable when CAVs travel after conventional vehicles. First, the driverless vehicle's control unit is abstracted for simulation for one lane with one leading vehicle and has a good vison; and then run following a vehicle obeying the EPA's FTP (tests defined by the US Environmental Protection Agency) and HWFET(highway driving) driving cycles. Fuel economy was estimated using the Virginia Tech Comprehensive Fuel Consumption model. Results showed considerable variation in fuel economy, showing CAVs decreasing the fuel consumption.

Manufacturers may not design for increased fuel economy. They may design a system with maximize speed and acceleration. This had worse fuel economy than the EPA fuel cycle. Also, the more advanced connected intelligence can improve performance, by increasing the amount of prediction time for sensing the surroundings.

Driverless cars will consume more energy than they currently have, because the convenience it brings will encourage us to increase the frequency of travel (Kockelman, 2017). However, electric and autonomous vehicles such as the Tesla Model S have shown that the demand for gasoline itself in driverless cars may be reduced. At present, a large number of infrastructures (such as charging stations) for CAVs are still in the early stages of development. This will give fuel companies a buffer to adapt to the new energy ecosystem.

3.4.2 Government

According to an estimation by Intel Corporation and Strategy Analytics, the economic effects of autonomous vehicles will total $7 trillion in 2050 (Table 5). This result is based on an assumption that in 2025, all vehicles will be CAVs and automated level will be in level 5.

Table 5 Summary of economics changes

Industry	Size of Industry ($ billions)	Dollar change in Industry ($ billions)	Percent change in industry (%)
Insurance	180	-108	-60%
Freight Transportation	604	+100	+17%
Land Development	931	+45	+5%
Automotive	570	+42	+7%
Personal Transportation	86	-27	-31%
Electronics & Software	203	+26	+13%
Auto Repair	58	-15	-26%
Digital Media	42	+14	+33%
Oil & Gas	284	+14	+5%
Medical	1067	-12	-1%
Construction & Infrastructure	169	-8	-4%
Legal Prefession	10	-5	-50%

Source (Tomita, 2017)

Governments need to be alert to employment issues. The arrival of CAVs will have a potentially profound impact on labor demand. In 2015, 15.5 million people in the United States were engaged in work that would be affected by autonomous vehicles (with varying degrees of influence), which accounted for one-ninth of American workers (BEA, 2015). These positions are divided into "motor vehicle operators" and "other on-the-job drivers." Among them, transporting passengers and drivers for cargo are the main job of the first category. They are most affected by autonomous vehicles and may be unemployed because of new technologies. In 2015, there were as many as 3.8 million workers in the United States who worked in such jobs. They were generally older men with lower levels of education and salary. The position of "Motor Vehicle Operator" is mainly concentrated in the transportation and warehousing industries. “Other on-the-job drivers” typically use motor vehicles to provide services or commute to the workplace, including emergency personnel, construction industry practitioners, maintenance installers, and personal home care assistants. Data for 2015 show that 11.7 million Americans are working in this category, mainly in the construction, administration, waste management, healthcare, and government industries. This portion of the workforce will also be affected by autonomous vehicles, but the impact is positive, and their productivity and working environment will be significantly improved.

3.5 Privacy and Cyber-Security

The most significant information security risk for CAVs is the threat of hackers and third-party control of cars. In the absence of autonomous driving, hackers can threaten the lives of passengers by only attacking steering, braking, and other driving-related controllers. Also, by attacking any sensor devices such as radars and cameras they can mislead the CAVs to make wrong decisions.

For the appearance of the Internet of Vehicles, cloud computing, cloud decision-making, and V2X (vehicle to everything) exposes more vulnerable parts of the vehicles to the Internet. 4G, WIFI, and other standard Internet communication methods applied to cars provide an approach which makes it easier for hackers to break into the vehicles' computer system.

There are no laws of CAVs security and privacy issues in the state legislature. However, from the federal level, related laws have been proposed in July 2015 (Autonomous Vehicles and Cybersecurity Concerns, 2019). This legislation allow inter-departmental investigation of the automotive network security problem. This is also one of the contents used by the National Highway Traffic System Administration (NHTSA) for formulating and publishing the relevant regulations. NHTSA requires the permission of visiting and distracting data form control unit of the car and equipment, and the conducting report and preventing measures for any attempts to intercepting data or controlling the behavior of the vehicle. In November of the same year, the Security and Privacy of Your Car Study Act of 2015 and the Autonomous Vehicle Privacy Protection Act of 2015 were proposed.

3.6 People's Acceptance

Driverless car technology has developed in different countries and has different policies for driverless cars. People's impressions of CAVs are primarily influenced by social media.

Most respondents had a positive impression of the technology, with the most positive responses coming from Australia (61.9%), followed by the U.S. (56.3%) and the U.K. (52.2%). Only a modest percentage of respondents had any negative impressions, with the highest incidence in the U.S. (16.4%), followed by the U.K. (13.7%) and Australia (11.3%). Approximately 30% of respondents in each country had a neutral opinion of CAVs. This survey was produced in 2014 that before the CAVs accidents happened.

3.7 Liability and Insurance

The automatic driving system does not have a legal theory that thoroughly elaborated the responsibility for motor vehicle traffic accidents, and it is in urgent need of new methods to clarify the liability by legislation. One of the notable trends is, as the role of the drivers shifted in the automated driving system, the legal position for liability of traffic accidents converted from drivers to manufacturers, software designers, and other subjects involving in design and production. In cases where humans and autonomous driving systems share control of the steering wheel, human drivers are responsible for the failure, and the automobile manufacturers or system providers are responsible for the product defect of the system behavior. For this purpose, it is necessary to record the relevant driving activity data to provide a basis for attribution of the responsibilities. Therefore, all countries required the automatic driving system install a “black box” to record data, to identify the cause of the accidents and clarify the responsibilities of all parties (Marchant, 2012). Also, considering the challenges posed by machine learning and deep learning to the CAVs, EU and other countries developed specialized rules, such as compulsory insurance, and compensation funds.

At present, most countries stipulate a compulsory insurance system for road tests for self-driving cars. For example, the California State Government requires the test license issued by the regulatory authorities. One of the prerequisites is that the test company that purchases insurance should not be less than $5 million or have a corresponding amount of guarantee. Also, other countries such as the United Kingdom, the Netherlands, Sweden, and China have proposed similar insurance policy systems (Saeed Asadi BagloeeMadjid Tavana, 2016).

The commercialization of CAVs must have risk-controlled technology, which requires the participation of insurance companies. From the perspective of risk control expertise, insurance companies are willing to underwrite and make CAVs officially commercialized. For example, the commercialization of autonomous logistics vehicles, the risk of the logistics industry is computable. The insurance company can calculate the failure rate and the compensation. The insurance company gives clear parameters that indicate that the risk of CAVs commercialization is under control.

CAVs' key technologies improve the safety performance of the car and can better realize the cooperation between human and machine. Traditional driving protection measures, such as airbags, are passively increasing the safety of the car. On the contrary, the technologies used in CAVs improved performance of safety actively. However, the current autonomous technologies cannot be applied immediately, reducing the occurrence of a security incident does not mean that there are no risk of road accidents. As long as there is a risk of safety, it still needs to be supported by the insurance industry.

Due to the significant reductions in the traffic accident rate, the risk premium for auto insurance will reduce. This will make the basis of the costs of insurance industry unstable. Considering the high proportion of auto insurance in the property insurance business, it may cause a huge threat to some property insurance companies. Various vehicles, including human-driven vehicles and CAVs in different levels, operate on the road at the same time. This phenomenon will bring different risk identification, different responsibility subjects, different attribution logic, and different response capabilities, which will form a new test for the auto insurance business.

3.8 Chapter Summary

This chapter describes the challenges and controversies facing the current CAVs. First, the technical challenges faced by CAVs are described: technical barriers of identification, decision making, and the popularity of the Internet of Vehicles. Due to imperfections in technology, there have been many accidents involving driverless vehicles around the world, and even caused casualties.

In the face of public concerns, various countries are actively adjusting laws and regulations to enable CAVs to adapt to the existing transportation system as soon as possible. In particular, regarding the division of responsibilities of driverless vehicles, it is necessary to set as many detailed regulations as possible to reduce the ethical problems faced by driverless vehicles.

CAVs can also have a profound impact on the economy. In the future, due to the advantages of the following mode of the CAVs, the traffic system has higher efficiency, which will affect the fuel economy to a certain extent. It is also controversial for whether the car manufacturers have the right to produce and operate the infrastructure. For the government, the full market entry of driverless vehicles requires a large budget. Also, the government needs to pay attention to the employment problems caused by driverless cars.

Another issue that has been widely discussed is the issue of cybersecurity. The development of emerging technologies has made the connected and autonomous vehicles system more fully exposed to the network. Breakthroughs in driverless vehicle technology are often accompanied by more fragile cybersecurity.

This chapter discussed the acceptance of CAVs in different countries. People generally have different attitudes towards the different automated level of CAVs. The last part introduces the liability and insurance issues related to CAVs.

Chapter 4

METHODOLOGY

This chapter summarizes two methodologies related to this thesis: the evaluation approaches of Pedestrian's Level Of Service (PLOS) and Bicyclists Level Of Service (BLOS) in urban areas and the algorithms related to coordination of CAVs at urban intersections.

4.1 Methods of PLOS and BLOS Evaluation

Pedestrians and bicyclists as non-motorized travel modes play a crucial role in the increasingly urbanized world and their operating environments need to be improved. Level of Service (LOS) is a quantitative assessment approach for measuring the performance of traffic modes and facilities (HCM 2010: highway capacity manual). Engineers and planners have defined multiple methods to determine non-motorized traffic LOS starting from the evaluation of comfort and security. The methodologies took into consideration many operating environments of pedestrians and bicyclists and introduced various factors which lead to much debate about the importance of each factor.

For the evaluation of PLOS, the earlier approaches depend on the LOS of vehicles (Nowar Raad, 2018). The later researches paid more attention to pedestrians about safety, comfort, and flexibility. These three aspects are expressed by the footpath width, the shoulder width if it exists, the existence of separation zone to other road users, the speed and volume of vehicles, and other specific facilities including on-street parking. Models developed by Fruin (Fruin, 1971), are based on the footpath capacity and the volume of pedestrians, which ignored other geometric designs (Landis B. V., 2001). In recent years, studies have established approaches based on new technologies to test the comfort, safety, and convenience of pedestrians (Miller, 2000). Most of them have focused on assessing the environment of "feeling" at the micro level for pedestrians; however, they ignored the factors on signal control and geometric design. After that, researchers used a combination of Fruin methods and other qualitative characteristics of streets. Among all the factors involved in these two aspects, a reasonable proportion is allocated, to each factor, and a more comprehensive evaluation model is established. It also provides a guide for the evaluation of other facilities (Landis B. V., 2001). Finally, the methods in Highway Capacity Manual (HCM) proposed a complete system and the model is calibrated through numerous field experiments. The evaluation models in this system are not uniform: they are divided into many types for different scenarios: segments and intersections to name a few. The methods can be summarized as follows: set the crosswalk and the number of lanes pedestrians need to cross as essential factors of analysis and follow by the speeds and volumes of vehicles. The methods used in HCM are described in detail in Chapter five.

