Connected and Autonomous Vehicle in Heterogeneous Traffic Flow: Modeling, Evaluation, and Management

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ABSTRACT

The objective of this dissertation is to develop a heterogeneous traffic flow model, in order to study the possible impact of connected and autonomous vehicles (CAVs) on future traffic flow. Based on a recently proposed two-state safe-speed model (TSM), a two-lane cellular automaton (CA) model was developed, wherein both the CAVs and conventional vehicles were incorporated in the heterogeneous traffic flow. In particular, operation rules for CAVs were established considering the new characteristics of this emerging technology, including autonomous driving through the adaptive cruise control (ACC) and inter-vehicle connection via short-range communication. Based on the proposed heterogeneous flow model, the mixed traffic flow with both conventional vehicles and CAVs was simulated and studied.

Simulation was conducted under various CAV-penetration rates in the heterogeneous flow. The impact of CAVs on the road capacity, traffic safety, and fuel consumption was numerically investigated. The fundamental diagrams indicate that the road capacity increases with an increase in the CAV-penetration rate within the heterogeneous flow. Up to a CAV-penetration rate of 30%, the road capacity increases gradually; the effect of the difference in the CAV capability on the growth rate is insignificant. When the CAV-penetration rate exceeds 30%, the growth rate is largely decided by the capability of the CAV. The greater the capability, the higher the road-capacity growth rate. The relationship between the CAV-penetration rate and the road capacity was

numerically analyzed, providing some insights into the possible impact of the CAVs on traffic systems.

In terms of impact on safety and fuel consumption, the frequency of dangerous situations and value of time-to-collision in the mixed traffic flow under different CAV penetration rates were calculated and used as indicators of CAV's impact on traffic safety. Acceleration rate and velocity difference distributions of the mixed traffic flow were presented to show the evolution of mixed traffic flow dynamics with the increase in CAV penetration rates. Results show that the condition of traffic safety and fuel efficiency is greatly improved with the increase in the CAV penetration rate. A more cautious car-following strategy of the CAV would contribute to a greater benefit on traffic safety, though less gain in capacity. With the increase in CAV penetration rate, the portion of smooth driving is increased. The velocity difference between vehicles is decreased and traffic flow is greatly smoothed. Fuel dissipation rate is lowered.

Lastly, an application of the proposed methodology was presented to investigate the impact of setting dedicated lanes for CAVs on traffic flow throughput. A fundamental diagram approach was introduced which reveals the pros and cons of setting dedicated lanes for CAVs under various CAV penetration rates and demand levels. The performance of traffic flow under different number of CAV-dedicated lanes was compared with mixed flow situation. Simulation results suggest that at a low CAV penetration rate, setting CAV-dedicated lanes deteriorates the performance of the overall traffic flow throughput, particularly under a low-density level. When CAVs reach a

dominant role in the mixed flow, the merits of setting dedicated lanes also decrease. The benefit of setting CAV-dedicated lane can only be obtained within a medium density range. CAV penetration rate and individual CAV performance are significant factors that decide the performance of CAV-dedicated lane. The higher level of performance the CAV could achieve, the greater benefit it will attain through the deployment of CAV-dedicated lane. Besides, the performance of CAV-dedicated lane can be improved through setting a higher speed limit for CAVs on the dedicated lane than vehicles on other normal lanes. This work provides some insights into the impact of the CAV-dedicated lane on traffic systems, and helpful in deciding the optimal number of dedicated lanes for CAVs.

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ABBREVIATIONS AND ACRONYMS

ACC	Adaptive Cruise Control
AV	Autonomous Vehicle
CA	Cellular Automaton
CACC	Cooperative Adaptive Cruise Control
CAV	Connected and Autonomous Vehicle
CR	Connection Range
CV	Connected Vehicle
DR	Detection Range
DSRC	Dedicated Short-Range Communications
HOV	High-Occupancy Vehicle
ITS	Intelligent Transportation System
NGSIM	Next Generation Simulation
SAE	Society of Automotive Engineering
TSM	Two-state Safe-speed Model
TTC	Time-to-Collision
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
V2X	Vehicle-to-Everything
WTP	Willingness-To-Pay

CHAPTER 1
Introduction

1.1 Background

Vehicle automation has gone through a long process over the past several decades (Ioannou and Chien, 1993, Reece and Shafer, 1993). At the early stage, autonomous driving mainly indicates semi-automatic vehicles with a driving-assistant function known as the Adaptive Cruise Control (ACC) (Marsden et al., 2001, Davis, 2004, Kesting et al. 2008). When cooperative driving was integrated, this technology is widely known as Cooperative Adaptive Cruise Control (CACC) (Van Arem et al., 2006, Shladover et al, 2012). Recent developments in information and communication technology have resulted in significant advancements in intelligent transportation systems (ITSs). Because of the latest advances in the automobile industry, connected and autonomous vehicles (CAVs) are coming to the fore.

Connected and autonomous vehicle, also widely known as the self-driving vehicle, or the driverless car, is an emerging technology in the automobile industry. There are many definitions regarding this emerging technology, one of the most widely accepted is a set of guidelines determined by the Society of Automotive Engineering (SAE), in which five levels of autonomous driving are defined to describe the different levels of autonomy in the self-drive technology. Level 1, also being called driver assistant, indicates the automobile with certain driver assistance system,

which assists the driver in the driving task under specific driving modes, such as steering or acceleration/deceleration, using information of the driving environment; Level 2 is called partial automation, indicates automobiles possessed one or more driver assistance systems, the system will execute driving in terms of steering and acceleration/deceleration instead of the driver, but the driver is still responsible for all the remaining aspects of the driving task; Level 3 is conditional automation, indicates the automated driving system has the capability to deal with all aspects of the driving task, on the condition that the driver will respond appropriately to the request of intervening from the automated driving system; Level 4 is called high automation, indicate the automated driving system has the capability to deal with all aspects of the driving task even the driver does not respond appropriately to the request of intervening; and finally, Level 5, the full automation, which means the automated driving system can deal with all aspects of the driving task under all roadway and environmental conditions that can be managed by a human driver.

It is widely expected that CAVs will be available on the mass market by 2022 or 2025 (Fagnant and Kockelman, 2015). Connected systems such as the vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) systems will be adopted in the transportation system along with the deployment of CAVs. These significant developments will change the highway-driving environment fundamentally. Equipped with computer sensors that can help detect near objects, along with the capability of communicating with other autopilot vehicles, the driving characteristics of the CAVs will be differ from those of conventional vehicles (Gora and Rüb,

2016). The CAVs are able to obtain more precise driving-condition parameters compared to human perception; thus, they are capable of instantly reacting to the changes in driving conditions unlike the delay observed in human reaction time or the negative effects of human error. Moreover, the CAVs can be driven in close proximity via the adaptive cruise control (ACC) technology; thus, the distance between two successive CAVs is considerably shorter than that between two conventional vehicles. In addition, inter-vehicle connections via dedicated short-range communications (DSRC) are able to enlarge the detection range of the distance sensors, and allow CAVs a greater capability (Lu et al., 2014). The potential merits such as improvement in road capacity, traffic safety, and efficiency are widely expected through the deployment of CAVs (Gruel and Stanford, 2016, Mahmassani, 2016). However, before the CAVs are fully deployed, a heterogeneous traffic flow comprising the conventional vehicles and CAVs will exist for a long period, which may bring uncertainty into the current transportation system. The extent to which the current transportation system can be enhanced through the deployment of this new technology is unknown. Meanwhile, CAV technology is still evolving with time. Varying levels of vehicle automation ranging from partial automation to full automation would exist during this time period. The relationship between the CAV-penetration rates and the possible improvement in the road capacity needs to be analyzed.

There are a lot predictions concerning the impact of CAVs on traffic safety. Some researchers argue that CAVs would reduce crashes 90% because more than 90% of traffic accidents are due to human drivers' error, autonomous vehicles are able to avoid such driving errors (National

Highway Traffic Safety Administration, 2008). Such prediction may seem too optimistic since it is based on a simple assumption, and it solely concerns about the utopic future but did not pay any attention to the transition period. Other researchers indicate that the introduction of CAVs would smooth the traffic flow, avoid stop-and-go driving and thus result in a significant reduction in fuel consumption and air pollution (Talebpour and Mahmassani, 2016, Ge et al., 2018). However, some researchers hold a quite different point of view over this problem. Their studies show that low-level automated vehicle in the mixed traffic flow would rather have a negative effect on traffic flow and road capacity. Improvement in traffic flow can only be attained when CAVs reached a high penetration rate in the mixed flow (Kerner, 2016, Calvert et al. 2017). Due to a lack of empirical data of CAVs, the impact of CAVs on traffic flow during this transition period has not yet been studied thoroughly.

Since the uncertainty mainly comes from the interaction between CAVs and regular vehicles in the heterogeneous traffic flow, enlightened from the managed lane strategy, CAV-dedicated lane is believed as one of the potentially effective solutions to these challenges. For better accommodating CAVs under current road system and improving the efficiency of this emerging technology, increasing attention has been given to the managed lanes approach. By allocating a number of lanes exclusive to CAVs, CAVs on the dedicated lanes can reveal their potentialities earlier than that in the heterogeneous traffic flow, even at a relatively low penetration rate stage. This strategy makes a separation of CAVs from the mixed traffic. CAVs are supposed to use the

dedicated lane on which homogeneous traffic flow of CAVs is created. On the other hand, setting CAV-dedicated lane will reduce the number of lanes for accommodating other regular vehicles. In particular, if not set properly, it will lead to a great waste of road resource and cause severe congestion in the traffic flow, decreases the overall throughput of the road. Naturally, the question of when it will be necessary to set such dedicated lane arises. It is generally expected that a certain threshold of CAV penetration rate may exist, above which the overall traffic flow performance will be better by setting a number of CAV-dedicated lanes, comparing to the performance of totally mixed traffic flow. Since the CAVs will be adopted gradually, and the CAV penetration rate among the heterogeneous flow will increase at a slow pace. Researchers have to decide how many lanes need to be allocated for CAVs considering the CAV penetration rate, in order to gain the maximum benefit of the dedicated lane approach. However, the impact of CAV-dedicated lane on overall traffic flow throughput is a complex problem. It involves not only the CAVs penetration rate but also the performance of the CAVs compared to regular vehicles. The performance of the overall traffic flow throughput also varies under different traffic demand levels. Thus, it is better to investigate this problem thoroughly than only determine a threshold penetration rate of CAVs for setting CAV-dedicated lanes.

1.2 Objectives

The primary objective of this dissertation is to develop a microscopic modeling approach to study the connected and autonomous vehicles (CAVs) related problems on the future traffic flow.

The following points are the specific objectives.

The first purpose is to establish a microscopic traffic flow model, wherein both the CAVs and conventional vehicles need to be incorporated in the heterogeneous traffic flow. The model will serve as the basis for conducting researches on CAV-related problems. Simulation study will be conducted under various CAV-penetration rates in the heterogeneous flow.

The second purpose is to study the impact of CAVs on capacity, safety and fuel consumption numerically. In real traffic, capacity is influenced by numerous factors, such as road conditions, road user conditions, driving behaviors of the user, weather conditions and so on. Vehicle composition naturally is an important factor that affects the capacity. In the field of traffic flow theory, fundamental diagram describes a statistical relation between the macroscopic traffic flow variables of flow, density, and velocity. Capacity is equivalent to the maximal flow rate attained in the free flow phase. The impact of CAVs on capacity can be revealed by comparing the fundamental diagrams under various penetration rates of CAVs. Moreover, several safety measurements will be introduced in the microscopic heterogeneous flow model in order to evaluate the impact of CAVs on traffic safety. A fuel consumption model will be integrated into the flow model to study the impact of CAVs on energy consumption.

Finally, the proposed model will be extended to a multi-lane model to study the CAV-dedicated lane approach. The performance of traffic flow under different number of CAV-dedicated lanes will be compared with the mixed flow situation. Based on the discussion, suggestions for better

accommodating CAVs through the dedicated lane approach will be proposed.

1.3 Structure

The structure of the dissertation is presented in the following Figure 1.1. Six chapters comprise this dissertation. Chapter 1 introduces the background and objectives of this research. Chapter 2 summarizes the related literature on connected and autonomous vehicle. The possible impact of CAV on traffic flow in the existing studies is discussed. In Chapter 3, a heterogeneous traffic flow model is introduced. Operation rules for CAVs considering the new characteristics of this emerging technology are established and integrated into a microscopic traffic flow model. In Chapter 4, the impact of CAVs on capacity, safety, and energy consumption is investigated via simulation respectively. In Chapter 5, the model is extended into a multi-lane model, simulation is carried out to study the CAV-dedicated lane approach. Finally, in Chapter 7, conclusions and recommendations for future studies are presented.

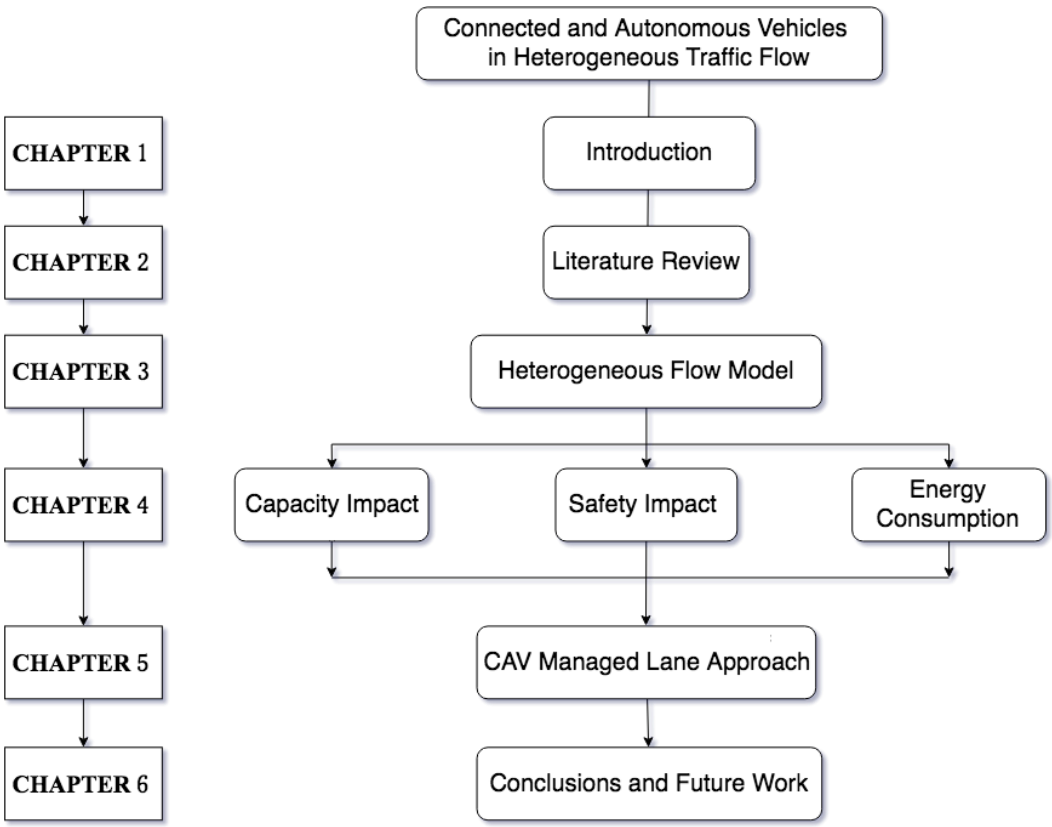


Figure 1.1 Structure of the dissertation

CHAPTER 2

Literature Review

Recent studies concerns connected and autonomous vehicles can mainly be divided into following several aspects: public acceptance and predictions on the adoption of CAVs, potential impacts of CAVs on traffic system with the gradual deployment of CAVs, traffic dynamics during the transition period and possible management approach for better-accommodating CAVs under current traffic system. Existing literature will be reviewed and summarized under each topic respectively.

2.1 Depicting a future traffic system incorporating CAV

During previous years, autonomous vehicle (AV) and connected vehicle (CV) are literally two different kinds of technology. Autonomous vehicle refers to semi-automatic vehicles that have some driving-assistant functions for autonomous driving, such as the ACC. In previous studies, advantages of autonomous vehicles such as smoother traffic flow, improvement in road capacity, and flow stability were frequently mentioned (Marsden et al., 2001, Davis, 2004). Ioannou and Chien (1993) developed an autonomous intelligent cruise-control system. They evaluated the performance of the system via computer simulation and found that the developed system contributes to faster and smoother traffic flow. Van Arem et al. (2006) studied the impact of a cooperative ACC on the traffic flow characteristics and found that traffic flow stability can be

improved along with a slight increase in flow efficiency. Kesting et al. (2008) employed an ACC strategy to improve traffic stability and increase the dynamic road capacity. In most previous studies on autonomous driving, the possible effects of the ACC technology were analyzed, focusing primarily on the car-following process and single-lane models were used without considering passing behaviors.

More recently, with the advancement in information and communication technology, the connected vehicle becomes an emerging technology in the automobile industry. This technology allows vehicles to communicate with each other and the world around them, which supplying useful information to help the driver make safer or more informed decisions. Studies concerning connected vehicles are also being extensively conducted. Lu et al. (2014) presented an overview of wireless technologies used in the connected vehicles and discussed the possible pros and cons of vehicular connectivity. Talebpour et al. (2016) presented a comprehensive simulation framework to model the behavior of the driver in connected vehicles under a connected environment and found that this technology can be used to improve the efficiency and reliability of a driverless transportation network. Since connected vehicle and automatic driving are two different emerging technologies, previous studies treated them separately.