Several methods were developed by researchers and engineers to present the bicycle suitability, such as the Bicycle Safety Index Rating (SBIR), Road Condition Index, bicycle suitability rating, BLOS, bicycle suitability score, and bicycle compatibility index (BCI) (Asadi-Shekari, 2013). Among them, BLOS is one of the most accurate methods. Most engineers use BLOS to design and plan cycling. The HCM proposed a detailed evaluation methodology which is being recognized by many researchers. It is a function of the width of the street that bicyclists need to cross, the bicyclists' operating space (wide outside lane, shoulder, or bike lane) and followed by the traffic volumes of bicycles and vehicles.

4.2 Methods of CAVs Intersection Coordination

The movements of CAVs at intersections are mainly divided into two situations: whether there is a signal system or not. The signal controllers for conventional vehicles aim to prioritize traffic movements and coordinate with neighboring controllers to avoid conflicting flows. Signal timing of intersections can be optimized to reduce the congestion delay. However, for CAVs, there exist more opportunities to minimize control delay through communication systems. Using advanced technologies of the Internet of Vehicles, it helps traffic system avoid unnecessary stops and provide safe vehicle trajectories.

Recent advancements in communication technologies and the Internet of Vehicles provide optimal solutions to pass through the intersection with or without signal controls. All connected vehicles can connect to the network, and the network allows facilities and vehicles to deliver messages about signal control information, the location, speed, and acceleration of vehicles and the pedestrian movements. Figure 5 shows the cooperative traffic control in the intersections.

Some papers based on the dynamic adaptive control system, proposed the intelligent traffic light management technology and mechanism for real-time traffic flow (Pandit, 2013). Although the intelligent traffic light transportation system can improve the flexibility of the dispatching of traditional traffic control and increase the traffic management capability at the intersection, they still have difficulties in meeting the requirements of the Internet of Vehicles system. K.Zhang et al. proposed a scheduling method based on vehicle status priority in traffic scenarios without traffic controls (Zhang, 2015). This method can effectively prevent the collision of vehicles in the intersection by assigning a successive level of specific vehicles and avoiding the contradiction between the different vehicle travel trajectories. Some studies established the principle of buffer allocation scheduling algorithm to provide a guide to vehicles to safely pass the intersections (Lin, 2017). Figure 2 shows the intersection channelization (Lin, 2017).

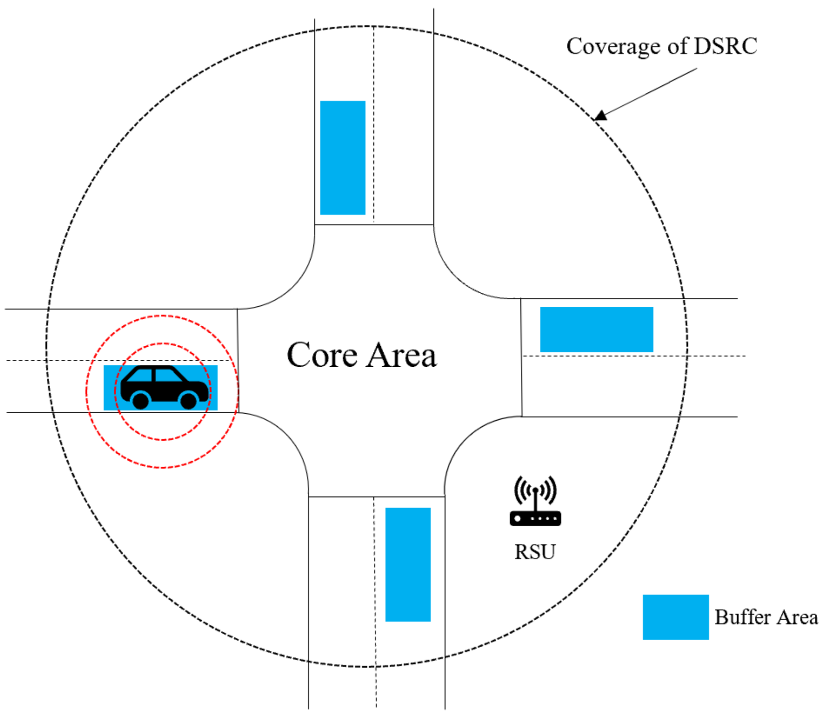


Figure 2 Intersection channelization

There are still some technical problems: First, the improved intelligent traffic light dispatching system cannot fully utilize the advantages of the Internet of Vehicles to improve traffic management capabilities. Second, most of the new scheduling algorithms in the non-signalized scenarios only have a single function and are limited to specific vehicle driving rules. Finally, in the process of adjusting the driving behavior of the vehicles, it enormously depends on the reliability of the communication and the stability of the driverless technology.

4.3 Chapter Summary

This chapter summarizes the methods of non-motorized traffic evaluation and CAVs coordination at the intersection. Research shows that a comprehensive evaluation of the LOS may have different approaches. For pedestrians, some methods are based on the size of the pedestrian's space to determine the LOS. Some research proposed that infrastructure is one of the essential factors for assessment. Recently, researchers prefer to use the combination of these two methods, after complex mathematical operations and regression analysis to build models to determine the PLOS. For bicyclists, it is usually more related to the roadway geometric design and the volume of bicycles.

For the CAVs coordination algorithm at intersections, it is more inclined to a technical problem about the Internet of Vehicles. Most of the theories involved optimization problems, but their optimization goals are different. Due to the characteristics of the Internet of Vehicles, these algorithms allow all types of vehicles with communication devices.

Chapter 5

HCM GUIDELINES

As the methods presented in HCM, to evaluate PLOS or BLOS on the intersections is to assign a grade from A to F. This grade is meant to correspond to the perceived level of service that roadways provide to pedestrians or bicyclists, respectively (Herbie Huff, Transportation, (U.S.), & Center, 2014). This chapter expounds the model for pedestrians and bicyclists separately and emphasizes two aspects: the number of the variables used during the calculation process, what they are and the contribution of each variable and the most critical variables. Table 6 shows the conversion between numerical scores and LOS grades and parameter "I" means the score of LOS.

Table 6 Conversion between numerical scores and LOS grades

Grade	Numerical Range
A	$I \leq 2.00$
B	$2.00 < I \leq 2.75$
C	$2.75 < I \leq 3.50$
D	$3.50 < I \leq 4.25$
E	$4.25 < I \leq 5.00$
F	$I > 5.00$

5.1 Pedestrian Level of Service

HCM did complex and comprehensive experiments to collect data. The model is suitable for urban intersections with signal systems. And the parameters in this model contain the traffic characteristics, geometric design, and signal control. Traffic characteristics include the width of crossing, the volume of motor vehicles, the speed of the vehicles, and the pedestrian delay time. For geometric factors, it includes the number of the lanes crossed and the effective walk time. Several parameters about signal control, such as cycle time, are also considered in this model. Here are the model developed by HCM.

$$I_{p,int} = 0.5997 + F_w + F_v + F_s + F_{delay}$$

$$F_w = 0.681(N_d)^{0.514}$$

$$F_v = 0.00569\left(\frac{v_{rtor} + v_{lt,perm}}{4}\right) - N_{rtci,d}(0.0027n_{15,mj} - 0.1946)$$

$$F_s = 0.00013n_{15,mj}S_{85,mj}$$

$$F_{delay} = 0.0401\ln(d_{p,d})$$

F_w: Width of the crossing

F_v: the volume of motor vehicles crossing the crosswalk

F_s: speed of the motor vehicles on the street being crossed

F_{delay}: pedestrians delay

N_d: number of lanes crossed

$v_{rtor} + v_{lt,perm}$: the sum of turning volumes coincident with walk phase, per 15 minutes

$n_{15,mj}$: the sum of all volumes that cross the crosswalk, per hour

$$n_{15,mj} = \frac{0.25}{N_d} \sum_{i \in m_d} v_i$$

$S_{85,mj}$: 85[th] percentile speed on the major street

$N_{rtci,d}$: number of right-turn channelizing islands on the crosswalk

$d_{p,d}$: average number of seconds of delay at the crosswalk

$$d_{p,d} = \frac{(C - g_{walk,mi})2}{2C}$$

C: cycle length

$g_{walk,mi}$: effective walk time when walking on the minor street

A sensitivity analysis provides a graphic representation of the relative importance of four terms in PLOS, the relative importance of these terms is relatively consistent. $\boldsymbol{F_w}$, is the major contributor to PLOS. The constant term contributes significantly. $\boldsymbol{F_s}$ is the next-most-important term, followed by $\boldsymbol{F_v}$ and $\boldsymbol{F_{delay}}$ in that order. Figure 3 shows the contribution of component factors of PLOS.

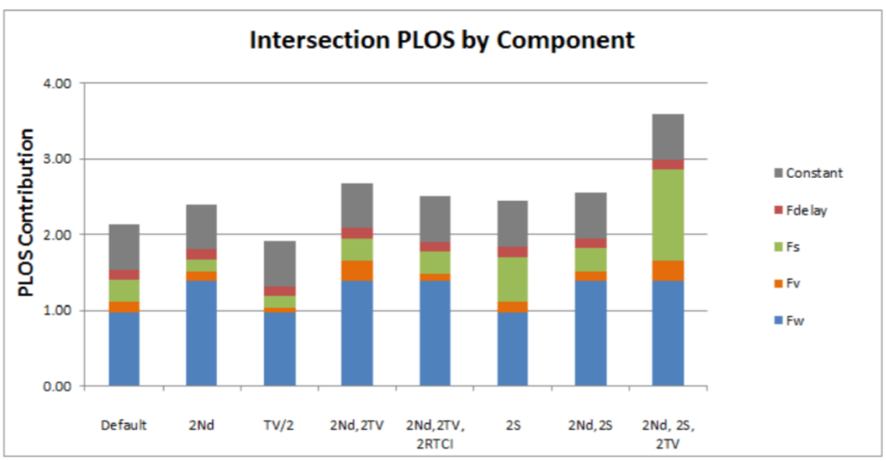


Figure 3 Contribution of Component Factors to Intersection PLOS in a Variety of Cases (Herbie Huff, Transportation, (U.S.), & Center, 2014)

The possible contributing factors were summarized as follows (Table 7):

Table 7 The Contribution Factors for PLOS

The contribution factors	
Traffic Characteristics	• The demand flow rate of motorized vehicles • Right-turn-on-red flow rate • The permitted left-turn flow rate • Midsegment 85th percentile speed • pedestrian flow rate
Geometric Design	• Street width • Number of lanes • Number of right-turn islands • The width of outside through lanes • Total walkway width • Crosswalk width • Crosswalk length
Signal Control	• Exists when the manual driving car in operation • Walk • Pedestrian clear • Rest in walk • Cycle length • Yellow change • Red clearance • Duration of phase • Pedestrian signal head presence
Coordinate with CAVs	• The right of way (yield to pedestrians when CAV≤ 25%) • Whether wearing a V2B sensor (smart pedestrian) • Time of waiting for CAVs or platoons passing • CAVs speed when coordinated

5.2 Bicyclists Level of Service

Here are the model developed by HCM.

$$I_{b,int} = 4.1324 + F_w + F_v$$

$$F_w = 0.0153W_{cd} - 0.2144W_t$$

$$F_v = 0.0066\left(\frac{v_{lt} + v_{th} + v_{rt}}{4N_{th}}\right)$$

$$W_t = W_{ol} + W_{bl} + I_{pk}W_{os}^*$$

$\boldsymbol{F_w}$: Width of the crossing

$\boldsymbol{F_v}$: the volume of motor vehicles crossing the crosswalk

W_{cd}: curb-to-curb width of the cross street

v_{lt}: left-turn demand flow rate (flow on the subject street)

v_{th}: through dethe mand flow rate

v_{rt}: right-turn demand flow rate

N_{th}: number of through lanes (shared or exclusive)

W_{ol}: width of the outside through lane

W_{bl}: width of bicthe ycle lane

I_{pk}: if on-street parking occupancy>0, define I_{pk}=0, otherwise I_{pk}=1

W_{os}: width of pavthe ed outside shoulder

W_{os}^{*}: prethe sence of curbs: if curb is present and W_{os}≥1.5, W_{os}^{*}= $W_{os} - 1.5$, otherwise W_{os}^{*}= W_{os}

A sensitivity analysis provides a graphic representation of the relative importance of three terms in BLOS. The constant is the major contributor to BLOS. $\boldsymbol{F_w}$ is the next-most-important term, followed by $\boldsymbol{F_v}$ in that order. Figure 4 shows contribution of component factors to BLOS.