With the rapid development of automobile technology, fully automated vehicles with connected ability, known as the connected and autonomous vehicle, are going to be a reality. In recent literature, lots of efforts have been paid to study public opinions towards this emerging

technology, most of them were based on the survey approach. Based on these studies, the possible future adoption patterns of CAVs were predicted. Bansal and Kockelman (2017, 2018) made a long-term forecast on U.S. adoption of CAV technology. Simulations were conducted under varying technology price, WTP and regulations over time. They predicted 24% (pessimistic) to 87% (optimistic) Level 4 U.S. vehicle fleets by 2045, and the state of heterogeneous traffic flow still will last for a considerably long period. Becker and Axhausen (2017) made a review of the existing literature of surveys investigating the general acceptance of automated vehicles. Panagiotopoulos and Dimitrakopoulos (2018) proposed a technology acceptance modeling framework to investigate the factors related to consumers' intentions on using and accepting CAVs. Their study shows that perceived usefulness of the technology has the strongest impact on consumers' opinion on adopting CAVs. Based on the theory of diffusion of innovations, Talebian and Mishra (2018) proposed an approach for forecasting long-term adoption of connected autonomous vehicles (CAVs), study results show that the automobile fleet will be near homogenous in about 2050 only if CAV prices decrease at an annual rate of 15% or 20%.

In the field of traffic modeling, researchers have also made great efforts on modeling CAVs, in order to develop a better understanding of future traffic system incorporating this emerging technology. Talebpour et al. (2016) presented a comprehensive simulation framework to model the behavior of the driver in connected vehicles under a connected environment and found that this technology can be used to improve the efficiency and reliability of a driverless transportation

network. Gora and Rüb (2016) presented fundamental concepts and assumptions to model self-driving connected cars. They presented several implementation methods along with some policy recommendations. Gong et al. (2016) developed a systematic car-following control algorithm for a connected and autonomous vehicle platoon, which is intended to realize the entire platoon's traffic smoothness and dynamic performance.

These studies are helpful in depicting the near future of traffic system with CAVs, while continuing efforts are being paid to gain a better understanding of it.

2.2 Impact of CAV on traffic flow

There are a great many studies focusing on the potential impact of CAVs on future traffic flow. In this section, the possible impact on capacity, safety and fuel consumption in recent literature is summarized.

2.2.1 Impact on capacity

The impact of CAVs on capacity in recent research was studied mainly based on two ways: the analytical approach and the simulation approach.

The analytical approach is intended to formulate capacity based on several key parameters such as the average headway and the penetration rate of CAVs. Hussain et al. (2016) developed an analytical model to estimate the freeway overall performance by formulating the average headway of the mixed traffic. Ghiasi et al. (2017) proposed an analytical capacity model and lane

management model of the mixed traffic using a Markov chain method. Olia et al. (2018) proposed an analytical framework in order to assess and evaluate the impacts of CAVs on the highway capacity. All these studies indicate that the capacity increase is achievable with the deployment of this emerging technology, while the potential benefit on capacity is highly sensitive to the CAV penetration rates and the performance of the technology.

Although the analytical is able to formulate capacity under considerable idealized conditions such as the averaged headway and the CAV penetration rate, this approach is not able to account for the stochastic factors in traffic flow. After all, traffic flow dynamic is both stochastic and sophisticated.

On the other hand, simulation enables us to study the capacity impact through the fundamental diagram approach. Shladover et al. (2012) estimated the potential effect on highway capacity under varying market penetrations of vehicles with adaptive cruise control (ACC) and cooperative adaptive cruise control (CACC) via microscopic simulation, found that CACC was able to increase capacity greatly after its market penetration reached moderate to high percentages. Arnaout and Arnaout (2014) established an agent-based microscopic traffic simulation model to study the impact of cooperative adaptive cruise control (CACC) on traffic flow characteristics. Results show a better traffic flow performance and higher capacity. Olia et al. (2018) used a traffic micro-simulation model which incorporating car-following and lane-merging modules to estimate the impacts of AVs on the capacities of highway systems, results indicate a maximum lane capacity of 6,450 veh per hour per lane (300% improvement) is achievable, under the condition that all

vehicles are cooperative automated driving.

All these studies suggest that the impact of CAVs on capacity is highly sensitive to individual CAV performance and CAV penetration rate among the vehicle fleet.

2.2.2 Impact on Safety

The impact of CAVs on safety was mainly studied based on the simulation approach. Li et al. (2017a, 2017b) studied the safety impact of adaptive cruise control in traffic oscillations with different combinations of parameters, as well as under different penetration rates of ACC vehicles, results show that the impact of ACC on traffic safety is largely affected by the parameters. Smaller time delays and larger time gaps are useful for improving safety performance. Reduction of collision risk can be improved with the increase in the ACC vehicle penetration rates. They also evaluated the impact of the CACC system on reducing rear-end collision risks on freeways based on an extend CACC model and several surrogated safety measures. Papadoulis et al. (2019) performed a safety evaluation regarding CAVs on motorways based on a proposed CAV control algorithm, results show that CAVs bring about the considerable benefit on reducing traffic conflicts at even a relatively low market penetration rate. Rahman et al. (2019) evaluated the safety impact of CAVs with lower level automation on an arterial road, results appear in a significant safety improvement both on segment and intersection in terms of crash risk. Recent literature indicates the introduction of CAVs will be beneficial for traffic safety.

2.2.3 Impact on fuel consumption

The introduction of CAVs would smooth the traffic flow, particularly in congested traffic, which also will improve fuel efficiency. Studies concern the impact of CAVs on fuel consumption are also being conducted extensively.

Barth and Boriboonsomsin (2009) investigated fuel consumption impacts of coordinated eco-driving: results show that 10%-20% fuel and carbon dioxide emissions reduction could be achieved in congested highway traffic. Mersky and Samaras (2016) proposed a fuel economy testing approach for autonomous vehicle. Simulation results indicated that up to 10% potential fuel economy gains can be expected by means of efficiency-focused control strategies. Ross and Guhathakurta (2017) conducted a scenario analysis in order to identify and quantify the impact of autonomous vehicles on energy. Ge et al. (2018) conduct an experimental study of CAVs among human-driven vehicles: their study shows that CAVs are likely to improve both safety and energy efficiency, not only CAV itself but also its neighboring human-driven vehicles. Stern et al. (2018) experimentally demonstrate that intelligent control of an autonomous vehicle is able to dampen stop-and-go waves, which potentially improves fuel economy. In the simulation approach, Dong et al. (2018) conducted a simulation study of a platoon of mixed vehicles: the results show that higher market penetration of CAVs results in better fuel efficiency of the fleet. Vahidi and Sciarretta (2018) studied the energy saving potentials of CAVs. Results show that of CAVs can contribute to 3-20% energy saving by means of anticipative and collaborative driving.

2.3 CAV in mixed traffic flow

Most of the existing models considering CAVs were developed and tested in a homogeneous traffic flow environment, however, increasing attention is being paid to study the CAVs in a mixed traffic flow environment, which consisting of both conventional vehicles and CAVs.

Based on a simulation framework with different technology-appropriate car-following models, Talebpour and Mahmassani (2016) studied the influence of CAVs on traffic flow stability and throughput, results show that the introduction of CAVs improves string stability and throughout of mixed traffic streams. Liu et al. (2018) developed a cooperative adaptive cruise control (CACC) modeling framework to study the impact of CACC on mixed traffic flow in multi-lane freeway facilities. In their work, the NGSIM oversaturated flow human driver model (Yeo et al., 2008) and a CACC car-following model (Milanés et al., 2014) are adopted for modeling conventional vehicles and CAVs respectively. Gong and Du (2018) developed a cooperative platoon control algorithm for a mixed flow platoon including both CAVs and HDVs, which is able to dampen traffic oscillation propagation and stabilize the traffic flow. Xie et al. (2018) proposed a generic car-following framework for modeling the heterogeneous traffic mixing regular and connected vehicles. Their study demonstrates that CAV can enhance the traffic flow stability and improve traffic efficiency particular in congestion traffic flow.

In the experimental approach, Stern et al. (2018) conducted a car-following experiment on a circuit track: results demonstrate that intelligent control of a single autonomous vehicle is able to

dampen the stop-and-go traffic flow. Ge et al. (2018) conducted an experimental validation of CAV design among regular vehicles: the results show that both safety and energy efficiency can be improved in the mixed flow, and CAV is helpful in mitigating traffic waves.

The gradual adoption of CAVs in current traffic system indicates a mixed traffic flow consists of both conventional vehicles and CAVs will last a long period. Studies on traffic dynamics in this transition period are still both urgent and lacking.

2.4 Management approaches considering CAV

In order to better accommodate CAVs, several strategies have been proposed in the recent literature, such as CAV-dedicated lane, exclusive autonomous vehicle zone, CAV-oriented intersection, etc.

At the roadway level, Chen et al. (2016) developed a mathematical framework for the optimal deployment of autonomous vehicle lanes in a road network. Optimal solutions to accommodate CAVs in terms of managed lanes were analyzed along with attempts to formulate the road capacity of the mixed traffic. Talebpour et al. (2017) investigated the effects of reserved lanes for AVs on congestion and travel time reliability. In their work, three different strategies were evaluated and compared, it found that optional use of the CAV-dedicated lane for CAVs can ease congestion and has better performance over other policies. Chen et al. (2017a) proposed a set of capacity formulation which takes into account the AV penetration rate, micro/mesoscopic characteristic and different lane policies for accommodating AVs, and verified that mixed-use policies can realize

higher capacities than strict segregation of CAVs and regular vehicle.

At the area level, Chen et al. (2017b) developed a mathematical framework for the design of autonomous vehicle zones. Mirheli et al. (2018) developed a signal-head-free intersection control logic in a fully connected and autonomous vehicle environment, which aims to maximize intersection throughput with safe trajectories. Lu et al. (2019) established a trajectory-based traffic management model for an exclusive autonomous vehicle zone. Hu and Sun (2019) proposed a trajectory optimization control framework for CAVs at multilane freeway merging area, which is useful for optimizing vehicles' lane-changing in the merging behavior. Liu et al. (2019) proposed a cooperative trajectory planning strategy, which is intended to facilitate CAVs in passing through an intersection with facilities of V2X communication. Wu et al. (2019) proposed a decentralized coordination multi-agent learning approach for the management of CAVs at autonomous intersections. Yu et al. (2019) proposed an optimization-based method for managing connected and automated vehicles at isolated intersections, results show that the proposed method performs better than reservation-based control.

These studies serve as the basis for further research considering CAVs in the heterogeneous traffic flow.

CHAPTER 3

Modeling

3.1 Introduction

This chapter introduces the heterogeneous traffic flow model established in the dissertation, which is a kind of microscopic traffic flow model. The cellular automaton (CA) model is a type of discrete model, which has been extensively applied in the field of microscopic-traffic modeling in the past few decades (Treiber and Kesting, 2013). In addition to the capability of describing the vehicular driving behavior, although, with relatively low accuracy on a microscopic scale comparing to continuous models, advantages such as simplicity and flexibility in adapting to sophisticated characteristics of real traffic have been demonstrated in many previous studies. Hence, in this study, a heterogeneous flow model was established wherein the conventional vehicles and CAVs were considered simultaneously based on the recent developments in the field of microscopic-traffic modeling. For modeling of regular vehicles, we applied the TSM model (Tian et al., 2015, 2016). While for modeling the CAVs, new rules were established in the heterogeneous-flow model.

There are several points that differ from modeling a human-driven vehicle. Firstly, a classical

adaptive cruise control model is used for the autonomous driving. For modeling of conventional vehicles, acceleration rate a is a constant value (the acceleration rate a will be further affected in the randomization step which accounts for the uncertainty in human driving). For modeling of CAV, its acceleration rate is calculated by the ACC model. Secondly, the randomization step involved in modeling human-driven vehicles is removed in the steps of modeling the CAV. Thirdly, in the car-following process of CAV, different following strategies are applied in calculating the anticipated gap according to the type of its preceding vehicle. Namely, a CAV would adopt different strategies between following a human-driven vehicle and following a CAV. When CAVs following a regular vehicle, a more cautious strategy is applied than following a CAV. Besides, connectivity means a better provision of information, we use the average speed of CAVs within connection range as an input parameter in calculating the anticipated speed for a CAV. For conventional vehicles, a reaction time of 1 s was assumed in calculating the safe speed. For CAVs, this reaction time is removed, since CAVs could react almost instantly compared to human drivers.

Connectivity of CAVs in this work is considered in the following two aspects. Firstly, it is assumed that CAV can acquire accurate speed information of all other CAVs within its connected range, which will contribute to a more accurate anticipated speed. Secondly, CAVs can distinguish whether its preceding vehicle is a conventional vehicle or a CAV via vehicle connectivity, thus different following strategy can be applied.

The cellular automaton (CA) model is a type of discrete model, which has been extensively

applied in the field of microscopic-traffic modeling in the past few decades. In addition to the capability of describing the vehicular driving behavior, advantages such as simplicity and flexibility in adapting to sophisticated characteristics of real traffic have been demonstrated in many previous studies. For example, Tian et al. (2016) established a two-state safe-speed model (TSM) to reproduce the metastable state, traffic oscillations, phase transitions, and other real traffic flow dynamics. They compared the TSM with a series of existing models, including traditional two-phase models such as the GMs, Gipps' Model, OVM, FVDM, and IDM, three-phase traffic models such as the KKW model, the Lee model, the MCD model, the model of Gao, and found that the TSM performs the best. Thus, we choose the TSM as the base of new model in terms of modeling regular vehicles. The CA model was also widely applied to study the possible impact of the emerging technologies on the traffic flow. Kerner (2016) analyzed the shortage of classical traffic theories concerning traffic breakdown, i.e., a transition from free flow to congested flow, and concluded that the traffic-flow models based on these theories may not be reliable for analyzing the possible impact of autonomous driving or other ITS-applications on the traffic flow. Hence, a traffic-flow model in the framework of the three-phase theory was suggested to analyze the impact of autonomous driving on the traffic flow. The traffic flow model in the framework of the three-phase theory can show and explain traffic breakdown by the F→S transition (free flow to synchronized traffic flow) in the metastable free flow. Kerner further investigated the performance of autonomous driving under mixed-traffic-flow conditions and found that autonomous driving can either decrease or increase the probability of traffic breakdown (Kerner,

2016). Hence, in this study, a heterogeneous flow model was established wherein the conventional vehicles and CAVs were considered simultaneously based on the recent developments in the field of microscopic-traffic modeling. For modeling of regular vehicles, we applied the TSM model. While for modeling the CAVs, new rules were established in the heterogeneous-flow model.

3.2 Methodology

The presented model is discrete in both space and time. All the variables involved are integers. The steps involved in the model are as follows. The model is described at each time step in the simulation. Since the time step in the simulation equals to 1 s, and the unit for vehicle speed is m/s, the distance (m) traveled by the vehicle in one time step numerically equals to its instantaneous speed (m/s). The same principle is applied when dealing with instantaneous speed (m/s) and the acceleration rate (m/s^2).

3.2.1 Deterministic speed update

$$v'_{\mathrm{det}} = \min(v+a,\ v_{\max},\ d_{\mathrm{anti}},\ v_{\mathrm{safe}}) \tag{1}$$

Here, v denotes current speed and v' denotes the speed at the subsequent time step, respectively. a denotes the acceleration rate and $v_{\max}$ is the maximum velocity. d_{anti} denotes the anticipated space gap, v_{safe} denotes the safe speed.

For regular vehicles, d_{anti} and v_{safe} are calculated as follows.

$$d_{\mathrm{anti}} = d + \max(v_{\mathrm{anti}} - g_{\mathrm{safety}},\ 0) \tag{2}$$

$d = x_l - x - L_{\text{veh}}$ denotes the real space gap ahead of the vehicle. x and x_l denote the position of the object vehicle and its preceding vehicle. L_{veh} denotes the vehicle length. $v_{\text{anti}} = \min(d_l, v_l + a, v_{\max})$ denotes the expected velocity of the preceding vehicle. d_l is the real space gap and v_l is the speed of the preceding vehicle, respectively. g_{safety} is a parameter concerning safety which aims in avoiding accidents, under the condition of limited human perception.

$$v_{\text{safe}} = \left[-b_{\max} + \sqrt{b_{\max}^2 + v_l^2 + 2b_{\max} d} \right] \tag{3}$$

$b_{\max}$ denotes the maximum deceleration rate. The round function $[x]$ returns the integer nearest to x. This equation works under two basic assumptions (i) the reaction time of human drivers is 1 s (identical time step of the CA model), (ii) no acceleration at the current time step.

For CAVs, corresponding $d_{\text{anti}}^{\text{cav}}$ and $v_{\text{safe}}^{\text{cav}}$ are defined as follows.

Since CAV is able to obtain its space gap through sensors, the anticipation distance for CAVs can be defined as the following equation.

$$d_{\text{anti}}^{\text{cav}} = \begin{cases} d + v_{\text{anti}}^{\text{cav}} & \text{if } v_l \text{ is a CAV} \\ d + v_{\text{anti}} - b_{\text{defense}} & \text{otherwise} \end{cases} \tag{4}$$

$$v_{\text{anti}}^{\text{cav}} = \min(d_l, v_l + a, v_{\max}, v_{li}) \tag{5}$$

Connectivity is considered in Equation (5), where v_{li} stands for the average velocity of the connected vehicles ahead of the object vehicle within its connection range (CR). Under certain cases, there will be no CAV exists within the distance of CR at all, v_{li} is set as the same value of $v_{\max}$ as a default setting. CAVs are supposed to be able to obtain the traffic information within the

CR through the technology of dedicated short-range commutation (DSRC). Connectivity will serve as an additional approach for CAVs in obtaining forward traffic conditions. The connection range will be larger than the detection range of sensors. b_{defense} denotes the randomization-deceleration rate of a regular vehicle under the defensive state, which will be further introduced in stochastic deceleration step of regular vehicles. In the operation of CAVs, a worst case is always being assumed to keep safe when following a regular vehicle. Due to the unpredictable nature of human driving, a regular vehicle is always considered to be in the defensive state.

When determining the safe speed v_{safe} for regular vehicles, reaction time of 1 s for human drivers has already been incorporated in Equation (3). For CAVs, the reaction time is reduced to 0. In reality, the reaction time of a CAV will not be 0 s. We assumed CAV is able to react instantly. Compared to perception capability of human drivers, CAVs have a limited capability of detecting objects located within its sensor detection range. Thus, the maximum velocity of CAVs is restricted to sensor detection range (*DR*).

$$v_{\text{safe}}^{\text{cav}} = \left[\sqrt{v_l^2 + 2b_{\max} \min\left(d_{\text{anti}}^{\text{cav}}, DR\right)} \right] \tag{6}$$

The maximum speed of CAVs is always assumed should be sufficiently low such that the vehicle can make a completely stop within its detection range. The maximum velocity of the CAVs is defined as equation (7)

$$v_{\max}^{\text{cav}} = \left[\sqrt{2b_{\max} DR} \right] \tag{7}$$

For regular vehicles, acceleration rate a is a constant value. Acceleration rate a_{ACC} for CAVs is determined by a classical ACC model, which is the function of autonomous driving (Kerner, 2016), defined as follows.

$$a_1 = K_1(d - vT_{\mathrm{ACC}}) + K_2(v_l - v) \tag{8}$$

$$a_{\mathrm{ACC}} = \lfloor \max(\min(a_1, a_{\max}), b_{\max}) \rfloor \tag{9}$$

Here, K_1 and K_2 are coefficients for the ACC driving. T_{ACC} is desired net time gap for CAV in deciding the distance to keep with its preceding vehicle. The calculated acceleration rate is further regulated by the range from $b_{\max}$ to $a_{\max}$, which accounts for the comfort factor. $a_{\max}$ and $b_{\max}$ represent the maximal acceleration rate and maximal deceleration rate, respectively. $\lfloor x \rfloor$ serves as the floor function which return the maximum integer no larger than x.

3.2.2 Stochastic deceleration for regular vehicles

$$v' = \begin{cases} \max(v'_{\mathrm{det}} - b_{\mathrm{rand}}, 0) & \text{with probability } p \\ v'_{\mathrm{det}} & \text{otherwise} \end{cases} \tag{10}$$

Randomization deceleration b_{rand} and stochastic deceleration probability p are defined as follows, respectively:

$$b_{\mathrm{rand}} = \begin{cases} a & \text{if } v < b_{\mathrm{defense}} + \lfloor d_{\mathrm{anti}}/T \rfloor \\ b_{\mathrm{defense}} & \text{otherwise} \end{cases} \tag{11}$$

$$p = \begin{cases} p_b & \text{if } v = 0 \\ p_c & \text{else if } v \le d_{\mathrm{anti}}/T \\ p_{\mathrm{defense}} & \text{otherwise} \end{cases} \tag{12}$$

Where b_{rand} denotes the randomization-deceleration rate. $p_{\mathrm{defense}} = p_{\mathrm{c}} + \frac{p\mathrm{a}}{1+e^{\alpha(vc-v)}}$ is a logistic

function, with its aim to define the randomization probability p_{defense}. In determining the b_{rand}, two different randomization-deceleration values are applied in order to describe the difference of driving behaviors between the defensive state and the normal state. Specifically, b_{defense} is the randomization-deceleration rate for the defensive state. The randomization-deceleration rate is identical with a under normal state.

For CAVs, no randomization-deceleration is applied.

3.2.3 Position update

$$x' = x + v' \tag{13}$$

x' denotes position at subsequent time step. The time step of the model is 1 s and each cell has a longitudinal distance of 0.5 m. The vehicle will move forward at a distance of its updated velocity.

3.2.4 Lane-changing rules

In order to extend the TSM to a two-lane traffic-flow model, a classical lane-changing model is deployed (Rickertet al., 1996), which is defined as follows.

Incentive criteria: $d(i, t) < \min\{v + \text{a}, v_{\max}\}$ and $d(i, t)_{\text{other}} > \min\{v + \text{a}, v_{\max}\}$ denote the incentive for a vehicle to change its current lane, which describe a situation that space ahead of the object vehicle i is not enough to operate at a higher velocity, and driving condition on target lane is better than its current lane.

The safety criteria $d(i, t)_{\text{back}} > v_{\max}$ ensures the vehicle immediately behind the object vehicle on the target lane will not crash with it when changed to the target lane. If the two conditions are met simultaneously, the object vehicle will change to the target lane under a lane-changing probability P_{lc}.

The lane-changing model adopted here is a classical lane-changing model which is widely applied in cellular automata traffic flow models. It is a symmetric lane changing model, thus there is no preference in using which lane in the simulation. The purpose of introducing the lane-changing is for better modeling the human-driven traffic flow. Since one-lane traffic flow model is not able to account for the passing behavior, and passing behavior is a common practice in real traffic flow. A single-lane model can only model the car-following process. By introducing the lane-changing model, the system can be closer to real traffic system and the result of this work would be more reliable. What is more, if using a single lane model, the system is not able to evolve spontaneously. Since no vehicle can pass. And the simulation result would overly rely on the initial distribution of the mixed vehicle fleets. However, this problem can be solved by introducing the lane-changing model. In the simulation of the two-lane freeway, the system can evolve spontaneously.

3.3 Simulation setup

In the CA model, the road segment is divided into cells and time into time steps. At each time step, each cell has only two states, which either is occupied by a vehicle or is empty. The simulation

was conducted on a 10-km two-lane road segment under the periodic boundary condition. First, the simulation involved conventional vehicles and CAVs randomly distributed in a mega-jam on the road segment. Under periodic boundary condition, whenever a vehicle reaches the endpoint of the road segment, the vehicle will be moved to the start point of the road segment instantly. Thus, the density and vehicle composition on the road segment will remain stable. Tables 3.1 and 3.2 list the parameters of the TSM and parameters for modeling the CAV, respectively.

Table 3.1 Parameters for modeling regular vehicle

Parameters	L_{cell}	L_{veh}	T	a	P_{lc}	$b_{defense}$
Units	m	m	s	m/s^2	-	m/s^2
Values	0.5	7.5	1.8	0.5	0.2	1
Parameters	P_a	P_b	P_c	g_{safety}	v_c	α
Units	-	-	-	m	m/s	s/m
Values	0.85	0.52	0.1	10	15	5

Table 3.2 Parameters for modeling CAV

Parameters	DR	CR	v_{max}	T_{ACC}	K_1	K_2	a_{max}	b_{max}
Units	m	m	m/s	s	s^{-2}	s^{-1}	m/s^2	m/s^2
Values	120	300	27	1.1	0.14	0.9	3	3

Velodyne Lidar HDL-64E has a capability of 120 ± 2 m in the detection range. In this study, the detection range DR equals to 120 m. A typical communication range used in the connected vehicles in the DSRC technology is 300 m. The maximum velocity of the CAVs is given by $[\sqrt{2b_{max}DR}]$, which equals to 27 m/s. To investigate the difference in the performance between autonomous vehicles and regular vehicles under the traffic-flow conditions, the same v_{max} is employed for conventional vehicles in the simulation.

Lane-changing probability is a parameter, which incorporates randomness in the lane-changing process. In this work, the lane-changing probability is set as 0.2, which is a typical value used in CA models for the lane-changing probability. Still, we fail to find any reference for determining some parameters in CAV driving, such as the lane-changing probability for CAVs. For these parts, we did not differ CAVs from regular vehicles in the modeling process.

Because of the lack of real data regarding the CAVs, the parameters required for the ACC process follow the ones in the study conducted by Kerner (2016). Specifically, T_{ACC} = 1.1 s with coefficients of ACC adaptation K_1 = 0.14 and K_2 = 0.9. $a_{\max}$= $b_{\max}$=3 m/s^2. Sensitivity analysis has also been conducted regarding *DR*, *CR*, and T_{ACC}, using different values in these parameters. Two different values of *DR* including 80 m and 160 m are applied in the sensitivity analysis of *DR*. Since the maximum velocity for CAV is determined by the value of *DR*, the sensitivity analysis regarding *DR* is just similar to simulation under different maximum velocity. The fundamental diagrams with different values in *DR* are presented in Appendix A. *CR* is the CAV connection range, which is used for providing speed information of other CAVs in the connection range, the fundamental diagrams with different values in *CR*, including 200 m and 400 m, are presented in Appendix B. There is little difference between the two cases with different *CR*, since the accuracy of this parameter is also determined by the CAV penetration rate simultaneously. Among these three parameters, T_{ACC} is the dominant one which defines how close CAV would keep in the car-following process, which also is a decisive factor on the road capacity. Two comparison

experiments are conducted simultaneously with T_{ACC} set as 0.8 s and 0.5 s, representing more advanced capabilities of the CAV.

The simulation is conducted 1 time at each discrete density value, each simulation lasts 20000 time steps, with the initial 10000 time steps eliminated to avoid transition effect. The random factor may affect the initial distribution of the vehicle fleet, but the general trend in the fundamental diagram from different simulations remains stable, which is illustrated in Appendix C. In the simulation, each time step corresponds to 1 s and the longitudinal distance of a cell corresponds to 0.5 m. P_{av} denotes the percentage of CAVs with respect to the total number of vehicles in the traffic flow. T_{ACC} denotes the desired net time gap in the adaptive cruise control (ACC) process of CAVs. A smaller value for T_{ACC} indicates CAV can keep a closer distance when following its preceding vehicle.

3.4 Numerical example

In this section, an example of a specific case is provided for a better understanding of the established model, which is also helpful in understanding the difference between modeling a CAV and a regular vehicle. The specific case is illustrated in Figure 3.1.

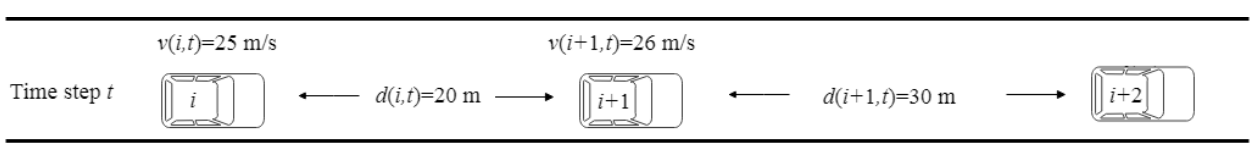


Figure 3.1 illustration of the demonstration case

The specific case is set as follows: At time step *t*, the velocity of vehicle *i* equals to 25 m/s, its

space gap equals to 20 m. The velocity of its preceding vehicle, vehicle i+1, equals to 26 m/s, and the space gap ahead vehicle i+1 equals to 30 m. In the following demonstration, two sceneries will be discussed based on the vehicle type of vehicle i.

If vehicle i is a regular vehicle, then in the deterministic speed update step, its expected velocity of the preceding vehicle v_{anti} = min (d_l, v_l+ a, $v_{\max}$) = min (30, 26.5, 27) = 26.5 m/s. Its anticipated space gap $d_{\text{anti}} = d$ + max ($v_{\text{anti}} - g_{\text{safety}}$, 0) = 20+max (26.5-10, 0) = 36.5 m. Its safe speed v_{safe} equals to 25 m/s, calculated by the equation (3). Then the update speed at time step t +1 of vehicle i v'_{det} = min(v+a, $v_{\max}$, d_{anti}, v_{safe}) =min(25.5, 27, 36.5, 25) = 25 m/s, regardless the stochastic deceleration for regular vehicle.

If vehicle i is a CAV, then its expected velocity of the preceding vehicle $v_{\text{anti}}^{\text{cav}}$ = min (d_l, v_l+ a, $v_{\max}$, v_{li}) = min (30, 26.5, 27, v_{li}) = min (26.5, v_{li}), where v_{li} denotes the average velocity of the preceding connected vehicles within the connection range. Here assume v_{li} = 25 m/s then $v_{\text{anti}}^{\text{cav}}$ = 25 m/s. Its anticipated space gap can be calculated by equation (4), which has different values based on the vehicle type of its preceding vehicle. If the preceding vehicle is a regular vehicle, then $d_{\text{anti}}^{\text{cav}}$= 44 m. If the preceding vehicle is a CAV, then $d_{\text{anti}}^{\text{cav}}$= 45 m. The safe speed calculated by equation (6) equals to 30.5 m/s. Besides, the acceleration rate of CAV is determined by the ACC model in equation (8) and equation (9), based on different values in T_{ACC}, the acceleration rate is different. Specifically, the acceleration rate equals to 0 m/s^2, 1 m/s^2, and 2 m/s^2 if T_{ACC} equals to 1.1 s, 0.8 s and 0.5 s, respectively. Thus the update speed at time step t +1 of vehicle i equals to 25

m/s, 26 m/s, and 27 m/s based on different T_{ACC} values, respectively.

Compare each value in the deterministic speed update equation (1), one can easily find the difference between modeling a CAV and modeling a regular vehicle. First, CAV can acquire more effective acceleration rate based on the ACC model, and it is deterministic driving, without the stochastic deceleration in modeling human-driven vehicles. Secondly, CAV has a larger anticipated space gap compared to its counterpart for regular vehicles. Thirdly, CAV has a higher safe speed, since CAV has the capability to react almost instantly, without the reaction time in human driving.

3.5 Empirical validation

The empirical dataset used to validate this study was presented by Next Generation Simulation (NGSIM, 2016), which was collected using double-loop detectors on eastbound Interstate 80 (I-80) freeway in the San Francisco Bay area in Emeryville, CA, on April 13, 2005. This data set provides 30-s processed, loop detector data. Speed (unit: feet/s), volume (unit: number) and occupancy (unit: percentage) at each detector for the 30-s time step is presented at each detector in each lane. A method proposed by Tian et al. (2015) was employed to obtain the effective single lane speed v_{ave}^{i} and flux f_{ave}^{i} over N lanes, which are given below.

$$v_{\mathrm{ave}}^{i} = \sum_{j=1}^{N} w_{ij}\, v_{ij}^{\mathrm{emp}},\ w_{ij} = \frac{f_{ij}^{\mathrm{emp}}}{\sum_{j''=1}^{N} f_{ij''}^{emp}},\ f_{\mathrm{ave}}^{i} = \frac{1}{N}\sum_{j=1}^{N} f_{ij}^{\mathrm{emp}} \tag{14}$$

Where f_{ij}^{emp} and v_{ij}^{emp} are the empirical flux and speed in lane j at detector station I.

I-80 is a five-lane freeway, with the left-most lane being a high-occupancy vehicle (HOV) lane. The traffic dynamic on the HOV lane is quite different from those in other lanes. Thus, to validate the extended model, only the data from lanes 2–5 were used. The loop detector data included in the dataset are separated by lanes. Since the heterogeneous flow model established in our work is a two-lane flow model. We cannot contain the empirical data directly in the validation process. In order to take into account the passing behavior, we obtain the effective single-lane data from each two of the original five lanes. Specifically, effective single-lane data from lanes 2–3 and lanes 4–5 are used to validate the extended two-lane model. This method can reduce the difference of the data from different lanes on the freeway segment while preserve lane-changing information in the averaged two-lane data.

Figure 3.2 presents the road structure of I-80. Specifically, the data sets measured by loop detectors from station 6 and 4 are applied as the inflow and outflow boundary conditions. The detector in station 5 measures the simulated speed time series and compared with the real data. Tian et al. provided specific simulation setup information (Tian et al. 2015).