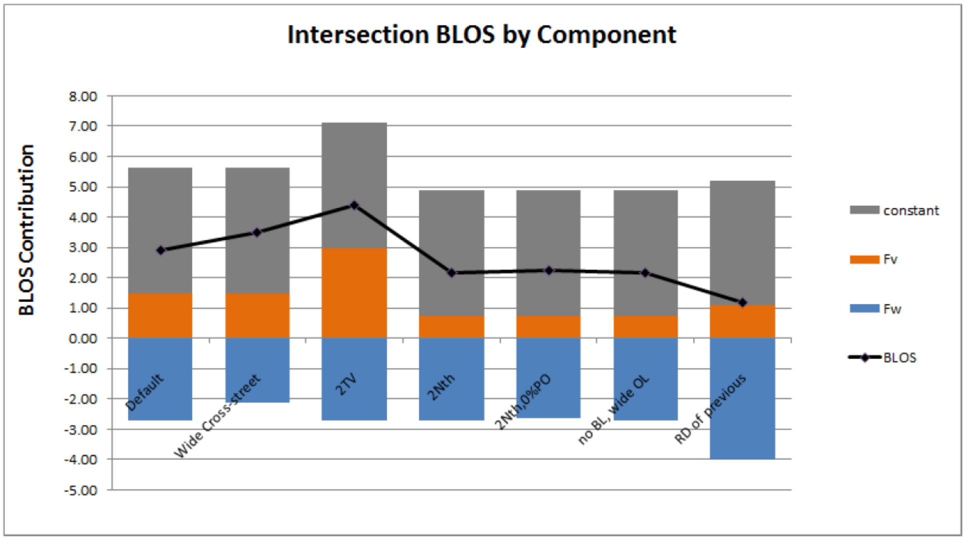


Figure 4 Contribution of component factors and the constant to intersection BLOS in a variety of cases(Herbie Huff, Transportation, (U.S.), & Center, 2014).

The possible contributing factors were summarized as follows (Table 8):

Table 8 The Contribution Factors for BLOS

The contribution factors	
Traffic Characteristics	• The demand flow rate of motorized vehicles • Right-turn-on-red flow rate • The permitted left-turn flow rate • Midsegment 85th percentile speed • Bicycle flow rate
Geometric Design	• Street width • Number of lanes • Number of right-turn islands • The width of outside through lanes • The width of bicycle lanes • The width of the paved outside shoulder
Signal Control	• Exists when manual driving cars in operation • Cycle length • Yellow change • Red clearance • Duration of phase serving bicycles
Coordinate with CAVs	• Right of way • Whether wearing a V2B sensor (smart bicycles) • The time when waiting for CAVs or platoons passing • CAVs speed when coordinated

Chapter 6

SIMULATION VIA VISSIM

In this chapter, five scenarios were established via VISSIM. There are some basic setting about roadway network, vehicle, and pedestrian routing decisions. For CAVs, some special parameters need to adjust to reflect the property of connected environment and autonomous driving behavior. After calibration and validation of the simulation model, extract simulation results and use SSAM to evaluate the safety performance of each scenario. In the last part, seven parameters were selected for building the regression model.

6.1 VISSIM and Assumptions

Traffic simulation refers to the use of computer simulation techniques to study traffic behavior. It is a technique for tracking and describing traffic movements over time and space. Through the simulation study of the traffic system, the distribution law of traffic flow state and its relationship with traffic control variables can be obtained. Traffic simulation software does not require the participation of real systems and is cost-effective. It can repeatedly provide the same road traffic conditions so that scenarios with different design can be compared directly. Besides, through traffic simulation software, it is possible to find which variables in the traffic flow have significant effects and how they interact with each other.

This thesis studies the impact of CAVs on pedestrians. Traffic simulation software is one of the best choices since CAVs have not been widely used in the real traffic system. This thesis chooses to use VISSIM. VISSIM is a microscopic traffic flow simulation system developed by PTV of Germany. The system is a discrete, random, microscopic simulation software in tenths of a second. The longitudinal movement of the vehicle is based on the "Psychology-Physiology Car Model" by Professor Wiedemann of the University of Karlsruhe, Germany. Lateral motion (lane change) uses a rule-based algorithm. The simulation of different driver behaviors is divided into conservative and aggressive.

Compared to other simulation software, like PARAMICS, TSIS, and HCS, VISSIM can simulate multiple signals, which is especially suitable for the simulation of urban transportation systems. The latest version already has a complete model for CAVs which is described in the next part in this chapter. Furthermore, the LOS evaluation models in VISSIM are based on HCM which meet the requirements of establishing the new evaluation models with CAVs. This thesis established five traffic system simulation scenarios corresponding to different proportions of CAVs.

6.2 Scenarios Building

In this study, VISSIM version 11 (student version) was used to develop the simulation model at urban intersections. There are five steps to develop a network model. The process for building the network can be summarized as follows:

- Draw links and connectors for roadways and crosswalks.
- Enter vehicle volumes at network endpoints and pedestrian volumes on crosswalks; enter routing decision points and associated routes; establish the reduced speed area.
- Enter signal heads in the network (Create signal controls with signal groups) or define conflict areas for scenarios with non-signalized intersections.

- Enter priority rules for permissive lefts, right turns on red, pedestrian crosswalks.
- Create evaluation nodes and run the simulation.

6.2.1 Basic Setting

In an urban area, the crash risks will increase when lane width is too full or too narrow (Karim, 2015). For a broader lane in an urban area, especially at the intersection, pedestrians need more time to cross the lanes, also increase the time and space of exposure. Therefore, in this simulation model, all the lane widths are set at 3.5 meters. For pedestrian crosswalks, the width is 3 meters, and for walkways, the width is set as 2 meters. Figure 5 shows the base network for all scenarios.

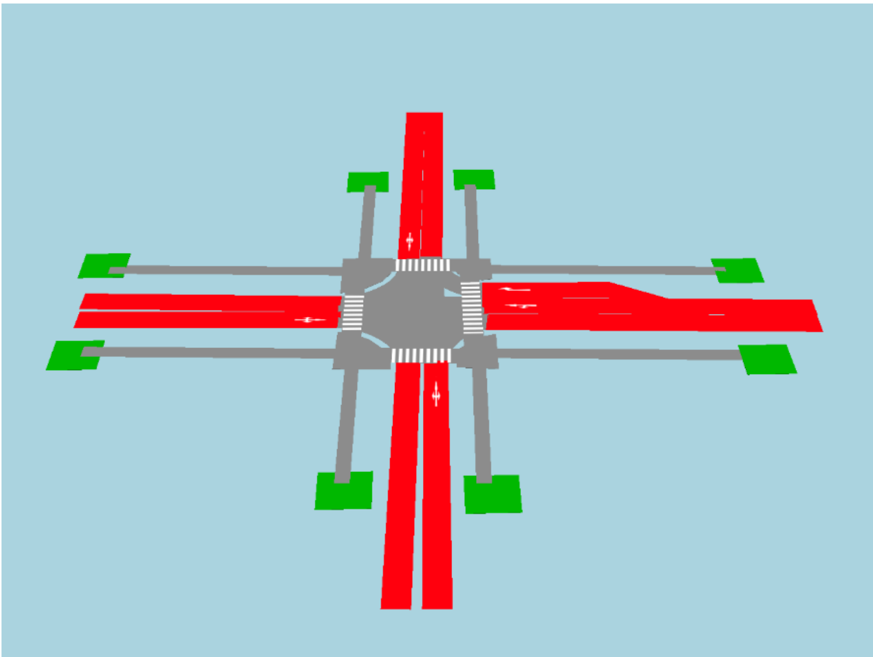


Figure 5 The Network Model

The vehicle traffic composition includes three types: human-driven vehicles, CAVs and freight vehicles (HGV). Figure 6 shows the routing decisions and traffic split proportions. Driving behavior is one of the essential attributes, and It could make the road network in the model more realistic. In this research, two driving behavior were selected: Urban (motorized) and AV (autonomous vehicles)-all-knowing. The AV all-knowing driving behavior model was developed by VISSIM and CoExist (a European project, aims at preparing the transition phase during which automated and conventional vehicles will co-exist on cities' roads). For Urban (motorized) behaviors, the number of interactive objects is set as 4. The standstill distance is 0.5 meters. And the car following model type is Wiedemann 74 (a car following model developed by Wiedemann in 1974). The basic concept of this model is that a driver with a high-speed vehicle will decelerate when reaches driver's self-feeling limit before reaching a low-speed vehicle. Since driver cannot judge the speed of the low-speed car accurately, driver's speed will drop slower than that low-speed car until the driver starts to accelerate slightly after reaching another self-feeling limit. The result of this logic is an iterative process of acceleration and deceleration.

The AV-all-knowing behavior type is fully described in the next section. For human-driven vehicles and HGV vehicle type, they follow the Urban (motorized) driving behavior; for CAVs, they follow the AV-all-knowing driving behavior. The traffic volume of each direction is a variable for developing the new models. But the split proportions are fixed.

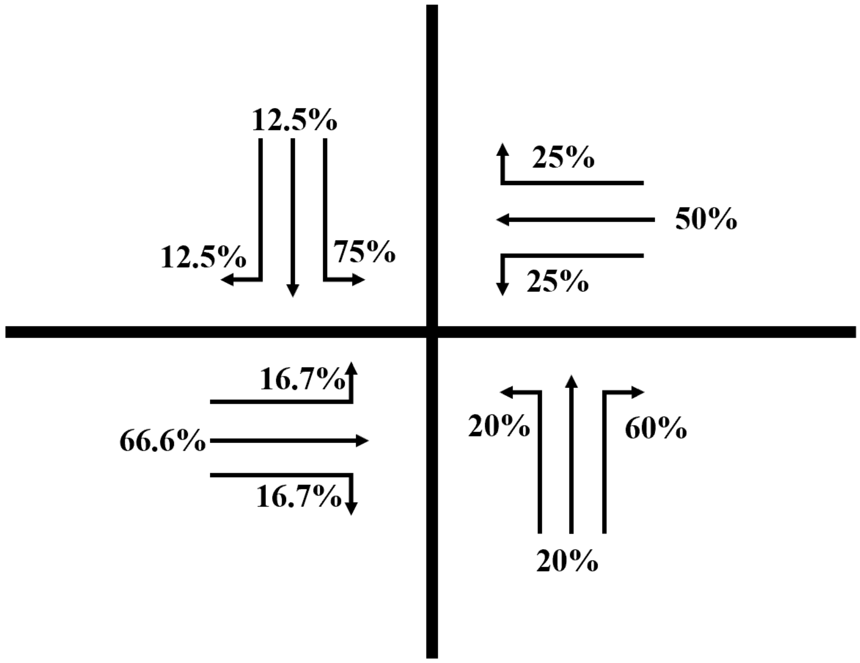


Figure 6 Vehicle route decision and traffic split proportions

About the pedestrian flows, Figure 7 shows the pedestrian area base and route decisions. The green squares represent pedestrian base and each base could add in different pedestrian volume. Red lines indicate the pedestrian routes. And for each intersection of red lines, pedestrians are programmed to go in any direction. Same as vehicles, the volume of pedestrians in each base are variables and the route decisions are fixed which are same size ratio.