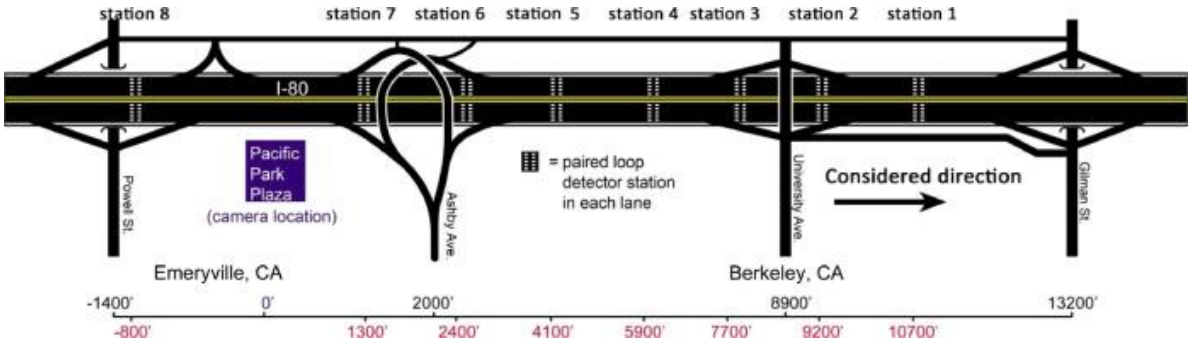
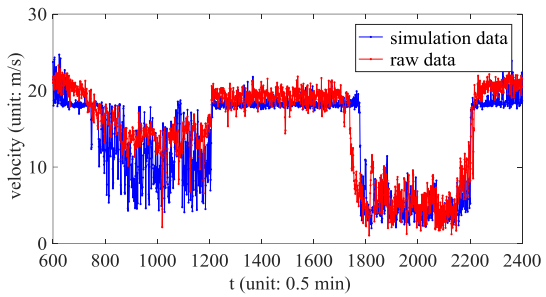


Figure 3.2 Sketch of I-80 near Berkeley (Tian et al. 2015)

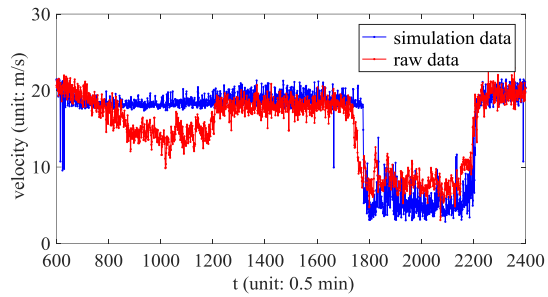
Figure 3.3 presents comparisons of speed–time series between simulation results and empirical data. Red curves are computed using Eq. (14) from real data. Blue curves indicate simulation results obtained with the extended model. (a) and (b) are results of the simulated two lanes under condition of no passing behavior. (c) and (d) with passing behaviors. (a) and (c) indicate the left lane, (b) and (d) indicate the right lane. The speed–time series of the real data, indicated in red in Figure 3.1, shows a typical pattern of highway-traffic flow during a particular day, wherein a decrease in speed is observed during the peak hours of the morning and traffic breakdown during the evening peak hours. The original TSM was proved to have the capability of reproducing the lane-average speed–time series through simulation as observed in the study by Tian et al. (2015). However, the speed–time series of each lane are different, i.e., the average speed in the lanes decreases from the left to right. As a single-lane flow model, the TSM is not able to incorporate the passing behaviors, which are common practice in real traffic flow. This study confirms that the TSM can be extended to a multi-lane flow model by applying the lane-changing model and setting specific speed limits for each lane based on the empirical data. Figure 3.3 (a) and Figure 3.3 (b) show the simulation results without the passing behavior, which is unsuitable compared to that seen in Figure 3.3 (c) and Figure 3.3 (d), wherein the passing behaviors are incorporated.

In this section, the simulation result shows that the performance of the extended traffic-flow model is in good agreement with the real traffic data. Thus proving the effectiveness of the

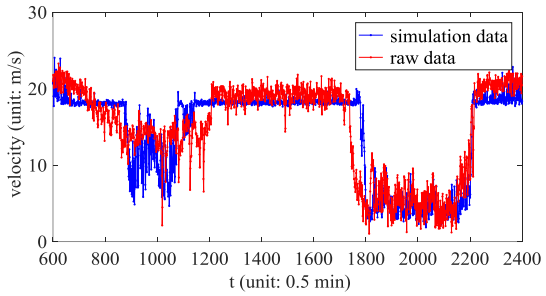
extended two-lane model. With its capacity of representing the real traffic dynamics of manual driving vehicles, this model is further used in simulating the heterogeneous flow including the CAVs to study the possible impact of the CAVs.



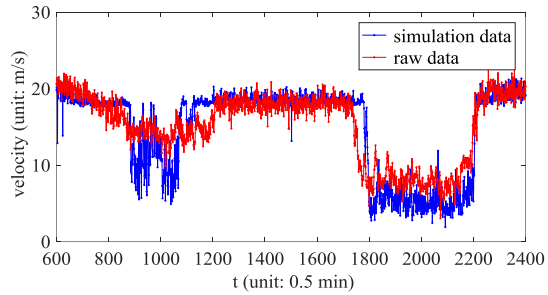
(a) Speed-time series on left lane without lane-changing



(b) Speed-time series on right lane without lane-changing



(c) Speed-time series on left lane with lane-changing



(d) Speed-time series on right lane with lane-changing

Figure 3.3 Validation of the two-lane TSM

CHAPTER 4

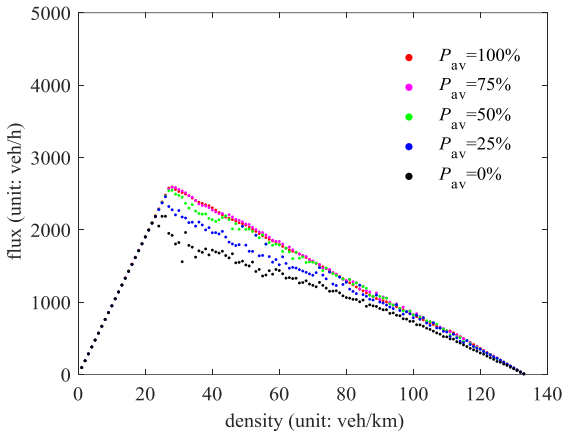
Evaluation

4.1 Introduction

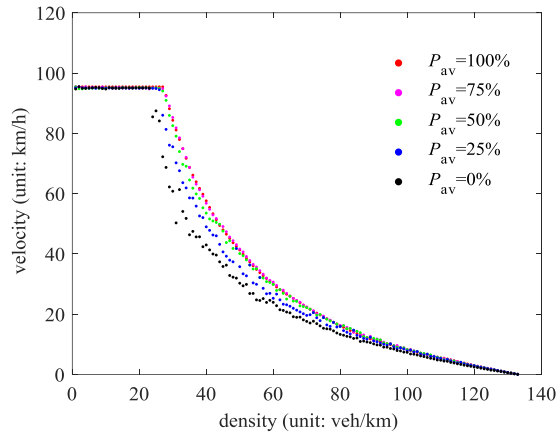
This chapter introduces the simulation results. The impact of CAV on capacity, safety, and fuel consumption is investigated and discussed. The simulation was conducted under periodic boundary. P_{av} denotes the percentage of the CAVs with respect to the total number of vehicles in the traffic flow.

4.2 Impact of CAV on capacity

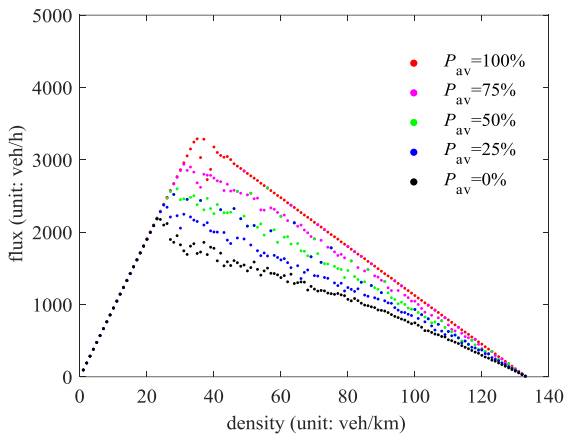
Figure 4.1 shows the relationship of the traffic flow and velocity with respect to the density under different penetration rates of autonomous vehicle P_{av} with T_{ACC} = 1.1 s (a, b), 0.8 s (c, d), and 0.5 s (e, f). First, the traffic flow increases linearly until it reaches the road capacity. Subsequently, the flow declines with further increase in the density. The diagram can be divided into two parts: the free-flow phase and congested-flow phase. The maximum flow rates, shown in Figure 4.1 (a), (c), and (e), help in reflecting the road capacity. Under different P_{av}, the road capacity varies. In other words, a higher penetration rate P_{av} corresponds to a higher capacity, indicating that the presence of CAVs can increase the road capacity. In the free-flow phase, the effect of the CAVs on the performance of the system is insignificant. The conventional vehicles



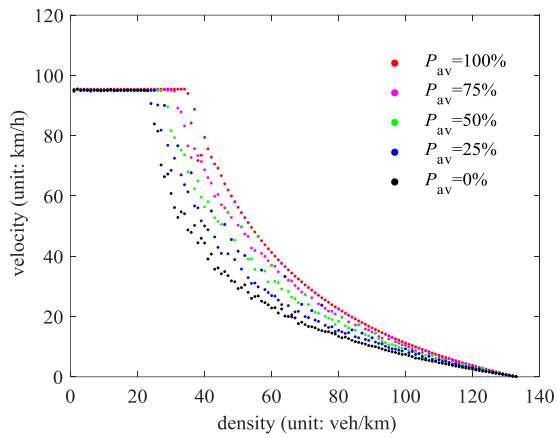
(a) Flow-density diagram with T_{ACC} = 1.1 s



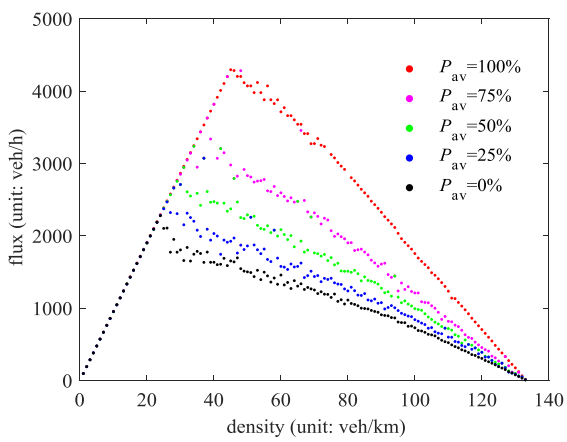
(b) Velocity-density diagram with T_{ACC} = 1.1 s



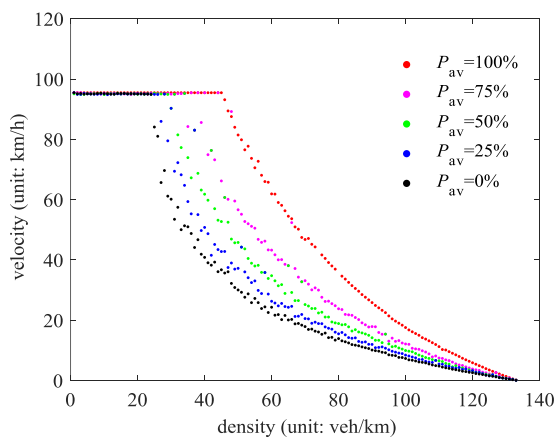
(c) Flow-density diagram with T_{ACC} = 0.8 s



(d) Velocity-density diagram with T_{ACC} = 0.8 s



(e) Flow-density diagram with T_{ACC} = 0.5 s



(f) Velocity-density diagram with T_{ACC} = 0.5 s

Figure 4.1 Flow-density diagrams and speed-density diagrams

and CAVs are able to operate at maximum velocity, without interacting with other vehicles. In the congestion phase, the CAVs are more advantageous than the conventional vehicles. A smaller gap between a CAV and its preceding vehicle could be achieved, further increasing the road capacity. Moreover, situations with a higher penetration rate P_{av} results in a longer free-flow phase, which is a direct effect of the increased road capacity.

Comparing the results of Figure 4.1 (a) and Figure 4.1 (b) with those of Figure 4.1 (c) and Figure 4.1 (d) and Figure 4.1 (e) and Figure 4.1 (f), we can find that the capability of the CAVs in terms of the desired net time gap plays a decisive role in the process, which can be understood easily. When it comes to connectivity, it is not so plausible that connectivity results in an increase in the capacity directly. Since the increase in capacity is largely based on the improvement of individual vehicle performance, in terms of a decrease in the average time gaps. Still, connectivity actually is a part of the reason that contributes to the decreased average time gaps and helps to avoid potential crashes at the same time. Further improving the capability of the CAVs compared to the conventional vehicles will lead to a greater improvement in the road capacity. However, the growth pattern in each situation seems different.

Figure 4.2 shows the relation between road capacity and CAV-penetration rate under the three situations with various T_{ACC} values. The figure shows that the increase in the road capacity is different for different T_{ACC} values. Before the CAV-penetration rate reaches a rate of 30%, the road capacity increases gradually. The effect of the difference in the CAV capability on the capacity

growth rate is negligible. At this stage, with CAVs being the minority in the heterogeneous flow, the connected condition is rarely fulfilled, and only autonomous driving is fully realized. As conventional vehicles are in majority, the increase in the road capacity resulting from the CAVs is limited. When the CAV-penetration rate exceeds 30%, the growth rate is largely decided by the improved capability of the CAVs in the ACC compared to conventional vehicles. An improved capability corresponds to a higher capacity growth rate and a higher road capacity.

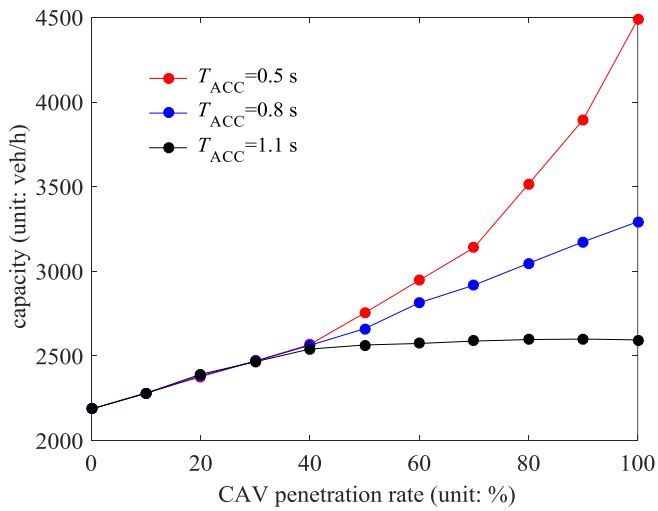


Figure 4.2 Relationship between road capacity and CAV-penetration rate

4.3 Impact of CAV on safety

4.3.1 Safety assessment

The model for modeling the mixed traffic flow is a rule-based CA model, which is discrete in both time and space. In the simulation, the model does not produce any crashes. Thus, the model cannot be used to measure crashes or traffic safety directly. This work adopted three rules to measure the number of dangerous situation that occurred during the simulation as an indicator for

traffic safety evaluation (Boccara et al., 1997). $d(i, t)$ indicates the space gap ahead of vehicle i at time step t and $v(i, t)$ indicates its velocity. In the model, all variables are integers and measured by units of the cell length. Each cell corresponds to a longitudinal length of 0.5 m. The time step in the simulation equals to 1 s. Thus, at each time step, a vehicle will move forward by a distance of its current speed. The speed of the vehicle in the simulation can be varied at a step of 0.5 m/s.

(1) $d(i, t) < v(i, t)$, indicating that the space between vehicle i and its predecessor vehicle i+1 is smaller than the current velocity, which means vehicle i could reach the position of its predecessor by the next time step.

(2) $v(i+1, t) > 0$, indicating that vehicle i+1is moving at time step t.

(3) $v(i+1, t+1) = 0$, indicating that vehicle i+1 will stop abruptly at time t+1.

Figure 4.3 shows the schematic illustration of an occasion described by the aforementioned three rules. The following vehicle is stopped due to a sudden stop made by its preceding vehicle. The phenomenon of sudden stops is very common in traffic oscillations and stop-and-go traffic flow. Traffic breakdown can be induced by individual vehicle's sudden brakes or stops. By measuring the number of aggressive stops in the traffic flow, possible insight could be shed into the mixed traffic flow dynamics and foster a deeper understanding of the impact of CAV on traffic safety at varying degree of penetration rates. Note that these rules are applied when the corresponding simulation is finished, and recorded time-space information of all individual vehicles during the simulation period is available. If the three conditions are satisfied

simultaneously, a rear-end accident may occur. The frequency of such occasion is calculated and considered as a negative sign of safety where a potential crash may occur, denoted as N (times/km/h).

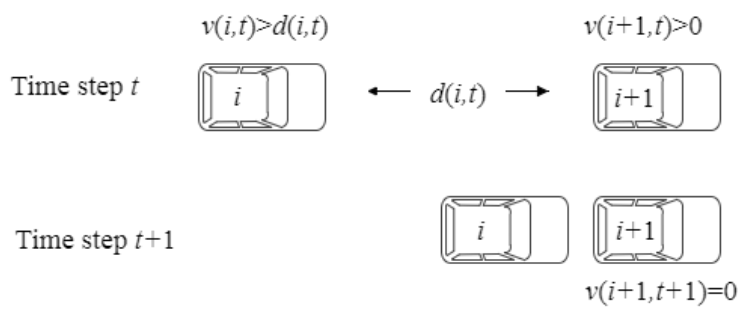


Figure 4.3 Schematic illustration of the rules for detecting dangerous situation

The second indicator for evaluating safety impact is the time-to-collision (TTC) (Minderhoud and Bovy, 2001). The time-to-collision is defined as the time that remains until a collision could occur if two successive vehicles maintain a speed difference, which has been applied in several studies for identifying safety impacts (Rahman and Abdel-Aty, 2018). The time-to-collision of vehicle i with respect to a leading vehicle i+1 at time step t can be calculated with:

$$TTC(i,t) = \frac{d(i,t)}{v(i,t)-v(i+1,t)} \qquad \forall v(i,t) > v(i+1,t) \tag{15}$$

Where $d(i, t)$ and $v(i, t)$ denote the real space gap and the speed of vehicle i at time step t, respectively. A time-to-collision can only be calculated when a positive speed difference exists between two successive vehicles.

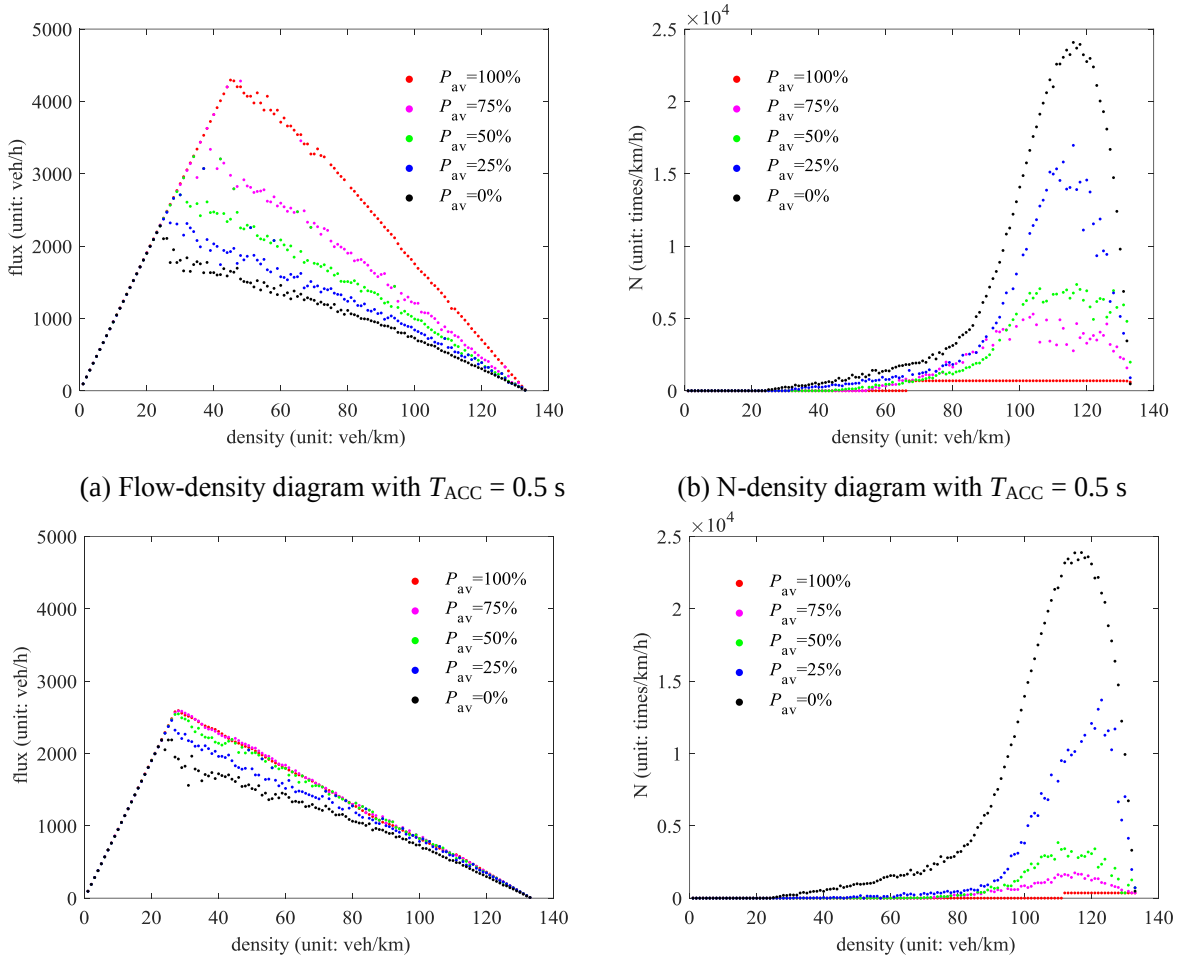
Besides, acceleration rates of vehicles in the mixed traffic flow and velocity difference between successive vehicles can be used to indicate to which extent the mixed traffic flow is

smoothed under various CAV penetration rates. A smoother traffic flow will contribute to a safer traffic system.

4.3.2 Simulation results and discussion

Figure 4.4 shows the relationship of road capacity, the frequency of aggressive vehicle stop with regard to density under various penetration rates of autonomous vehicle P_{av}, with T_{ACC} =0.5 s (a, b), 1.1 s (c, d) respectively. Five cases under various CAV penetration rates are included in each scenario. From Figure 4.4 (a, c) we can directly observe that a smaller T_{ACC} value and a higher penetration rate of CAV corresponds to a higher gain in road capacity. Capacity is equivalent to the maximal flow rate attained in the free flow phase. It is understandable that a smaller desired net time gap attained by CAVs contributes a larger improvement in capacity. Since CAVs can drive more closely within the traffic flow, and a larger penetration rate of CAV in the mixed flow reinforces this process. Figure 4.4 (b, d) indicates that the introduction of CAVs in the mixed flow would be beneficial for traffic safety. Under both cases, even with a different parameter in the desired net time gap, the frequency of aggressive stop decreases with the increase in the CAV penetration rate within the mixed flow. The system will attain a considerable gain in terms of safety when CAV penetration rate reaches 25%, and this effect is much more evident when CAVs are under a more cautious strategy in the ACC process. The difference between the two cases indicates that a more cautious strategy in the ACC performance would contribute to a greater improvement in traffic safety. The simulation results indicate that in the coming future, the trade-off between

capacity gain and safety improvement needs to be taken into account in the deployment of CAV technology.



(a) Flow-density diagram with T_{ACC} = 0.5 s

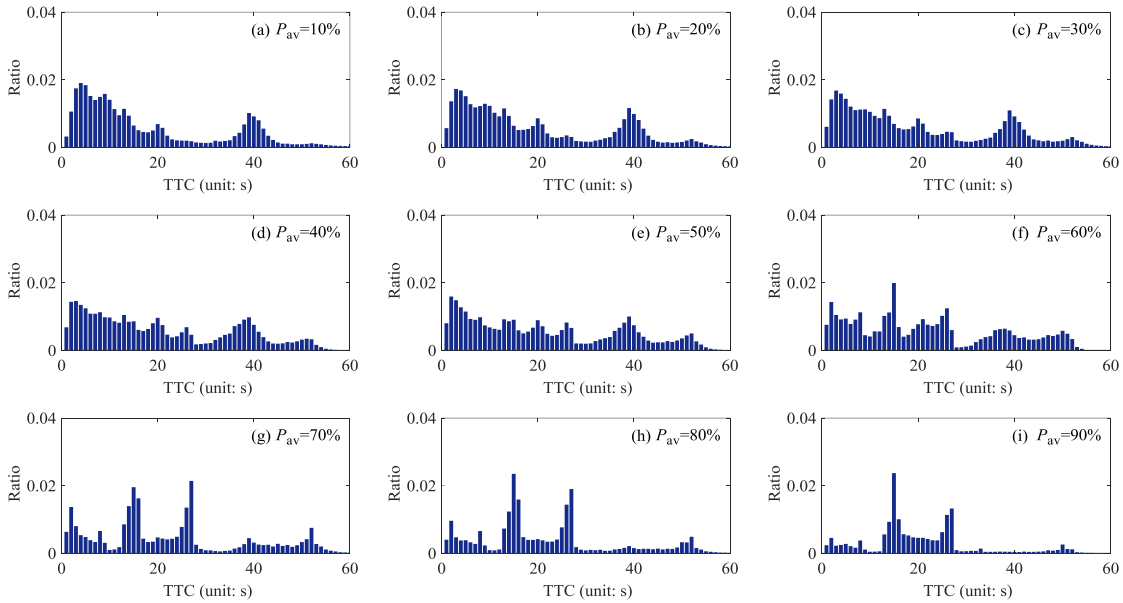
(b) N-density diagram with T_{ACC} = 0.5 s

(c) Flow-density diagram with T_{ACC} = 1.1 s

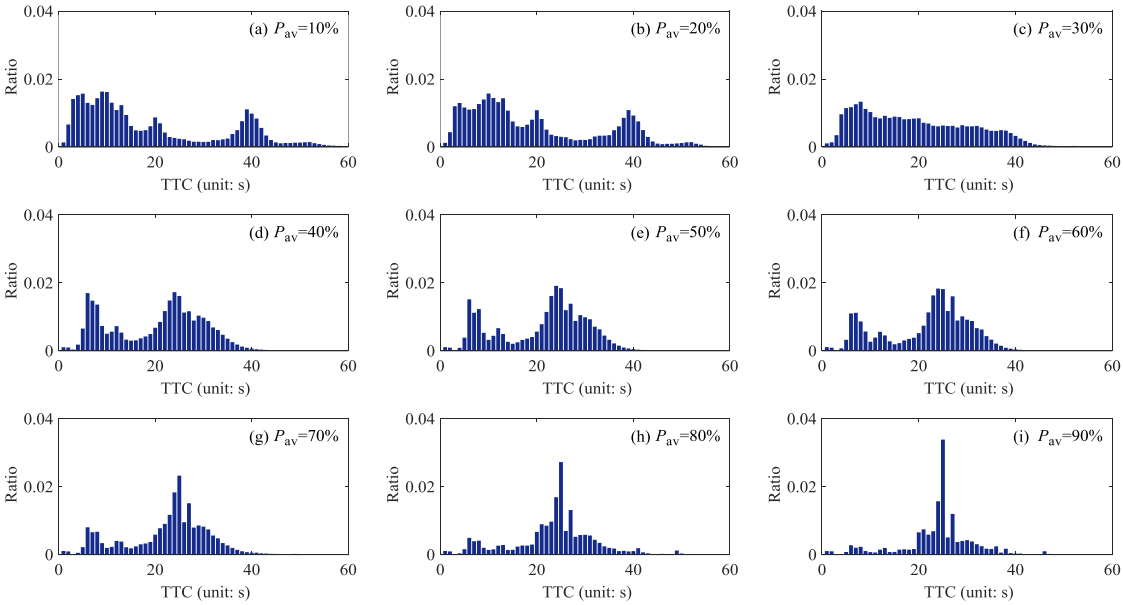
(d) N-density diagram with T_{ACC} =1.1 s

Figure 4.4 Flow-density diagram and relation between frequency of aggressive vehicle stop and density

Figure 4.5 presents the time-to-collision distributions of two cases with different T_{ACC} values, with penetration rates of autonomous vehicle P_{av} range from 10% to 90%, T_{ACC} =0.5 s (a) and 1.1s (b), density equals to 50 veh/km/lane. The ratio of low *TTC*, namely the most left region in the plot, represents the negative effect on traffic safety, which indicates a crash is likely to occur if the



(a) Time-to-collision distributions with T_{ACC} =0.5 s



(b) Time-to-collision distributions with T_{ACC} =1.1 s

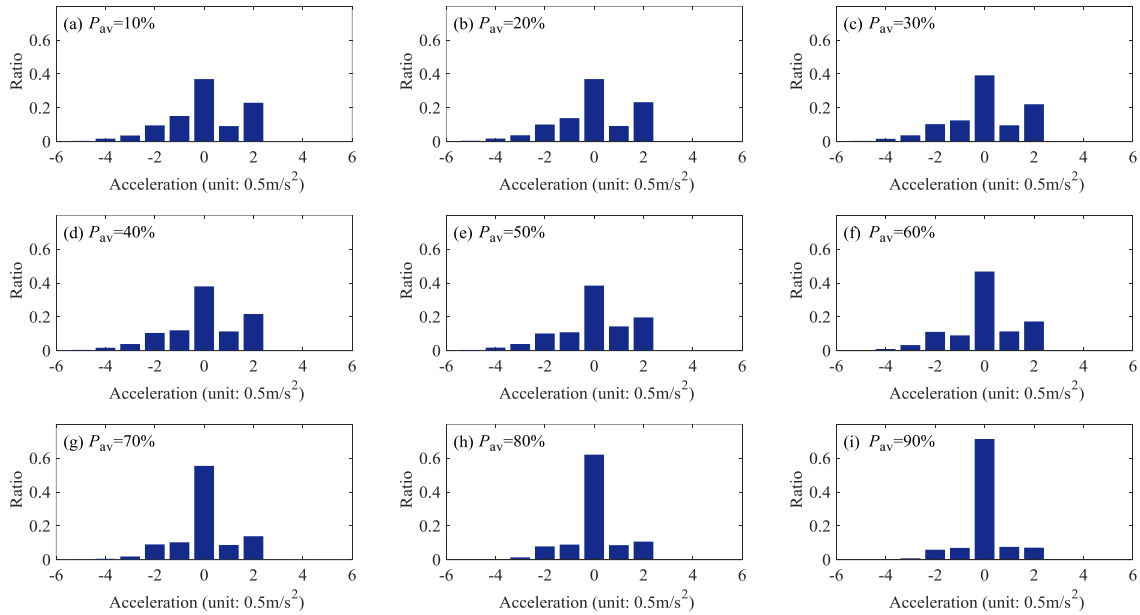
Figure 4.5 Time-to-collision distributions of two cases with different T_{ACC}

vehicle is not operated properly under such cases. In contrast, a higher *TTC* indicates the positive performance. In the first case (T_{ACC} =0.5 s), improvement is not noticeable at a low CAV penetration rate. Significant improvement on safety can only be observed when CAV reached a

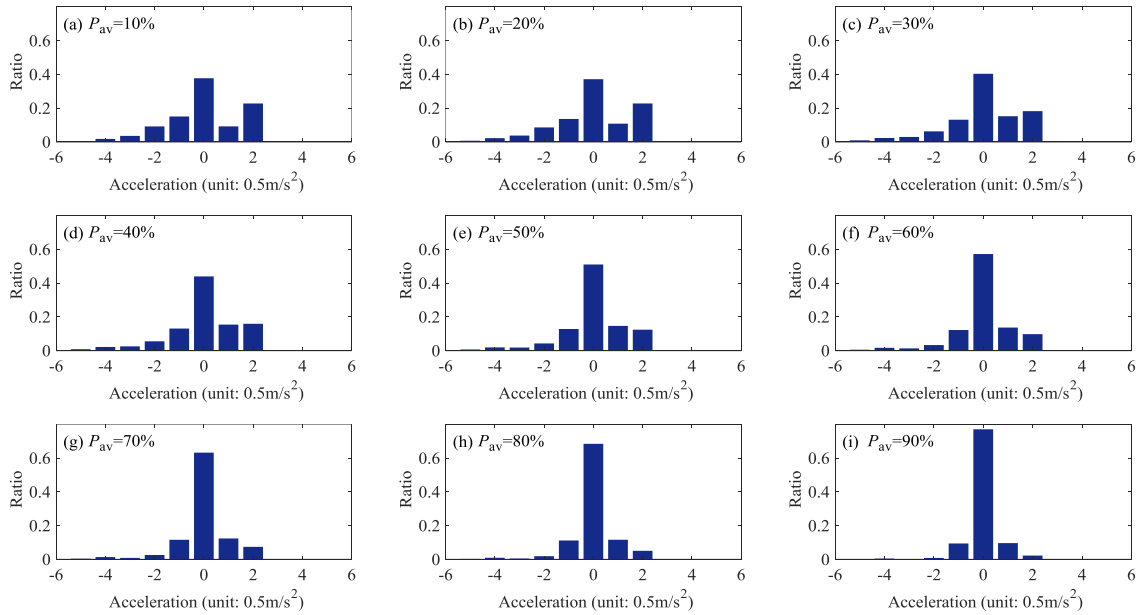
major component in the mixed flow. While in the latter case (T_{ACC} =1.1 s), improvement in safety can be observed even CAVs at a relatively lower penetration rate. The difference between the aforementioned two cases indicates that the performance in CAV driving actually has a direct impact on the evaluation of safety effect on the mixed traffic flow. A more cautious strategy on the CAV driving would possess a greater benefit on traffic safety at the beginning of introducing CAVs in the current traffic system. Besides, we can also observe that with the increase in CAV penetration rate, the ratio of large *TTC* values also decreases a lot. Under a lower CAV penetration rate, the traffic flow presents a stop-and-go pattern, which means that both large *TTC* values and small *TTC* values coexist in the system. Large *TTC* values mainly come from the downstream front of traffic wave and small *TTC* values come from the upstream side of the wave. With the increase in CAV penetration rate, traffic flow tends to be smoother, the gap space difference and the speed difference between vehicles are decreased, which results in a decrease in the ratio of both large *TTC* and small *TTC* values.

Figure 4.6 presents acceleration rate distributions of two cases with different T_{ACC} values, with P_{av} from 10% to 90%, T_{ACC} =0.5 s (a) and 1. 1s (b), density equals to 50 veh/km/lane. Under both cases, a gradual increase in the ratio of the acceleration rate 0 can be easily found, which indicates that the introduction of CAV would boost the portion of smooth driving within the mixed traffic flow. With the increase in CAV penetration rate, the ratio of high deceleration rate is also decreased, which indicates that a smoother traffic flow can be attained. Comparing the results from two cases,

we can find that the results of the latter case with a higher T_{ACC} value is better than the first case with a lower T_{ACC} value. This indicates that a more cautious car-following strategy of the CAV would contribute to a greater benefit on smoothing the traffic flow.