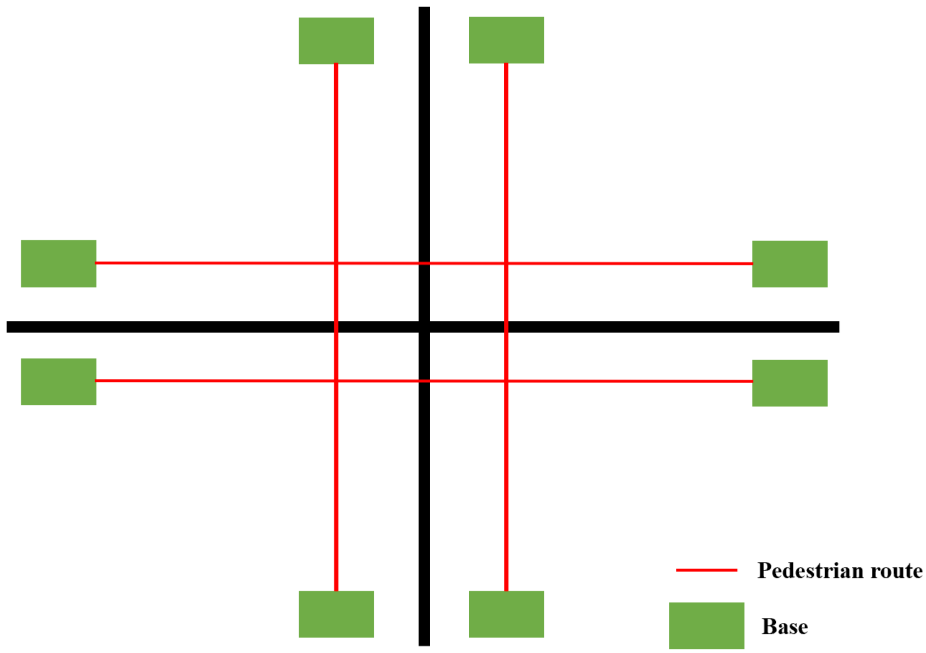


Figure 7 Pedestrian base and route split

The signal control data for vehicles is displayed in Figure 8. It is a four-phase fixed system. The cycle time is 120 seconds. Every phase has 24 seconds green time, 5 seconds yellow time and 1 second all-red time. That means the inter-stage time is 5 seconds. One stage for each approach is 4 seconds. For the right turn movement from east to north, the green time is 52 seconds.

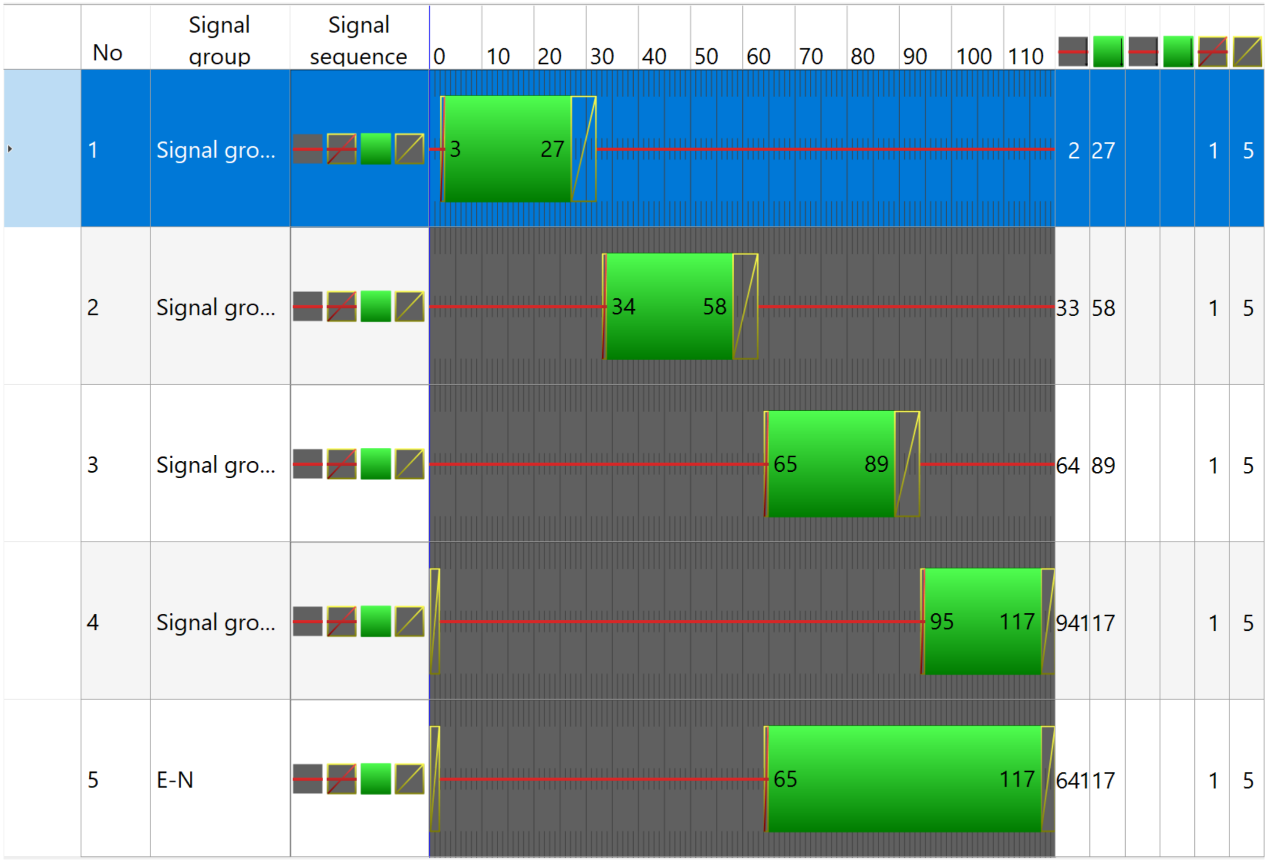


Figure 8 Signal control data for vehicles

Table 9 summarizes the basic setting of five scenarios.

Table 9 Basic setting for five scenarios

Scenarios	Vehicle composition	Lane width (meters)	Crosswalk width (meters)	Vehicle volume	Pedestrian volume	Priority Rules	Driving behavior	Speed of Urban driving behavior	Speed of AV-all-knowing behavior
1	100% CAVs	3.5	3	Variables	Variables	Pedestrian yield to vehicles;Right turn has priority	AV-all-knowing (CoExist)	Variables	Variables
2	75% CAVs,23% of Human-Driven cars,2% HGV	3.5	3	Variables	Variables	Pedestrian yield to vehicles;Right turn has priority	AV-all-knowing (CoExist); Urban (motorized)	Variables	Variables
3-a	50% CAVs,48% of Human-Driven cars,2% HGV	3.5	3	Variables	Variables	Pedestrian yield to vehicles;Right turn has priority	AV-all-knowing (CoExist); Urban (motorized)	Variables	Variables
3-b	50% CAVs,48% of Human-Driven cars,2% HGV	3.5	3	Variables	Variables	Signal system; vehicles yield to a pedestrian	AV-all-knowing (CoExist); Urban (motorized)	Variables	Variables
4	0% CAVs,98% Human Driven cars,2% HGV	3.5	3	Variables	Variables	Signal system; vehicles yield to pedestrian; Right turn has priority	Urban (motorized)	Variables	Variables
5	25% CAVs,48% of Human-Driven cars,2% HGV	3.5	3	Variables	Variables	Signal system; vehicles yield to a pedestrian; Right turn has priority	AV-all-knowing (CoExist); Urban (motorized)	Variables	Variables

6.2.2 CAVs setting in VISSIM

To define CAVs behavior in VISSIM, the logic is the same as normal vehicles. There are five aspects included in driving control logic: conflict resolution, signal control, following behavior, lane change behavior and lateral behavior (Peter Sukennik, 2018).

When building a simulation model, there are mainly three conflicts.

i) Normal conflict: In road traffic management and control process, normal conflicts cannot be eliminated. The simulation software needs to minimize the frequency of its occurrence. For example, if the right turn is not controlled by the traffic light, the occurrence of conflicts between the right turn vehicles and the straight bicycles or pedestrians in the other direction is inevitable. The existence of such conflicts reduces the traffic capacity of vehicles and pedestrians. The simulation model must reflect this situation.

ii) Potential conflict: A potential conflict is a collision that is caused by the isolation of signal light. This conflict type will happen when an accident occurs or when the vehicles violate regulations. For example, when the intersection is blocked, the vehicles will not evacuate in time, however, the conflicting phase vehicle has entered the intersection. Therefore, when creating a simulation model, this kind of conflict zone should set a priority rule.

iii) Simulation conflict: The simulation conflict refers to the abnormal vehicle conflict caused by the vehicle changing lanes when the simulation system processes the vehicle position relationship. VISSIM defines the maximum time that the vehicle has to wait the lane change and stops in the emergency position. When reached maximum time limit, the vehicle will disappear from the road network. The time and location of the vehicle disappearing is recorded in the VISSIM error file. The simulation conflicts should be reduced as much as possible so that the model can truly reflect the actual situation of the intersection.

The following behavior includes the following distance and standstill distance. Lane change behavior includes braking distance and standstill distance. For the gap acceptance at intersections (conflict areas only) rear gap equals the time to break to full stop in front of the conflict zone.

There are three predefined driving behaviors for different types of autonomous vehicles developed by CoExist project: AV Cautions, AV normal and AV all-knowing. AV Cautious enforces absolute braking distance, AV Normal is similar with a human driver but without the stochastic spread. The definition about AV all-knowing, set the absolute breaking distance as the vehicles can stop safety anytime (without a crash), even if the leading vehicle stops instantly. AV all-knowing has the largest interaction vehicles and objects parameters. In this thesis, AV all-knowing is set as the default CAVs type.

There are two definitions to describe the character of a connected environment: number of observed vehicles or objects and the number of interaction vehicles or objects. One characteristic of CAVs assumptions about interaction behavior is that the automated vehicles can see the signal ahead, but only can connect one or two vehicles surrounding itself since the sensors cannot see through the leading vehicles. When the number of objects is smaller than vehicles, the behavior will be standard: the following network objects are modeled as vehicles in VISSIM. The vehicles treat these network objects as a preceding vehicle.

The environment in this simulation process used the Internet of Vehicles communication. It reflects by the distance of headways. The standard driving acceleration behavior cannot use reliable information about the future behavior of the leading vehicle. To allow CAVs keep a small headway even during an acceleration process, a new parameter is used. This value usually defines a percentage that is larger than 100% of the average acceleration and using this value when the leading vehicle is accelerating.

6.2.3 Calibration and Validation of the VISSIM Model

The VISSIM model cannot provide the necessary results until the model is calibrated and validated (Wu, 2017). Multiple calibration parameters offerred by VISSIM can be modified. In this thesis, average standstill distance, additive part of desired safety distance, multiple parts of desired safety distance, the minimum headway and the minimum gap time were selected as the calibration parameters. The number of conflicts was used to calibrate these parameters.