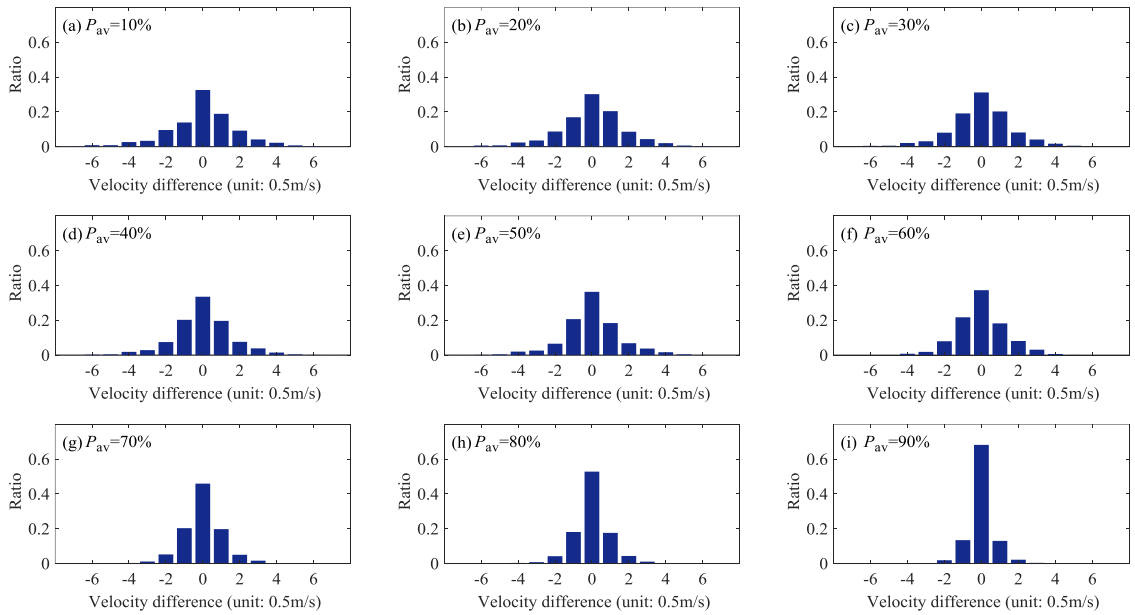
(a) Acceleration rate distributions with T_{ACC} =0.5 s



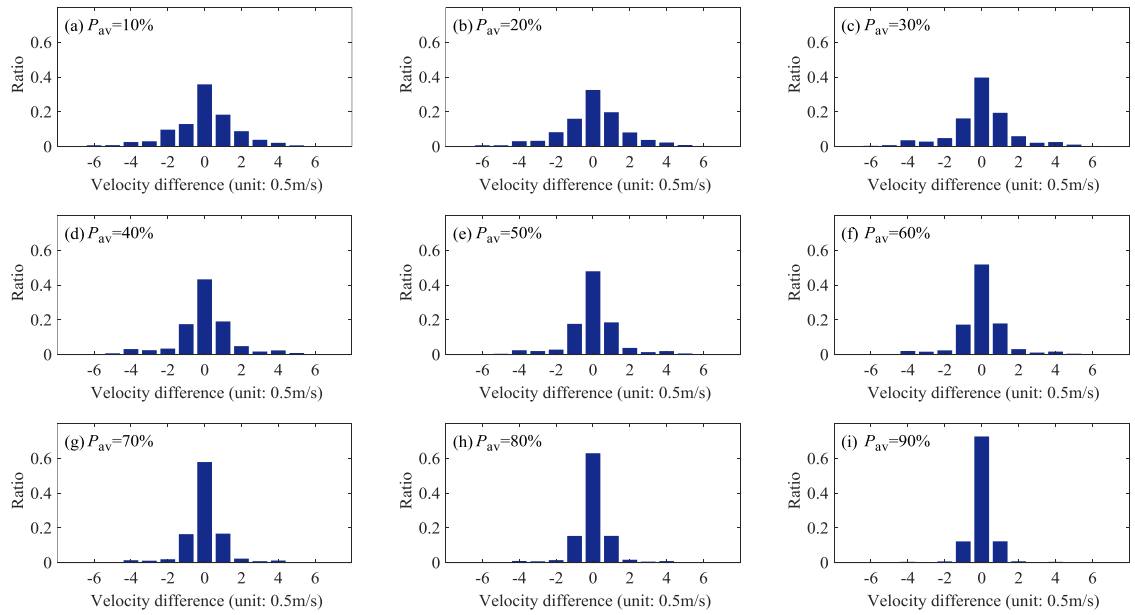
(b) Acceleration rate distributions with T_{ACC} =1.1 s

Figure 4.6 Acceleration rate distributions of two cases with different T_{ACC}

Figure 4.7 presents velocity difference distributions of the aforementioned two cases, T_{ACC} =0.5 s (a) and 1. 1s (b), density equals to 50 veh/km/lane. The distribution shows the difference in



(a) Velocity difference distributions with T_{ACC} =0.5 s

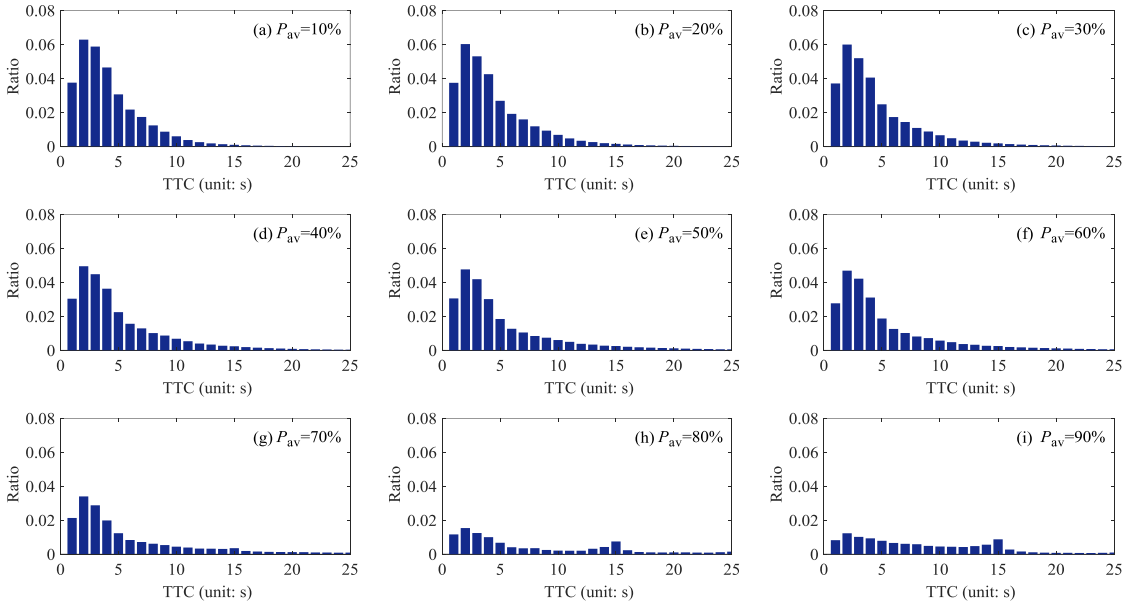


(b) Velocity difference distributions with T_{ACC} =1.1 s

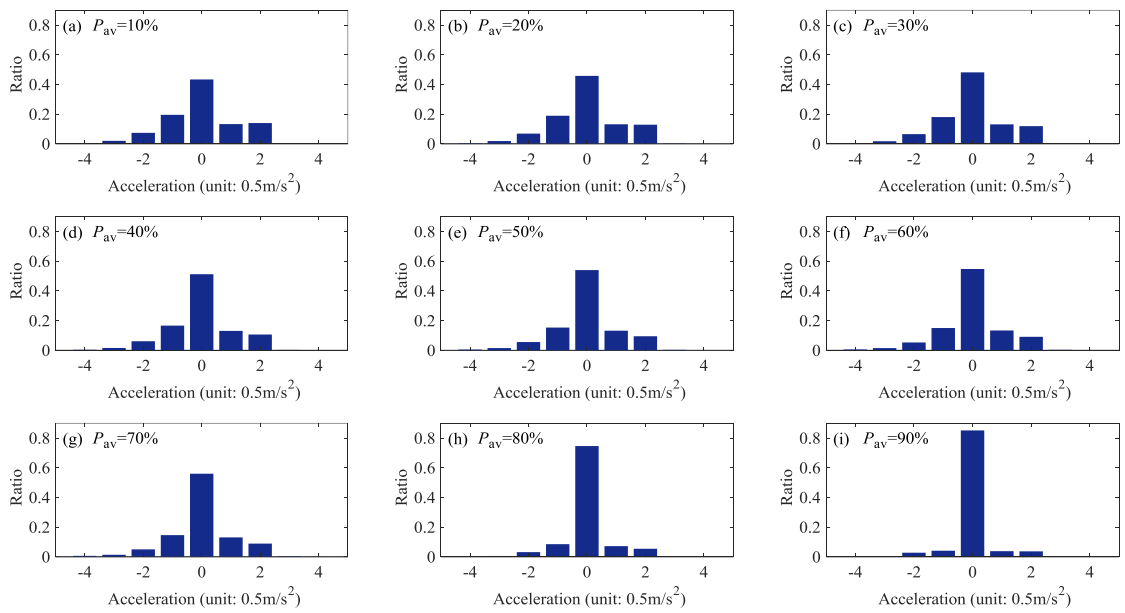
Figure 4.7 Velocity difference distributions of two cases with different T_{ACC}

velocity between each vehicle and its leading vehicle during the simulation period. In general, the velocity difference follows a bell-shaped distribution. However, the shape of the distribution evolves with the increase in the CAV penetration rate in the mixed traffic flow. Under a low CAV penetration rate of 10%, the distribution presents a bell shape with a lower peak and covers a wide range. With the CAV penetration rate increase, the ratio of velocity difference of 0 gradually increase, and the shape of the distribution evolves to a higher peak within a narrow range. The velocity difference has a tendency to cluster around the value of 0. This phenomenon suggests that with the increase in the CAV penetration rate, the velocity difference between vehicles is decreased and traffic flow is smoothed.

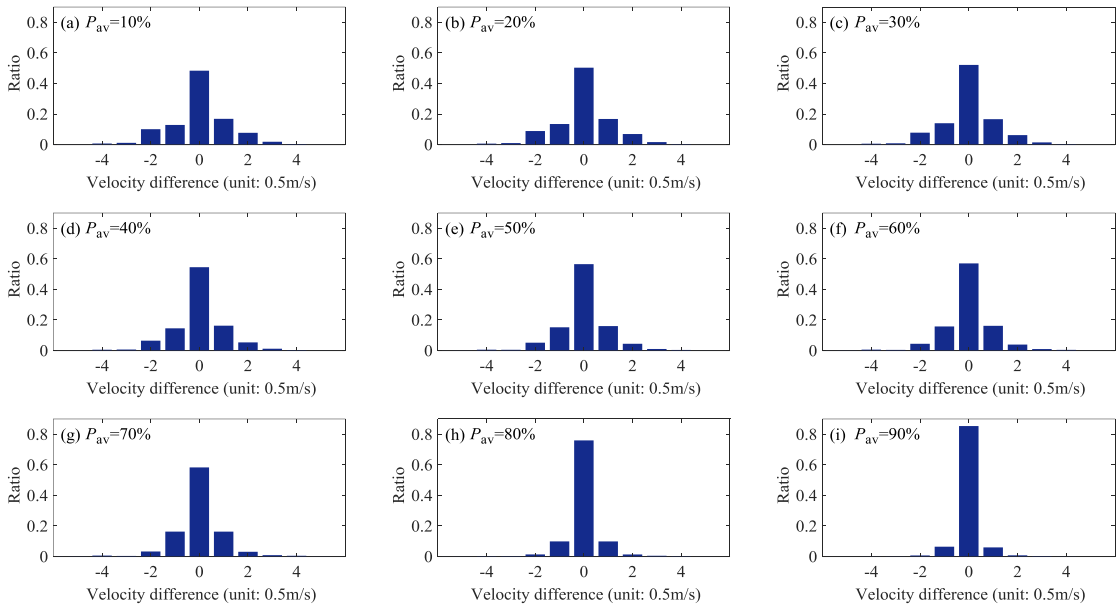
Besides, simulation results were obtained at a different demand level, with density equals to 100 veh/km/lane, T_{ACC} =0.5 s. Figure 4.8 presents the time-to-collision distributions, acceleration rate and velocity difference distributions, respectively. Results show a similar pattern with the aforementioned cases.



(a) Time-to-collision distributions with T_{ACC} =0.5 s, density=100 veh/km/lane



(b) Acceleration rate distributions with T_{ACC} =0.5 s, density=100 veh/km/lane

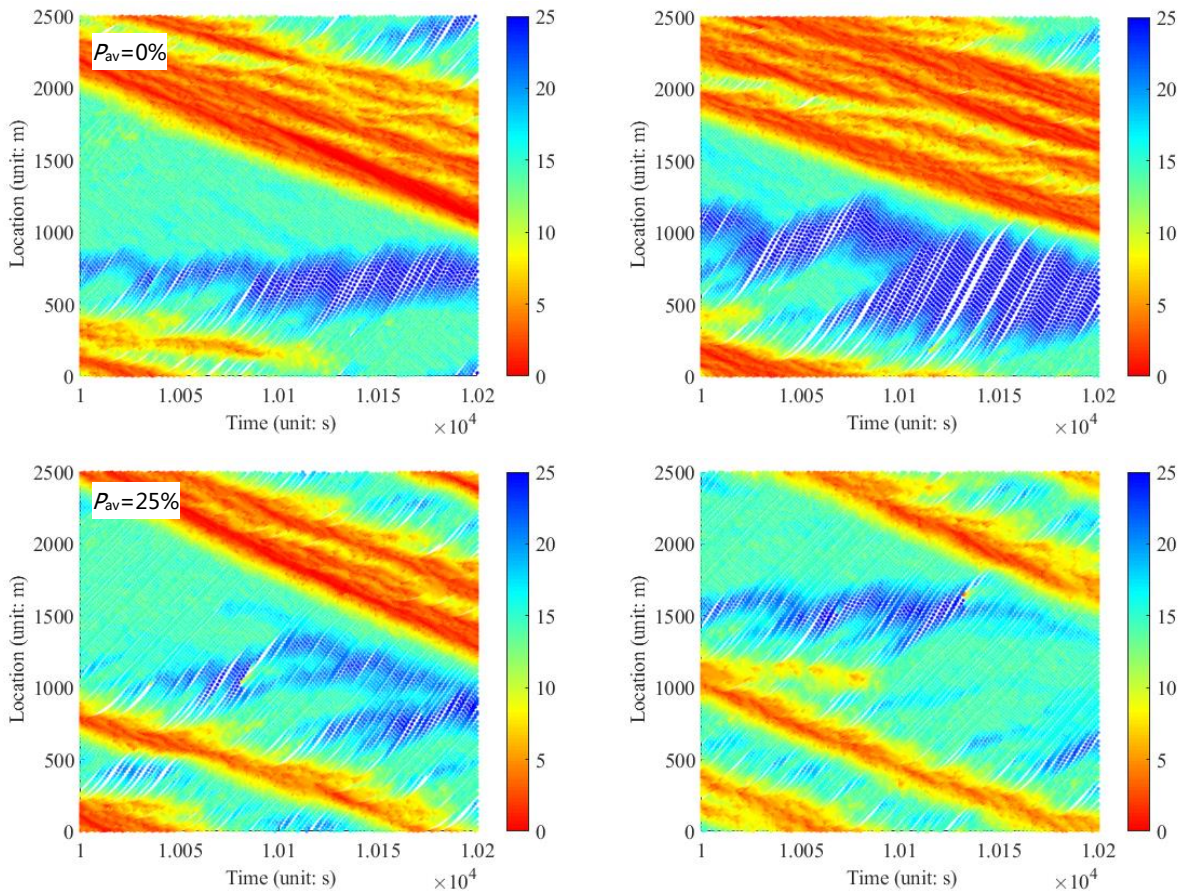


(c) Velocity difference distributions with T_{ACC} =0.5 s, density=100 veh/km/lane

Figure 4.8 Time-to-collision, acceleration rate, and velocity difference distributions under a different density

Figure 4.9 and Figure 4.10 show the spatiotemporal diagrams of two cases, with T_{ACC} set at 0.5 s and 1.1 s respectively. Density equals to 50 veh/km/lane. Left row is lane 1 and right is lane 2. The color bar indicates velocity. Under each case, different CAV penetration rates P_{av} including 0%, 25%, 50% and 75% are included to show how mixed traffic flow dynamics would evolve with the gradual adoption of CAV within the mixed traffic flow. At 0% CAV penetration rate and at a density of 50 veh/km/lane, typical go-and-stop traffic waves that travel backward along the road can be observed directly. With the introduction of CAVs, traffic waves gradually eased with the increase in the CAV penetration rate. At a CAV penetration rate of 25%, the scale of traffic waves is slightly dampened. When the CAV penetration rate reaches a rate of 50%, in the first case, the traffic waves have already been dissipated. While in the latter case, with a higher T_{ACC} value in the

CAV following process, the remaining dissipated traffic wave still can be observed. This phenomenon indicates that both the CAV penetration rate and the performance of CAV are the important factors shaping the future mixed traffic flow dynamics. In the first case, when the CAV penetration rate reaches a rate of 75%, part of the mixed flow recovered to a free flow state, while in the second case, there is no such effect. The aforementioned two cases revealed possible evolution pattern in the mixed traffic flow dynamics after the introduction of CAVs under current traffic system.



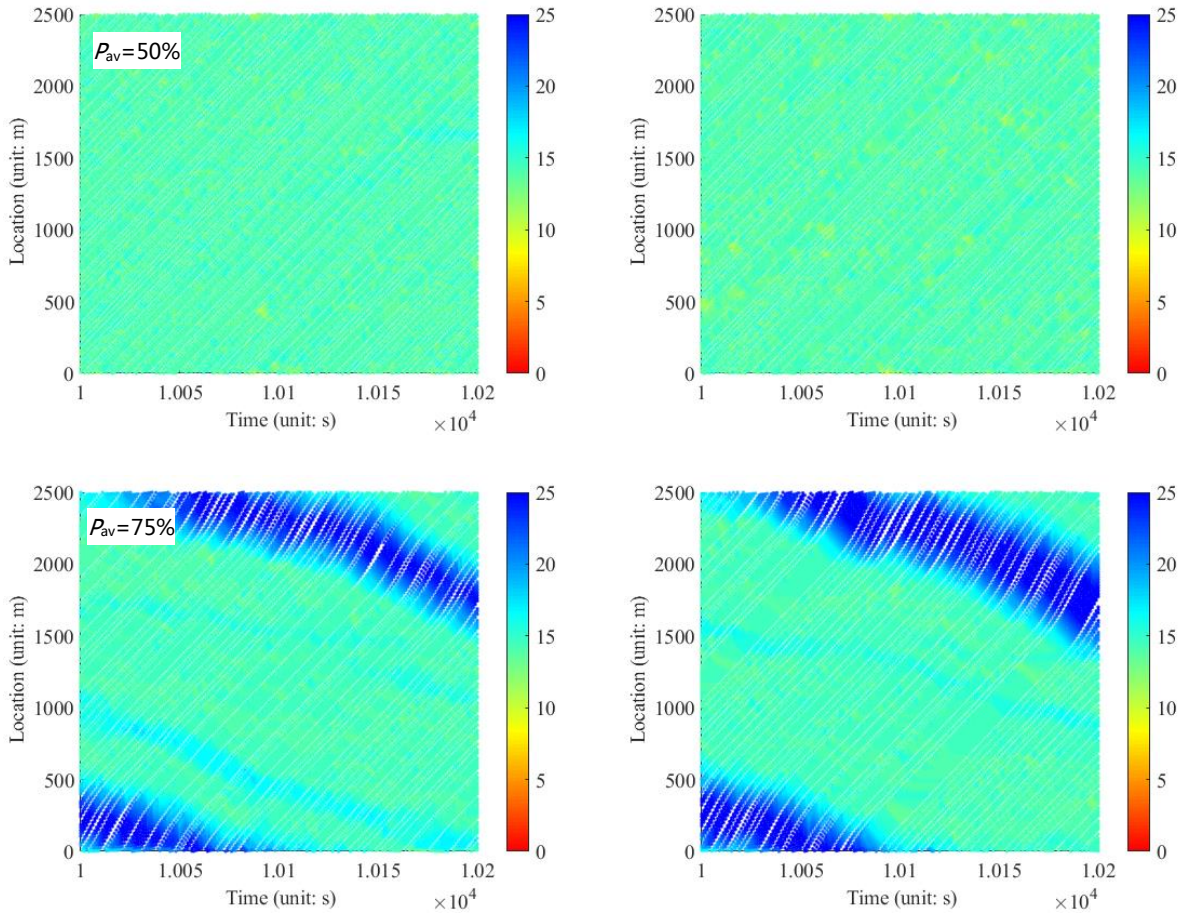
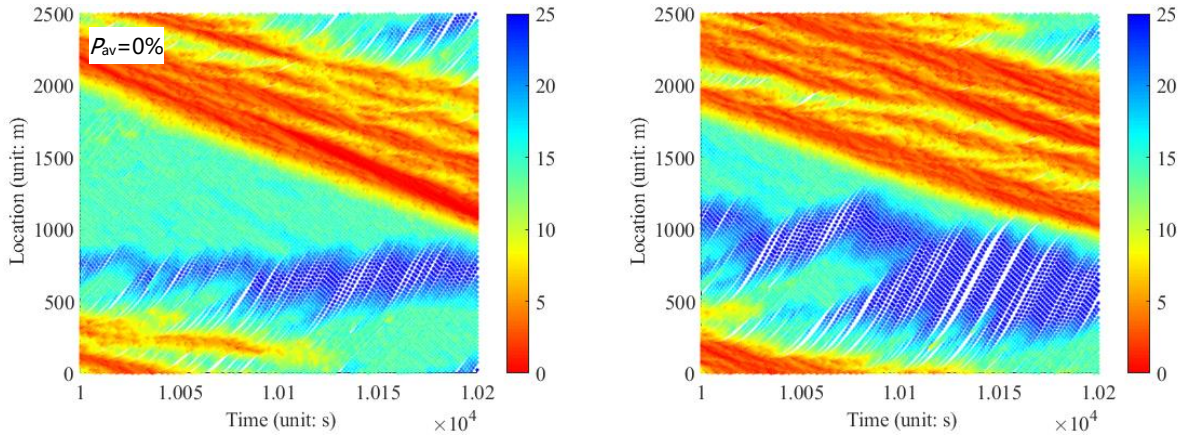


Figure 4.9 Spatiotemporal diagrams with T_{ACC} equals to 0.5 s



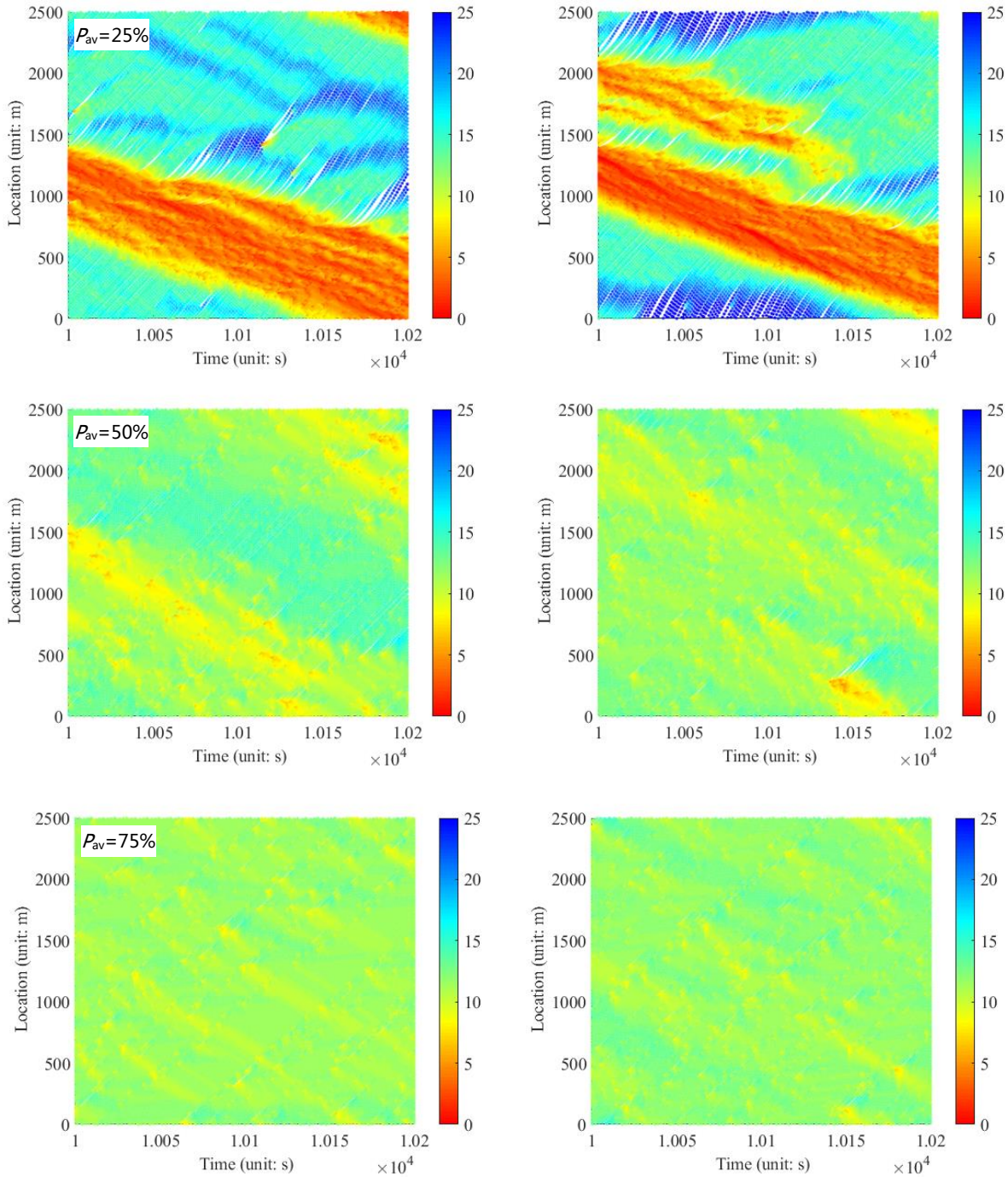


Figure 4.10 Spatiotemporal diagrams with T_{ACC} equals to 1.1 s

4.4 Impact of CAV on energy consumption

This part presents the fuel consumption and emission model that integrated into the heterogeneous flow model (Akcelik and Besley, 2003). The instantaneous speed and acceleration properties of vehicles in the simulated mixed flow are used to evaluate fuel consumption and emissions of the entire system. The evaluation presented in the following section is based on the assumption that all the vehicles including both CAVs and conventional vehicles are gasoline vehicles. Although CAVs might well be electronic vehicles, conventional vehicles also may include electronic vehicle, in order to compare the simulation results of the mixed traffic flow, both CAVs and conventional vehicles are assumed as gasoline vehicles.

4.4.1 Fuel consumption and dissipation model

The fuel consumption rate $F(i, t)$ and fuel dissipation rate $d(i, t)$, for an arbitrary vehicle i at time step t, is defined as follows,

$$F(i,t) = \begin{cases} [\alpha + \beta_1 R_T v + (\beta_2 M_v a^2/1000)_{a>0}]\Delta t, \text{ for } R_T > 0 \\ \alpha \Delta t, \text{for } R_T \leq 0 \end{cases} \tag{16}$$

Where α is the constant idle fuel rate (mL /s), which applies during all modes of driving (estimation of fuel for maintaining engine operation). β_1 is the efficiency parameter which relates fuel consumed to the energy provided by the engine, i.e., fuel consumption per unit of energy (mL/kJ). R_T is the total tractive force (kN) required to drive the vehicle, which is the sum of rolling resistance (F_f), air drag force (F_w), cornering resistance, inertia force (F_j) and grade force. v denotes instantaneous speed (m/s). β_2 is the efficiency parameter which relates fuel

consumed during positive acceleration to the product of inertia energy and acceleration, i.e. fuel consumption per unit of energy (mL/(kJ·m/s^2)). M_v is the vehicle mass (kg) including occupants and any other load, average vehicle mass for light vehicles is adopted in this study. a is instantaneous acceleration rate (m/s^2), negative for deceleration. Δt is the time step in the simulation, which equals to 1 s.

In this study, vehicle turning and road gradient are not considered, the total traction force can be calculated as the following equation (Yang et al. 2009):

$$R_T = F_f + F_w + F_j = M_v g f + \frac{1}{2} C_D A \rho u_r^2 + \delta M_v a \tag{17}$$

Where $f = 0.01\left(1 + \frac{v}{44.73}\right)$ is the rolling friction coefficient. C_D is the air resistance coefficient. A is the vehicle frontal area. ρ is the air density which can be regarded as a fixed constant. u_r is the relative velocity of the vehicle and air, $u_r \approx v$ is adopted in this work. δ is the rotating mass inertia factor.

Dissipation was considered only in the deceleration scenario. Since deceleration (i.e. rolling resistance and brake) results in the dissipation of unexpected energy. The dissipation rate d (i, t) is defined as follows (Pan et al. 2018),

$$d(i,t) = \begin{cases} F(i,t-1) - F(i,t), & for \;\; v(i,t) < v(i,t-1) \\ 0, & other \end{cases} \tag{18}$$

Table 4.1 lists the parameters along with typical values evolved in the fuel consumption and dissipation model.

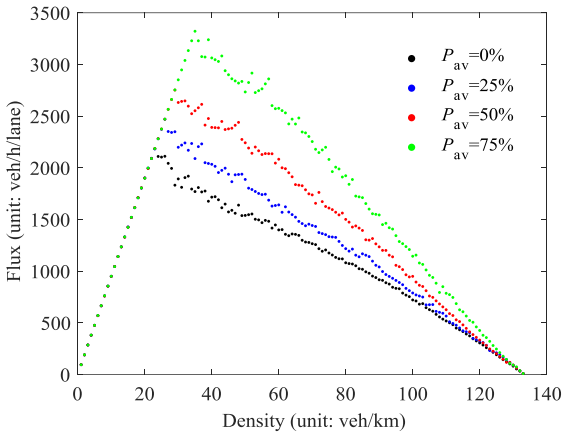
Table 4.1 Parameters for the fuel consumption and emission model

Notation	Description	Typical values
α	Constant idle fuel rate (mL/h)	1350
M_v	Loaded vehicle mass (kg)	1400
g	Gravity of Earth (N/kg)	9.8
C_D	Air resistance coefficient	0.54
A	frontal area (m^2)	2.1
ρ	Air density at 20℃(kg/m^3)	1.205
δ	rotating mass inertia factor	1.1

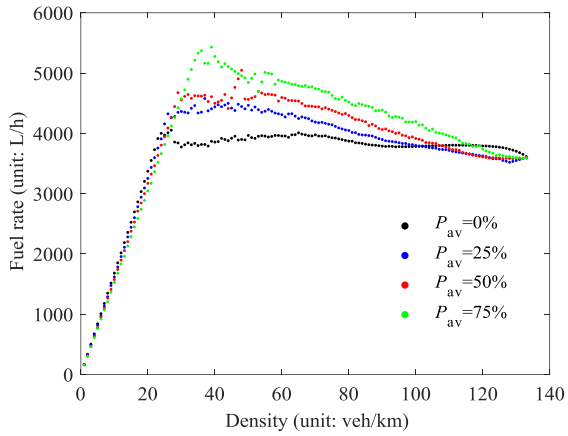
4.4.2 Simulation results and discussion

Figure 4.11 presents the relationship of flow rate (a), fuel rate (b), fuel dissipation rate and fuel rate per kilometers with regard to density under various penetration rates of autonomous vehicle P_{av} with T_{ACC} =0.5 s. Figure 4.11 (a) presents the flow-density diagram. With the increase in the CAV penetration rate, the capacity, namely the maximal flow rate, is increased. The case with a higher CAV penetration rate attains a higher flow rate, especially in the congested flow region. Figure 4.11 (b) indicates the relationship between density and fuel rate of the simulated system. In the free flow phase, the fuel rate increases linearly with the increase in density. At this stage, all vehicles, including both regular vehicles and CAVs, are able to operate freely. The fuel rate is solely determined by the total number of vehicles on the simulated road segment. After the flow reaches its maximum, the fuel rate gradually decreases due to the gradual decrease in the flow rate. Before density reaches a highly congested region, the fuel rate in the case with a higher CAV penetration rate is larger than the case with a lower CAV penetration rate, which is because the former one attains a higher flow rate. When the density exceeds 110 veh/km, the fuel rate in cases

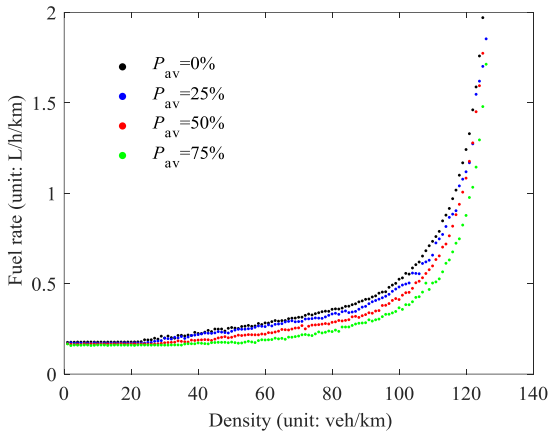
with CAVs is slightly smaller than the case with no CAV. Figure 4.11 (c) shows the relationship of fuel rate for traveling a unit distance with regard to density. In the free flow phase, the fuel rate for traveling a unit distance maintains a stable level, there is no obvious difference between cases with different CAV penetration rates. However, in the congested flow phase, the fuel rate first slightly increases in the medium-density region and then sharply increases in the highly congested region. Cases with a higher CAV penetration rate have a lower fuel rate value, which indicates the introduction of CAV is beneficial for improving the fuel efficiency of the entire system. Figure 4.11 (d) shows the relationships between fuel dissipation rates with regard to density under various CAV penetration rates. In the free flow phase, the dissipation rate stays at a low level, since vehicles are able to travel at a free flow speed, the fuel is contributed to the velocity at a high level. Cases with higher CAV penetration rates have slightly lower fuel dissipation rates, which is because regular vehicles have a random deceleration in the modeling process, while CAVs are deterministic driving. In the medium-density region, the dissipation rate increases gradually with the increase in density. This is caused by the constraint driving in the congested traffic flow. At this stage, fuel is not in a position to transform to kinetic energy at a high rate anymore. Cases with higher CAV penetration rates show lower dissipation rates, which mean the introduction of CAVs indeed improves fuel efficiency in congested traffic flow. When the density reaches 110 veh/km, the dissipation rate attains its peak and then decrease sharply with further increase in density. This is because vehicles in the highly congested region are hardly able to move anymore.