Finally, it was found that changing the calibration parameters did not impact the number of conflicts. Therefore, in this case, the default value of parameters was used. In other words, average standstill distance was 2 meters, additive part of desired safety distance was 3 meters, multiple parts of desired safety distance was 3 meters, the minimum headway gap was 5 meters, and the minimum gap time was 3 seconds. Then, the calibrated models were validated with a new set of field data, including the pedestrian volumes, and the vehicle volumes. Furthermore, the animation of the

VISSIM simulation models was checked for any unusual events. Finally, VISSIM was calibrated and validated.

6.3 Simulation Results.

According to the five scenarios described in the previous chapter, changing three parameters in each scenario (pedestrian volume, the speed of conventional vehicles and the speed of CAVs) was used to find how the PLOS is affected under different road condition in these five scenarios.

The first part is the pedestrians delay time in each scenario (Figure 9 to Figure 14) when they have the same setting of pedestrians, conventional vehicles, and CAVs.

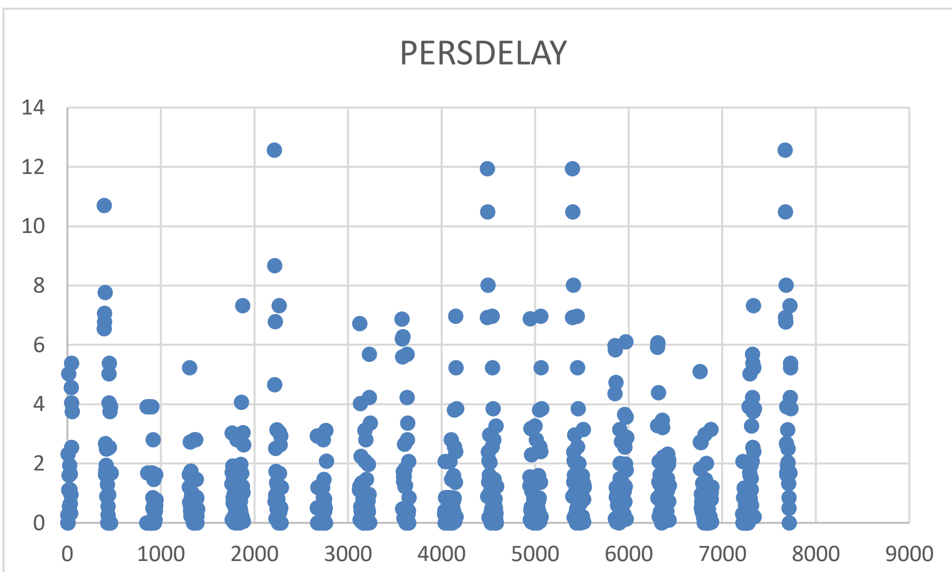


Figure 9 Scenario 1: 100% of CAVs without signal system

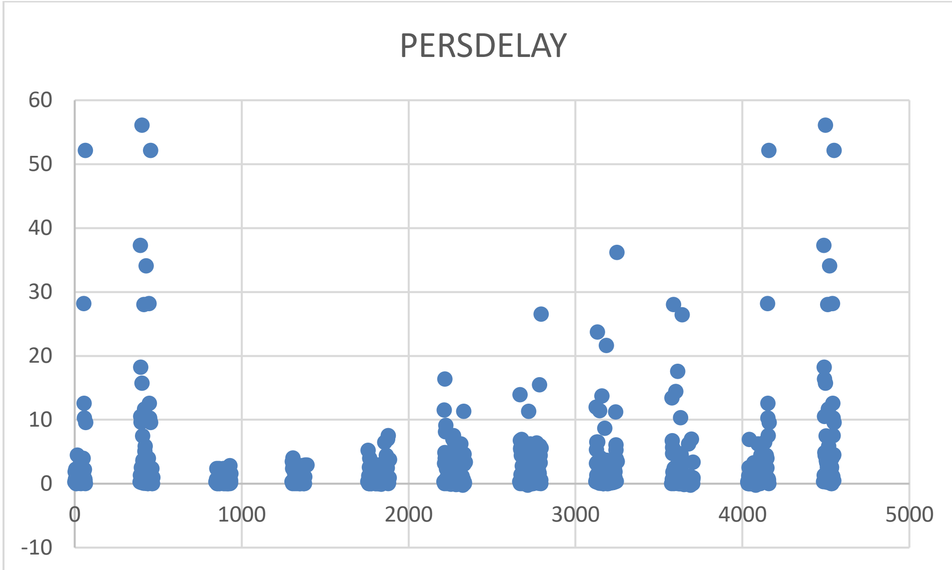


Figure 10 Scenario 2: 75% CAVs without signal system

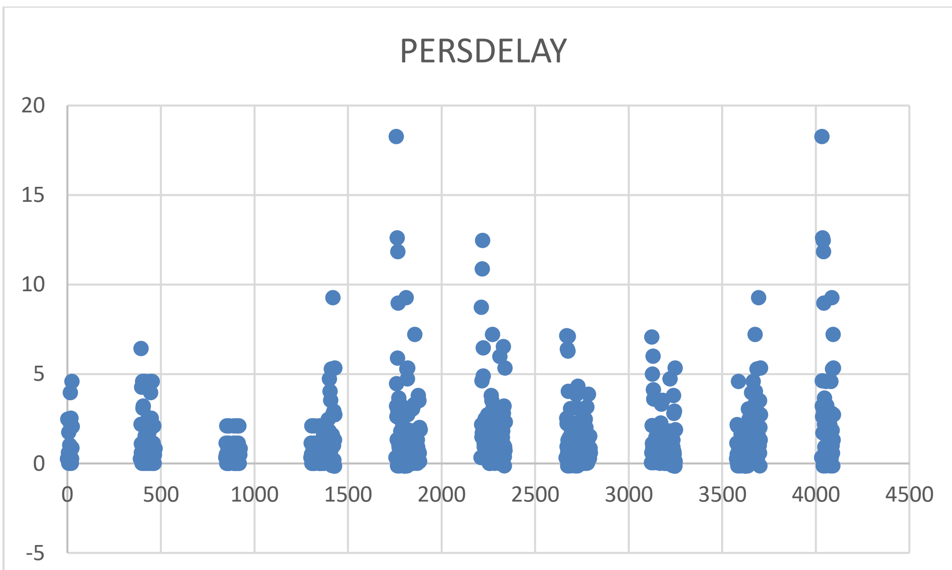


Figure 11 Scenario 3-a 50% CAVs without signal system

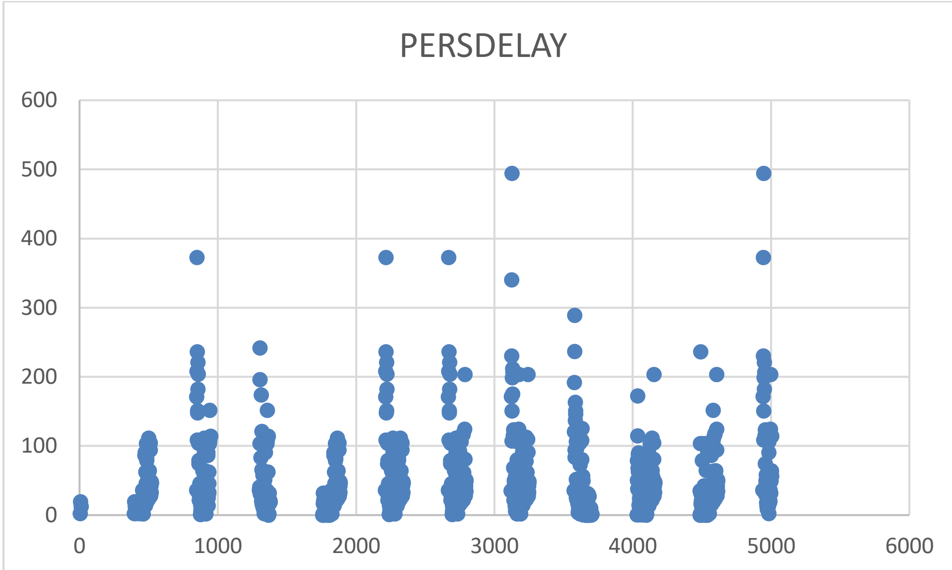


Figure 12 Scenario 3-b 50% CAVs with signal system

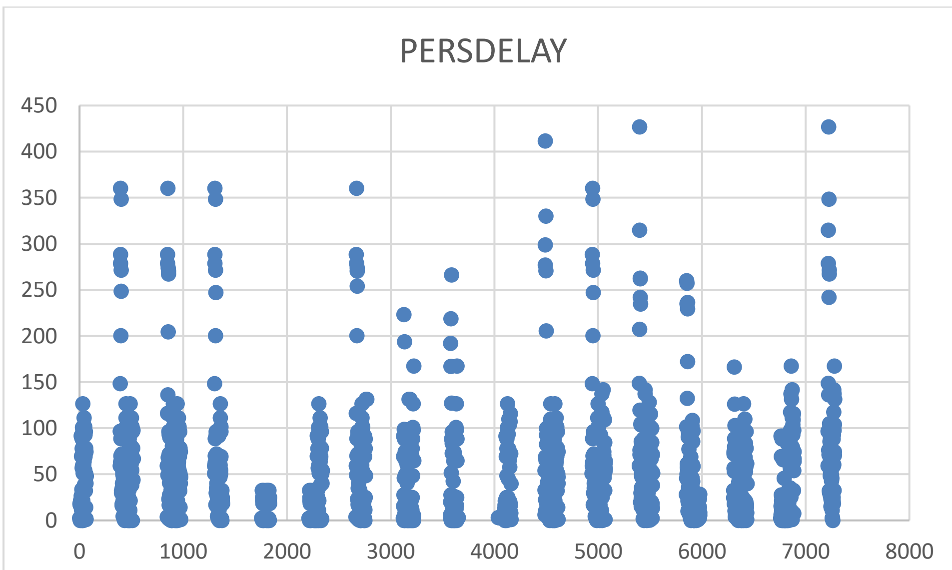


Figure 13 Scenario 4:0% CAVs with the signal system

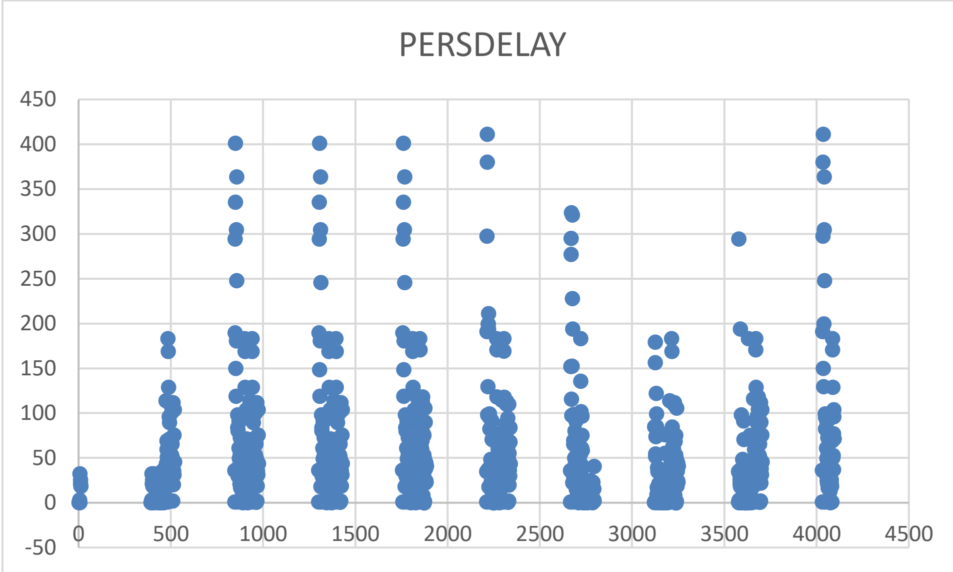


Figure 14 Scenario 5:25% CAVs with the signal system

In Figure 9-14, PERSDELAY means the delay time (in seconds) of per person. And these five scatter plot figures reflect the delay time of pedestrians in five scenarios. With the signal system, the maximum delay time is greater than the scenarios without signal systems which is approximately 600 seconds versus 60 seconds. However, without signal systems, the performance of scenario 2 is not as good as others. With the signal system, scenario 3 has a relatively small delay time.

The next parts (Figure 15 to Figure 20) show the average pedestrian delay time in different movements for different scenarios.

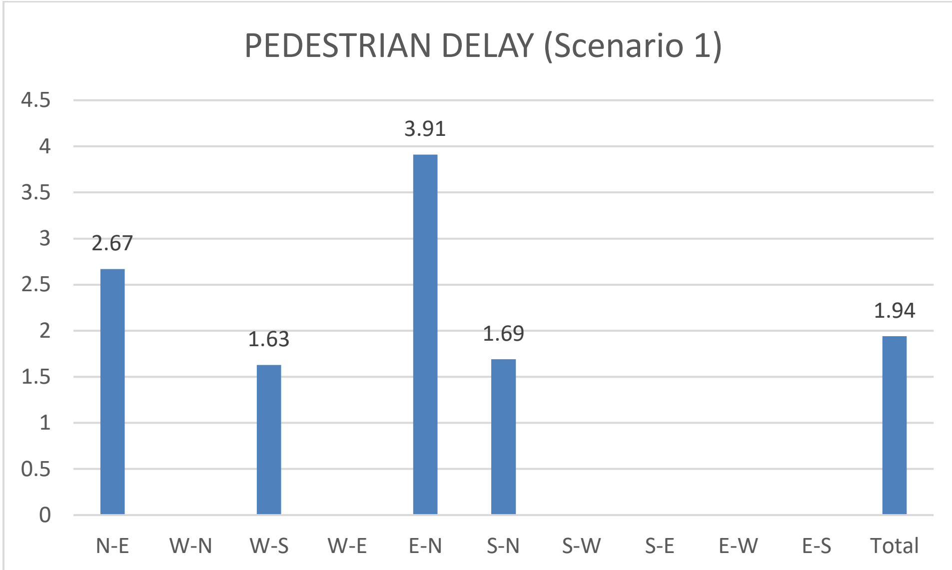


Figure 15 Average delay time from different movements in scenario 1

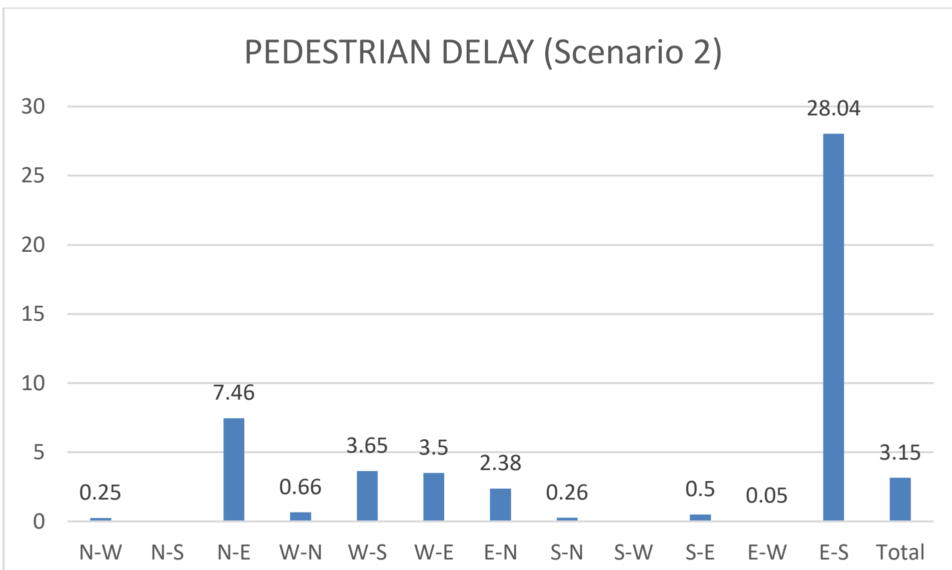


Figure 16 Average delay time from different movements in scenario 2

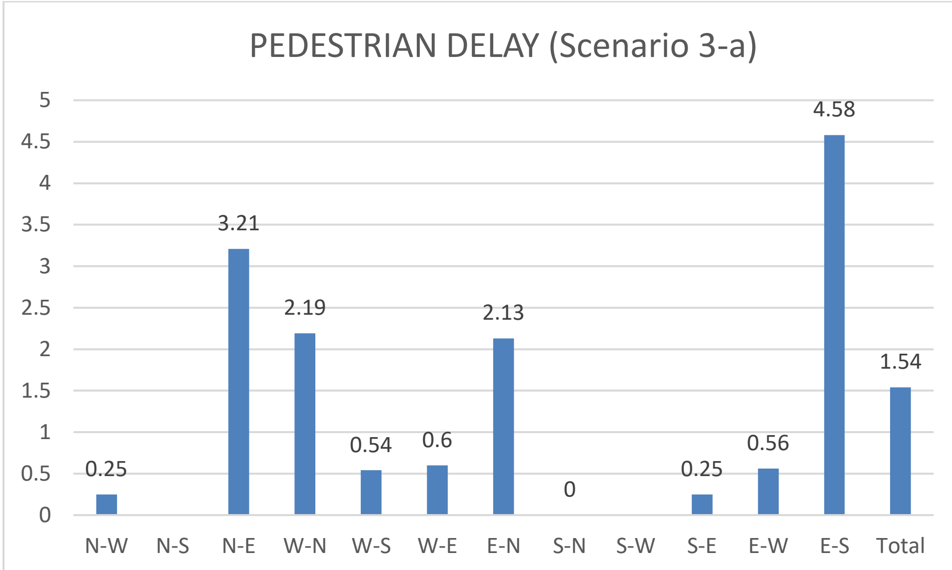


Figure 17 Average delay time from different movements in scenario 3-a

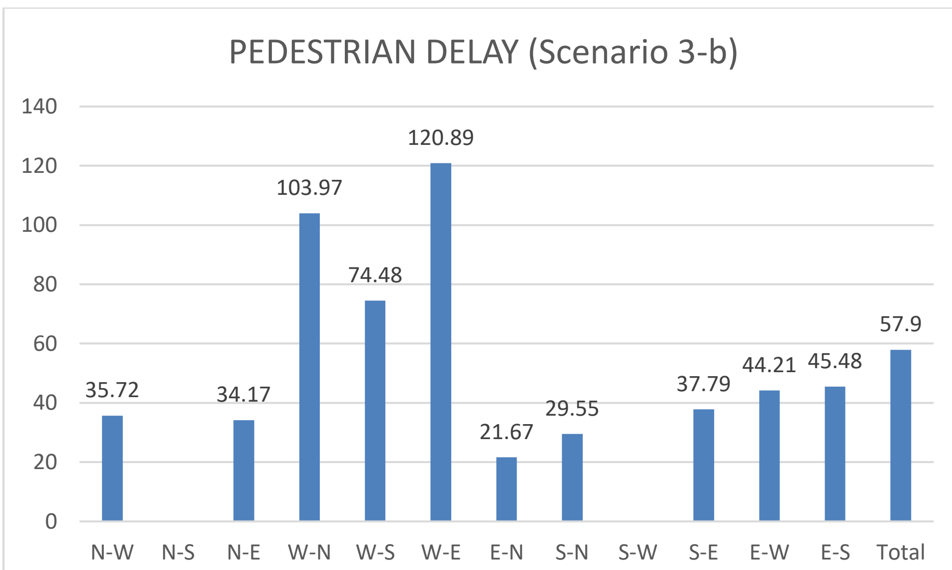


Figure 18 Average delay time from different movements in scenario 3-b

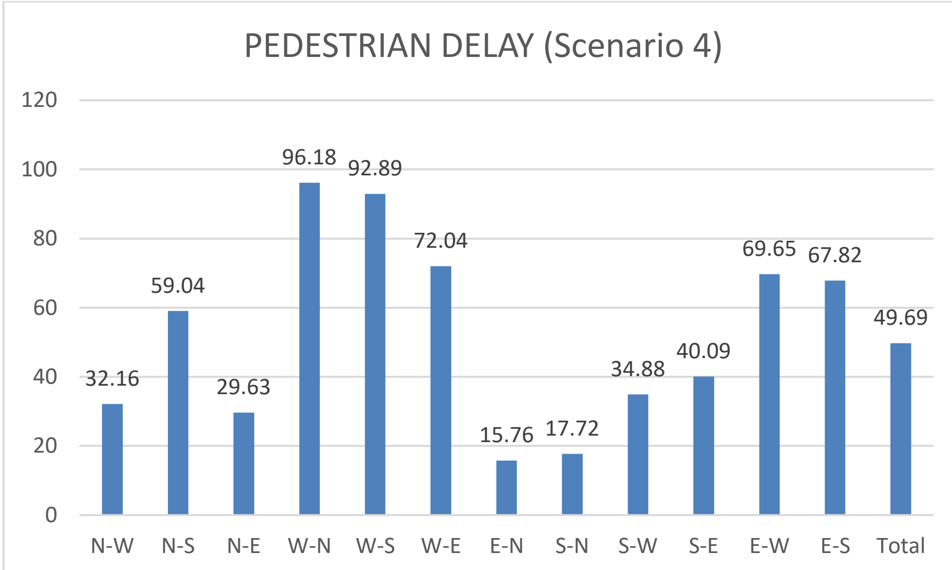


Figure 19 Average delay time from different movements in scenario 4

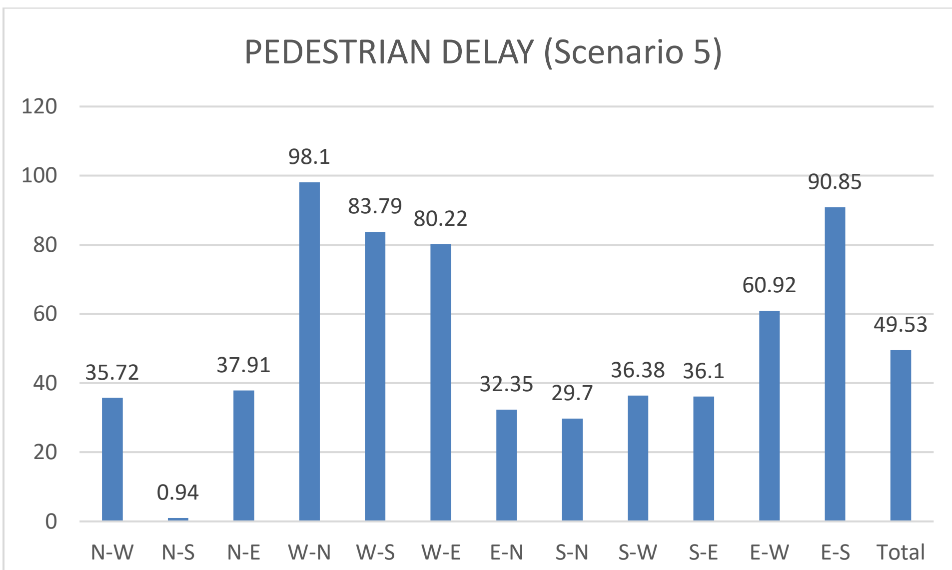


Figure 20 Average delay time from different movements in scenario 5

In Figure 15-20, PEDESTRIAN DELAY means the delay time distribution varies from movements in each scenario. Numerically speaking, the part also reflects that with signal system, the delay time is higher than without signal system. When with signal system, movements from West to other directions have a poor performance than other directions. For scenarios without signal system, the delay time of the movement of East to South is higher.

One crucial premise needs to be mentioned that the results of the two parts described above were obtained from the default values of the parameters (Table 10). Both vehicle and pedestrian volumes are at a small level, especially as an urban intersection. Therefore, the performance of scenarios without signal systems is better than with signal systems. As the volume of CAVs increases, the number of CAVs in a platoon will increase. The possibility for pedestrians to find an acceptable crossing headway distance will decrease. That is to say, in the scenarios without the signal control, the pedestrians' delay time will be higher. This thesis simulated multiple times that include the larger span value of traffic and pedestrian volumes. In this section, one of these cases is enumerated.

Table 10 Default values of each parameter

Simulation Time (second)		3600 simulation seconds
Human-driven vehicle speed (mph)		50
CAVs speed (mph)		50
Signal control system		Figure 14
Lane width (meters)		3.5
Crosswalk width (meters)		3
Walkway width (meters)		2
Pedestrian volume	Base 1	200
	Base 2	300
	Base 3	200
	Base 4	300
	Base 5	200
	Base 6	200
	Base 7	200
	Base 8	200
Vehicle volume	North	200
	South	250
	East	400
	West	300

6.4 Surrogate Safety Assessment Model (SSAM) Analysis

SSAM software can automate conflict analysis by directly processing vehicle trajectory data from VISSIM. It can provide a summary of the total number of conflicts broken down by type of conflict. Also, SSAM could calculate some surrogate safety measures for each event. Five measures were relevant to evaluate traffic safety, which are TTC, PET, MaxS, DeltaS, DR, and MaxD. Each surrogate safety measure is defined as follows:

- TTC (Time to collision): the time distance to a collision of two road users if they keep their directions and velocities. The shorter the TTC, the more dangerous the situation.

- PET (Post-encroachment time): the period from the moment when the first road user is leaving the conflict area until the second road user reaches it.
- MaxS: the maximum speed of either vehicle throughout the conflict measured in meter per second.
- DeltaS is the difference in vehicle speeds observed during the simulation time where the minimum TTC value for this conflict was observed measured in meter per second.
- DR: the initial deceleration of the second vehicle measured in meter per square second.
- MaxD: the maximum deceleration of the second vehicle measured in meter per square second.

SSAM was not explicitly designed for pedestrian conflict analysis, so there is no vehicle or entity type available in the trajectory file format by which to identify pedestrian conflicts. In other words, SSAM cannot estimate the pedestrian-to-vehicle conflicts without simulating the pedestrian as vehicles in VISSIM. Therefore, to identify pedestrian-to-vehicle conflicts from all kinds of conflicts, the CSV file exported by SSAM can be of help. Filter out any conflict where MaxS is smaller than 5 mph (7.3 ft/sec), and this conflict related to pedestrians (which is about the walking pace of pedestrians).

At the time this research was conducted the current version of SSAM only permitted the vehicle to vehicle conflict, yet VISSIM allowed the vehicle to pedestrian interactions. An alternative approach to the one described above was to use VISSIM for simulating the vehicle-pedestrian activities, store the trajectory files, then produce a video of the simulation activities. Playing the video back and manually observing the TTC and PET using the internal clock of the video would produce the needed data.

Two values for surrogate measures of safety were used in SSAM to detect the conflicts, which are maximum TTC and maximum PET. TTC is defined as the time distance to a collision of two road users if they keep their directions and velocities. PET is defined as the period from the moment when the first road user is leaving the conflict area until the second road user reaches it. For example, if the maximum TTC is set as 1.5, then SSAM will only generate the conflict data that contains TTC value less than 1.5. In general, SSAM utilizes a default maximum TTC value of 1.5 seconds and a maximum PET value of 5 seconds to delineate the vehicle-vehicle conflicts. However, the pedestrian-vehicle conflict is different from vehicle-vehicle conflicts. That is why the maximum TTC and PET thresholds need to be established for pedestrian-vehicle conflicts.

Several trials were investigated to get the optimum thresholds for TTC and PET that would define a vehicle-pedestrian conflict. Finally, it was found that when the TTC threshold ranged from 2 to 3 and the PET ranged from 5 to 9, SSAM provided a better estimate of the number of conflicts that matched the field data.

Table 11 shows the results of scenario 1 from SSAM software:

Table 11 The results of conflicts prediction and the confliction type with default value.

Summary Group	Total	crossing	rear end	lane change
All scenarios	100	4	80	16
Scenario 1 (100% CAVs)	13	0	7	6
Scenario 2 (75% CAVs)	6	1	4	1
Scenario 3-a (50% CAVs)	13	3	8	2
Scenario 3-b (50% CAVs with the signal system)	32	0	30	2
Scenario 4 (0% CAVs with the signal system)	14	0	12	2
Scenario 5 (25% CAVs with the signal system)	22	0	19	3

All these three types include vehicle to vehicle collisions and pedestrian to vehicles collisions. From the previous discussion, when MaxS was smaller than 5 mph (7.3 ft/sec), the conflicts would count as pedestrian and vehicles conflicts.

6.5 Regression

Based on the model developed by HCM, this thesis combined the characteristics (delay time and the number of pedestrian and vehicle conflicts) obtained from VISSIM and SSAM, a new linear regression model of PLOS evaluation was established, which contained seven essential attributes as follows.

$$\boldsymbol{Val}(\boldsymbol{LOS}) = \boldsymbol{C} + \boldsymbol{V}_H + \boldsymbol{S}_H + \boldsymbol{V}_{\boldsymbol{CAVs}} + \boldsymbol{S}_{\boldsymbol{CAVs}} + \boldsymbol{T}_{\boldsymbol{delay}} + \boldsymbol{N}_{\boldsymbol{C}}$$

$\boldsymbol{V}_H$: $the\ volume\ of\ human\ driven\ vehicles$

$\boldsymbol{S}_H$: $the\ speed\ of\ human - driven\ vehicles$

$\boldsymbol{V}_{\boldsymbol{CAVs}}$: $the\ volume\ of\ the\ CAVs$

$\boldsymbol{S}_{\boldsymbol{CAVs}}$: $the\ speed\ of\ CAVs$

$\boldsymbol{V}_{\boldsymbol{p}}$: $the\ volume\ of\ pedestrian\ flow$

$\boldsymbol{T_{delay}}$: $pedestrian\ delay\ time$

$\boldsymbol{N_C}$: the conflicts between pedestrians and vehicles

For every scenario, multiple simulations were carried out with different values of the seven parameters. The average delay time and LOS value were extracted from VISSIM. The number of conflicts between pedestrian and vehicles were from SSAM. Each simulation corresponds to different set of these seven parameters plus the value of LOS. Results for are shown in Table 12.

Table 12 Simulation results

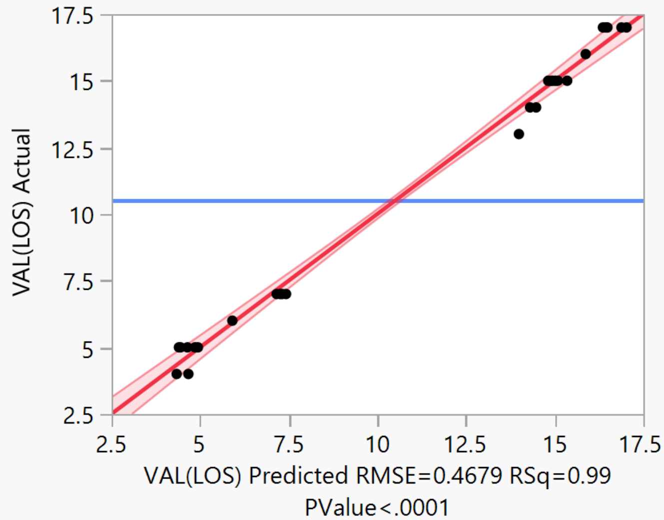
V-H	S-H	V-CAVs	S-CAVs	V-P	T-Delay	N-C	Signal	VAL(LOS)
1000	30	1000	50	1800	149.77	14	1	13
400	40	400	30	1800	154.04	19	1	14
400	40	400	40	2200	157.29	13	1	14
500	30	500	40	1200	160.77	3	1	15
1000	50	1000	30	600	163.15	28	1	15
2000	30	0	0	1800	175.73	16	1	15
800	40	0	0	1800	178.46	14	1	15
800	40	0	0	2200	178.91	19	1	15
1000	30	0	0	1200	181.03	10	1	15
2000	50	0	0	600	182.07	6	1	16

This study uses JMP software for regression analysis. And the equation below shows the relationship between PLOS and seven parameters. Figure 21 and Figure 22 were extracted from JMP, which show the figure of actual ploy versus predicted plot and the model analysis.

$$\boldsymbol{Val(LOS) = -2.393V_H - 0.011S_H + 0.047T_{delay}} - 0.006\boldsymbol{V_{CAVs}} + \boldsymbol{0.0207S_{CAVs} + 0.0019N_C + 0.045V_p + 5.41 + \mathrm{Match}(\mathrm{signal})\binom{0{:}-1.49}{1{:}1.49}})$$

Whole Model

Actual by Predicted Plot



Effect Summary

Source	LogWorth	PValue
T-Delay	7.058	0.00000
Signal	3.420	0.00038
S-CAVs	1.545	0.02852
V-P	1.309	0.04904
S-H	0.838	0.14533
V-CAVs	0.719	0.19094
N-C	0.046	0.89860
V-H	0.034	0.92460

Figure 21 Predicted plots of the new model

Summary of Fit

RSquare	0.99404
RSquare Adj	0.99177
Root Mean Square Error	0.46792
Mean of Response	10.53333
Observations (or Sum Wgts)	30

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	8	766.86874	95.8586	437.8127
Error	21	4.59793	0.2189	**Prob > F**
C. Total	29	771.46667		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	5.4136477	0.914597	5.92	<.0001*
V-H	-0.000024	0.00025	-0.10	0.9246
S-H	0.0116969	0.007734	1.51	0.1453
V-CAVs	-0.000642	0.000475	-1.35	0.1909
S-CAVs	0.0207165	0.008809	2.35	0.0285*
V-P	-0.000451	0.000216	-2.09	0.0490*
T-Delay	0.047751	0.005992	7.97	<.0001*
N-C	0.0019496	0.015115	0.13	0.8986
Signal[0]	-1.491246	0.353053	-4.22	0.0004*

Figure 22 Model analysis

The coefficient of determination (R^2) is a vital statistic reflecting the goodness of fit of the model, which is the ratio of the sum of the squares of the regression to the sum of the total squares. R^2 takes values between 0 and 1 and has no units. The larger R^2 is (close to 1), the better the fitted regression equation. In this model, the value of R square equals to 0.994 which means a strong fit.

6.6 Chapter summary

This chapter described the simulation and regression processes. Five scenarios corresponding to the different proportions of the CAVs were established via VISSIM.

The basic setting and CAVs parameter setting about roadway network were the same in different scenarios. After simulation, SSAM would evaluate the safety performance of each simulation and found out the number of potential conflicts between pedestrians and vehicles. Seven parameters were used for building the regression model: the speed and volume of human-driven vehicles, the speed, and volume of CAVs, the volume of pedestrians, average delay time of pedestrians and the number of potential conflicts between vehicles and pedestrians. The results show a strong relationship between these seven parameters and LOS.

Chapter 7

SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

7.1 Summary

Over the past decades, CAVs have evolved from a concept to reality and created a great deal of global research and discussion. CAVs can sense their environment with radar, lidar, GPS and computer vision technologies. Advanced control systems convert the sensed data into navigational roads, as well as obstacles and related signs. Simultaneously, the Internet of Vehicles provides a platform for the application of CAVs. Through wireless communication, facilities, vehicles, pedestrians and other road users can connect with each other and exchange information. And that makes the traffic system have a higher capacity and flexibility.

Due to some incomplete technologies related to CAVs, they have caused issues related to several aspects: safety, economy, regulation and policy, liability and insurance and cyber-security. Several accidents have been caused by CAVs which have raised concerns about the safety of CAVs. There are numerous studies and projects focused on improving the safety of CAVs. However, only a small number of studies have looked at the issues of coexistence between CAVs and other road users. This thesis focused on the impact of CAVs on pedestrians and developed a method to quantify the impact.

The methodology implemented in this thesis was based on HCM. HCM proposed a comprehensive approach to evaluate PLOS and BLOS on intersections in urban areas. The model is a function of factors related to traffic characteristics, geometric design and signal control systems. This thesis followed this idea and put CAVs as a crucial factor in the model.

To reflect the integration process of CAVs into the existing transportation system, five scenarios that respond to the different proportion of CAVs were established. In addition, CAVs are still in the experimental stage. This thesis used VISSIM to simulate the traffic system. VISSIM has advantages for simulating CAVs. It has a complete setting for CAVs to reflect the properties of CAVs. Also, the LOS evaluation approaches in VISSIM are based on HCM, which makes it convenient to get the value of LOS.

In this thesis, SSAM was chosen to analyze the safety performance of each scenario. SSAM is a software developed by the Federal Highway Administration (FHWA) to predict potential conflicts. It can analyze the trajectories file from VISSM directly, using the parameters of maximum speed to identify the conflicts between pedestrians and vehicles.

After simulation and analysis from SSAM, seven parameters were selected for developing the regression model: the speed and volume of human-driven vehicles, the speed, and volume of CAVs, the volume of pedestrians, the average delay time of pedestrians and the number of potential conflicts between vehicles and pedestrians. JMP accomplished the regression model and the analysis process. A stronger correlation was found between selected factors and the value of LOS (r = 0.9).

7.2 Conclusions

This thesis developed a model to evaluate the impact of CAVs on pedestrians on intersections in urban areas. This model used for evaluating the PLOS and is a function of the factors related to CAVs, pedestrians, and other traffic characteristics. This model is suitable for urban intersections that have one lane in each direction with or without signal system. The most novelty in this model is that it could analyze the impact of CAVs on pedestrians regardless of the proportion of CAVs in the transportation system.

When with a lower volume of CAVs and human-driven vehicles, the performance of PLOS without signal system would be better than with signal system. For the potential conflicts between pedestrians and vehicles, when the speed is higher, the number would be higher and impact the value of LOS. From the regression analysis, the pedestrian delay time has the most positive contribution to the value of LOS.

The results of this thesis have contributed to understanding the impact of CAVs on pedestrians during the process of the CAVs' application development. And this model can provide a reference to researchers and governments to pay attention to the coexistence issues related to CAVs.

7.2.1 Merits

There are two significant advancements reported in this thesis that are original. First, using VISSIM and SSAM, a successful application of CAVs was in the real world. Furthermore, the impact of CAVs or pedestrians was evaluated. Second, a PLOS evaluation model during CAVs environments was established. The PLOS by comparing different proportions of CAVs in a traffic system were estimated. This will provide a reference when dealing with the coexistence issue between CAVs and pedestrians.

7.2.2 Demerits

At the same time, since the factors that influence the PLOS are complex and include traffic characteristics, signal control system and coordination methods between CAVs and traditional vehicles one can argue that more work needs to be done. The regression model required abundant simulation data to improve accuracy. For future studies, the number of simulation runs need to be expanded.

This article establishes a model for evaluating PLOS in urban intersections through a study of the impact of CAVs on pedestrians. During the regression process, the factors selected were all related to traffic characteristics and signal controls. The factors about geometric design are also important for PLOS; for example, the number of vehicle lanes and the width of the walkways.

The factors related to CAVs are insufficient, especially for the impact of CAVs platoons on pedestrians. This factor will highly increase the delay time of pedestrians. And in the real world, pedestrians cannot perform like simulation models. People have a different definition of what is the safety environment for crossing. It is quite possible that without signal systems, some people would not cross the roads.

7.3 Recommendations and future work

In future research, more parameters with the geometric design can be selected for a more comprehensive model. And the evaluation model in this thesis could be extend to include the bicyclists. That means the impact of CAVs on bicyclists can be evaluated in the same method.

REFERENCES

Asadi-Shekari, Z. M. (2013). Non-motorised level of service: Addressing challenges in pedestrian and bicycle level of service. *Transport reviews, 33*(2), 166-194.

Autonomous Vehicles and Cybersecurity Concerns. (2019). Retrieved from SQUIRE PATTON BOGGS: https://www.squirepattonboggs.com/~/media/files/insights/publications/2016/11/autonomous-vehicles-and-cybersecurity-concerns/autonomousvehiclescybersecurityconcerns.pdf

BEA. (2015). *current-cost net capital stock of private nonresidential fixed assets for 2015*. Retrieved from Bureau of Economic Analysis: https://www.bea.gov/

Boudette, B. V. (2016, 6 30). *Self-Driving Tesla Was Involved in Fatal Crash, U.S. Says*. Retrieved from The New York Times: https://www.nytimes.com/2016/07/01/business/self-driving-tesla-fatal-crash-investigation.html

Congress, G. C. (2016, March 24). *CMU study shows autonomous vehicle algorithms can have considerable effect on fuel economy; need for new approaches in testing*. Retrieved from Green Car Congress: https://www.greencarcongress.com/2016/03/20160324-cmu.html

Favarò, F. M. (2017). Examining accident reports involving autonomous vehicles in California. *PLoS one, 12*(9).

Fruin, J. J. (1971). *Pedestrian planning and design.*

Gardner, G. (2010, August). Power to the Pedals. *World Watch Magazine, 23*.

Green, J. (2018, 4 2). *Tesla: Autopilot was on during deadly Mountain View crash*. Retrieved from the Mercury News: https://www.mercurynews.com/2018/03/30/tesla-autopilot-was-on-during-deadly-mountain-view-crash/

HCM 2010: highway capacity manual. (2010). Washington, DC, U.S.: Transportation Research Board.

Herbie Huff, R. S., Transportation, C. D., (U.S.), U. T., & Center, U. o. (2014). *The Highway Capacity Manual's method for calculating bicycle and pedestrian levels of service : the ultimate white paper*. Los Angeles: Los Angeles, Calif. : Lewis Center for Regional Policy Studies, 2014.

Index, A. V. (2018). *Assessing countries openness and preparedness for autonomous vehicles.* Retrieved from KPMG International: https://assets.kpmg/content/dam/kpmg/xx/pdf/2019/02/2019-autonomous-vehicles-readiness-index.pdf

Jolovic, D. a. (2012). Evaluation of VISSIM and FREEVAL to assess an oversaturated freeway weaving segment. *In TRB Annual Meeting*, p.12p.

Karim, D. M. (2015). Narrower lanes, safer streets. *InProc. CITE Conf* (pp. 1-21). Regina.

Kockelman, K. (2017). *An assessment of autonomous vehicles : traffic impacts and infrastructure needs--final report.* Austin, TX : Center for Transportation Research, The University of Texas at Austin, Springfield, Virginia : Available through the National Technical Information Service 2017.

Landis, B. V. (2001). Modeling the roadside walking environment: pedestrian level of service. *ransportation Research Record: Journal of the Transportation Research Board, 1773*(1), 82-88.

Landis, B. V. (2001). Modeling the roadside walking environment: pedestrian level of service. *Transportation Research Record: Journal of the Transportation Research Board, 1773*, 82-88.

Lin, P. J. (2017). Autonomous vehicle-intersection coordination method in a connected vehicle environment. *Intelligent Transportation Systems Magazine, 9*(4), pp. 37-47.

Marchant, G. E. (2012). The coming collision between autonomous vehicles and the liability system. *Santa Clara L. Rev, 52*(2012), 1321.

Miller, J. J. (2000). Calibrating pedestrian level-of-service metrics with 3-D visualization. *Transportation Research Record: Journal of the Transportation Research Board, 1705*, 9-15.

Mirheli, A. L. (2018). Development of a signal-head-free intersection control logic in a fully connected and autonomous vehicle environment. *Transportation Research Part C: Emerging Technologies, 92*, 412-425.

Nowar Raad, M. I. (2018, September 1). What Are the Most Important Factors for Pedestrian Level-of-Service Estimation? A Systematic Review of the literature. *Transportation Research Record: Journal of the Transportation Research Board*, 18-03950.

Pandit, K. D.-N. (2013). Adaptive traffic signal control with vehicular ad hoc networks. *EEE Transactions on Vehicular Technology, 62*(4), pp. 1459-1471.

Papadoulis, A. M. (2019). Evaluating the safety impact of connected and autonomous vehicles on motorways. *Accident Analysis & Prevention, 124*, 12-22.

Peter Sukennik, P. G. (2018, 02 07). Retrieved from CoEXist: https://www.h2020-coexist.eu/wp-content/uploads/2018/10/D2.4-Vissim-extension-new-features-and-improvements_final.pdf

Petritsch, T. A. (2006). Pedestrian level-of-service model for urban arterial facilities with sidewalks. *Transportation Research Record, 1982*(1), 84-89.

Polus, A. J. (1983). Pedestrian flow and level of service. *Journal of transportation engineering 109, 109*(1), 46-56.

Saeed Asadi BagloeeMadjid Tavana, M. A. (2016, 12). Autonomous vehicles: challenges, opportunities, and future implications for transportation policies. *Journal of Modern Transportation*, pp. 284-303.

Sandt, L., & Owens, J. M. (2017). Discussion Guide for Automated and Connected Vehicles, Pedestrians, and Bicyclists.

Schoettle, B. M. (2014). A survey of public opinion about autonomous and self-driving vehicles in the US, the UK, and Australia.

Sherony, R., & Zhang, C. (2015). Pedestrian and Bicyclist Crash Scenarios in the U.S. *2015 IEEE 18th International Conference on Intelligent Transportation Systems* (pp. 1533-1538). Las Palmas, Spain: IEEE.

Tomita, H. (2017, December 17). *Awaiting the realization of fully automated vehicles: Potential economic effects and the need for a new economic and social design*. Retrieved from VOX CEPR Policy Portal: https://voxeu.org/article/potential-economic-and-social-effects-driverless-cars

Uber Puts First Self-Driving Car Back on the Road Since Death. (2018, 12 22). Retrieved from Transportation Topics: https://www.ttnews.com/articles/uber-puts-first-self-driving-car-back-road-death

Wu, J. (2017). *Analysis of Pedestrian Safety Using Micro-simulation and Driving Simulator.*

Zhang, K. D. (2015). State-driven priority scheduling mechanisms for driverless vehicles approaching intersections. *IEEE Transactions on Intelligent Transportation Systems*, *16*(5), pp. 2487-2500.