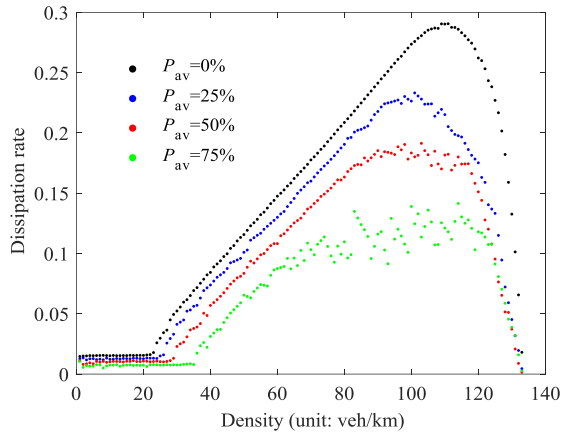
(a) Flow with regard to density



(b) Fuel rate with regard to density



(c) Fuel rate per kilometers with regard to density

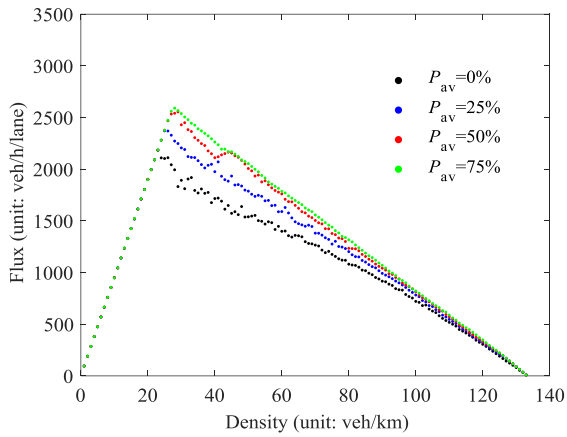


(d) Fuel dissipation rates with regard to density

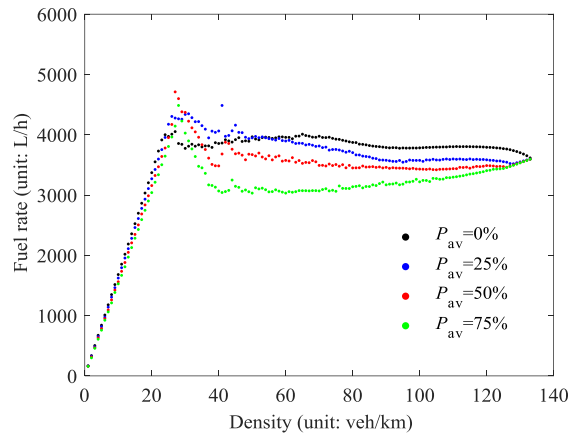
Figure 4.11 Fuel consumption and dissipation rate with density, with T_{ACC} equals to 0.5 s

Figure 4.12 presents the findings of a comparative case, with T_{ACC} equal to 1.1 s. Figure 4.12 (a) shows the flow-density relationships under this case. In comparison with the former case, with a decline in car-following performance of CAVs, the capacity gain through the gradual introduction of CAVs is weakened. Figure 4.12 (b) displays the relationships between density and fuel rate under different CAV penetration rates. Compared to the preceding case, the fuel rate of the system during the congested flow region is decreased with the increase in CAV penetration rate. At the system level, there are two parts that determine the fuel consumption in the mixed

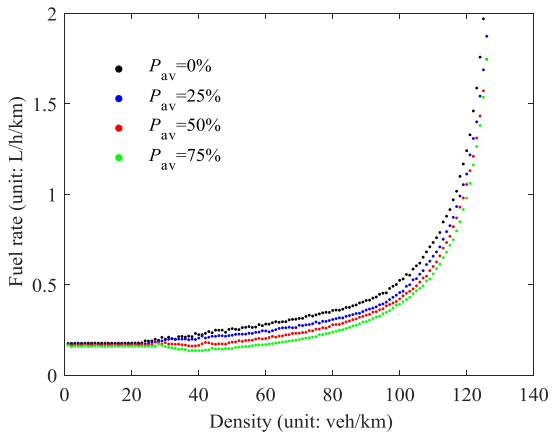
traffic flow. A higher level of flow rate corresponds to a higher amount of fuel consumption, while a higher CAV penetration rate is helpful in decreasing the total fuel consumption. Figure 4.12 (c) and Figure 4.12 (d) present the relationship of fuel rate for traveling a unit distance and fuel dissipation rate with regard to density, respectively. The result shows a similar pattern in the former case, which indicates that with the gradual introduction of CAVs, fuel efficiency will be enhanced.



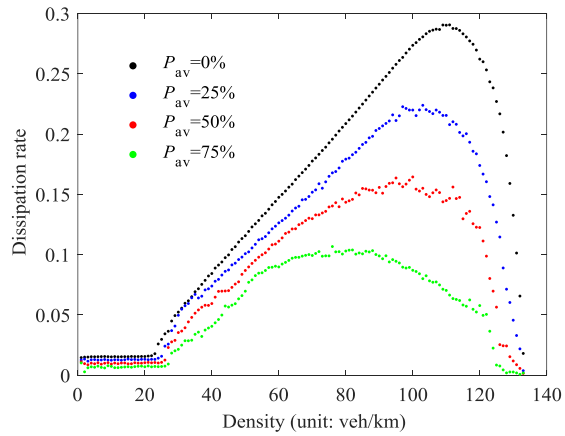
(a) Flow with regard to density



(b) Fuel rate with regard to density



(c) Fuel rate per kilometers with regard to density



(d) Fuel dissipation rates with regard to density

Figure 4.12 Fuel consumption and dissipation rate with density, with T_{ACC} equals to 1.1 s

4.5 Summery and conclusions

In this chapter, the possible impact of the CAVs on the road capacity, safety, and fuel consumption under different penetration rates is numerally investigated. The simulation results indicate that the introduction of CAVs will change the traffic-flow dynamics, increase the road capacity, and improve both traffic safety and fuel efficiency, while the penetration rate and performance of the CAV in heterogeneous traffic are the key factors that determine such impact.

Before the CAV-penetration rate reaches 30%, the increase in the road capacity is gradual; moreover, the effect of the difference in the CAV capability on the growth rate is insignificant. When the CAV-penetration rates exceed 30%, the growth rate is to a great extent decided by the CAV capability on the desired net time gap. A higher capability corresponds to a higher capacity growth rate.

The frequency of dangerous situations in the mixed flow under different CAV penetration rates indicates that the condition of traffic safety would be greatly improved with the increase in the CAV penetration rate. More cautious car-following strategy of CAV would contribute to a greater benefit on traffic safety, though less gain in capacity. Acceleration rate and velocity difference distribution of the mixed traffic flow indicate that the introduction of CAV would contribute to a higher portion of smooth driving in the mixed traffic flow. Velocity difference between vehicles is decreased and traffic flow is greatly smoothed. Spatiotemporal diagrams of mixed traffic flow were presented to show the effect of CAVs on damping the stop-and-go traffic

flow.

The introduction of CAVs will also improve the fuel efficiency of the entire traffic system. With the increase in CAV penetration rate, the fuel dissipation rate is lowered. The fuel rate for traveling a unit distance is decreased, particularly in the congested traffic flow. However, such effects are insignificant in free traffic flow.

CHAPTER 5

Management

5.1 Introduction

In this chapter, an application of the proposed methodology is presented to investigate the impact of setting dedicated lanes for CAVs on traffic flow throughput. In order to compare the traffic flow throughput under various scenarios with a different number of CAV-dedicated lanes, a three-lane heterogeneous flow model was applied. Three policies are defined. Namely, 0 CAV-dedicated lane, 1 CAV-dedicated lane, and 2 CAV-dedicated lanes. There are primarily two categories of situation in the lane-changing process. One is lane-changing behavior between lanes with identical lane policy, such as between two CAV-dedicated lanes or two regular lanes. For this kind of lane-changing behaviors, as long as the traffic condition in the target lane is better than its current lane, the vehicle, including both regular vehicle and CAV, would change to target lane with a lane-changing probability P_{lc}. The other is lane-changing behavior between lanes with different lane policies, such as lane-changing behavior between the CAV-dedicated lane and regular lane.

$d(i, t)$ denotes the space gap ahead of vehicle i at time step t. v and a are the velocity and acceleration rate of the vehicle, respectively. $v_{\max}$ is the maximum velocity. $d(i, t)_{\mathrm{other}}$ denotes the

space gap ahead of vehicle i on target lane at time step t, $d(i, t)_{\text{back}}$ is the space behind vehicle i on target lane.

(1) Lane-changing rules between lanes with identical lane policy (Rickert et al. 1996):

Incentive criteria: $d(i, t) < \min\{v + \text{a}, v_{\max}\}$ and $d(i, t)_{\text{other}} > \min\{v + \text{a}, v_{\max}\}$ indicate space ahead of the object vehicle i is not enough for traveling with a higher velocity, and the driving condition in the target lane is better than that in the current lane.

The safety criteria $d(i, t)_{\text{back}} > v_{\max}$ indicates that, when changing the lanes, the vehicle immediately behind the object vehicle moving on the target lane will not crash the object vehicle after changing lanes. When the two conditions are fulfilled simultaneously, the object vehicle will move onto the target lane with a lane-changing probability P_{lc}.

(2) Lane-changing rules between lanes with different lane policies:

For the regular vehicles initially located on the CAV-dedicated lane, as long as the safety criteria $d(i, t)_{\text{back}} > v_{\max}$ is satisfied, regular vehicles are ordered to change to the normal lanes with a lane-changing probability of 1, thus, they will gradually change lanes to regular lanes in the initial transition period. For all regular vehicles on regular lanes, they are not allowed to change lanes to the CAV-dedicated lane.

For all CAVs on 3 lanes, identical lane-changing rules of the situation (1) are applied, which indicate that CAVs can use both CAV-dedicated lane and other normal lanes. Whether a CAV will

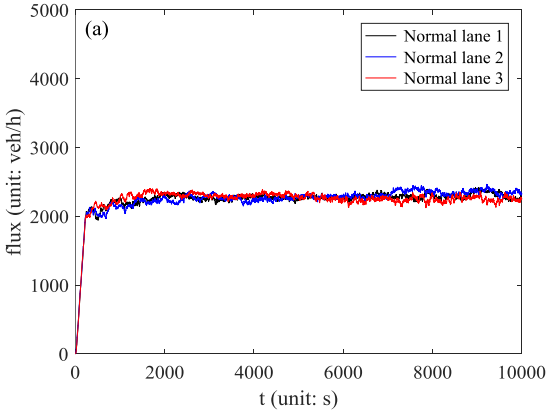
choose a CAV-dedicated lane or a regular lane is just based on the traffic condition on its current lane and that on the target lane.

In the simulation, CAVs and regular vehicles are distinguished and labeled with different feature. Before lane-changing rules are applied, vehicle type is first determined, and for these two types of vehicle, the afore-mentioned different lane-changing rules are employed respectively. For vehicles on the middle lane, the default setting is to consider the left lane as target lane first, then the right lane. For a multi-lane highway, inner lanes normally attain a higher average speed than outside lanes and the incentive goal of lane-changing is to attain a higher travel speed. If its left and right lane both meet the lane changing conditions, possible results will include changing to the left lane, changing to the right lane or maintaining its current lane. As for the conventional vehicle, the lane-changing behavior still will be decided by the lane-changing probability. The lane-changing probability represents the stochastic factor in the lane-changing process. CAVs are able to travel on each lane of the road segment. In some of the tested scenarios, such as with 80% CAV market penetration and 1 lane (out of 3 lanes) dedicated to CAVs, a mixed flow of the two types of vehicle can be expected on both of the two normal lanes. Also, there is a physical limitation when attributing too many lanes to CAVs while CAV penetration rate is low, since the normal lane may not be able to accommodate all the conventional vehicles. In the practical simulation, it is physically impossible to reach certain aforementioned situations. Under such cases, it either leads to ever-growing jam, or a mis-obedience of the rules by the human drivers. Simulation results are

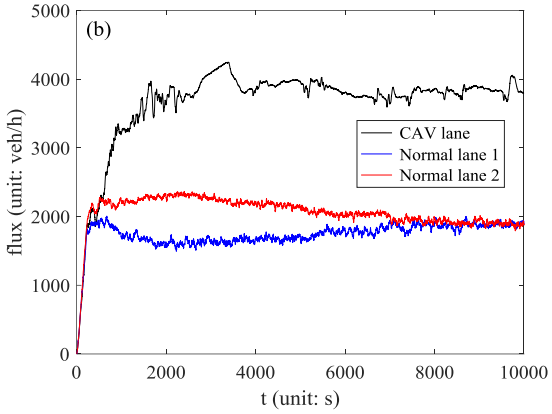
excluded when such a physical limitation is exceeded.

5.2 Simulation results and discussion

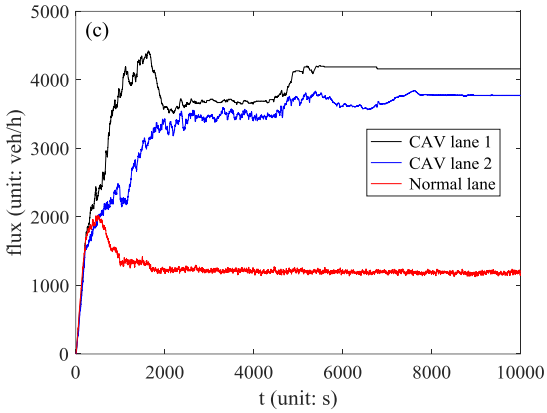
Figure 5.1 shows the flow-time diagrams under different CAV-dedicated lanes policies, namely (a) with 0 CAV-dedicated lane, (b) with 1 CAV-dedicated lane and (c) with 2 CAV-dedicated lanes. The CAV penetration rate P_{av} is 60%. Vehicle density at 60 veh/km/lane and T_{ACC} is 0.5 s. T_{ACC} is the desired net time gap of a CAV with respect to the preceding vehicle in the ACC process. The simulation involved conventional vehicles and CAVs initially randomly distributed in a mega-jam on the road segment. Then all the vehicles will gradually change lanes based on the set lane policy. Figure 5.1 displays the initial transition process. For the first case, since there is no CAV-dedicated lane set under this case, the flow rate results are similar between lanes. While in the latter two cases with a different number of CAV-dedicated lanes, flow rates differ between lanes. As expected, the CAV-dedicated lane attained a greater flow rate than other normal lanes, this is the merit of setting CAV-dedicated lane, while its negative effect on other lanes also should not be neglected. Due to the setting of CAV-dedicated lanes, the flow rate of other lanes also is decreased. This phenomenon is much clearer in the case (c) with two CAV-dedicated lanes. To evaluate the overall effect of CAV-dedicated lanes on traffic system, instead of focusing on the improvement on specific lanes, it is the overall throughput that should be considered.



(a) Flow-time series in the case of no CAV-lane



(b) Flow-time series in the case of 1 CAV-lane



(c) Flow-time series in the case of 2 CAV-lanes

Figure 5.1 Flow-time series under different number of CAV-dedicated lanes

To form an overall understanding of this problem, in the subsequent part, the overall flow-density relationship is presented. Each simulation last 20000 time steps. Data from the initial 10000 time steps is eliminated to avoid the transition effect. Four sets of simulation were conducted, with results presented as follows. Among former three experiments, only the value of T_{ACC} is different. Namely, a series of values including 0.5 s, 0.8 s, and 1.1 s were applied, which represents a decreasing level of ACC performance. The maximum speed for all vehicles in the simulation is identical. In the last experiment, T_{ACC} equals 0.5 s, and the maximum speed for CAVs on CAV-dedicated lane is higher than vehicles on normal lanes.

Figure 5.2 presents the results of the relationship between the traffic flow with respect to the density. The T_{ACC} for CAVs is set at 0.5 s. Each subplot represents a case with a fixed CAV penetration rate, with P_{av} ranging from 10% to 90%. Figure 5.3, Figure 5.4 and Figure 5.5 share the same setting. In each subplot, the results of three scenarios are presented simultaneously. Each scenario corresponds to a different lane policy. Namely, 0 CAV-dedicated lane, 1 CAV-dedicated lane and 2 CAV-dedicated lanes. In the case of 0 CAV-dedicated lane, the traffic flow is completely heterogeneous flow on all the three lanes of the road segment. In the other two cases, a different number of CAV-dedicated lanes include 1 lane and 2 lanes are set. Under normal cases, traffic flow on the CAV-dedicated lane should be homogeneous flow, while that on other lanes is heterogeneous flow. Generally, the overall traffic flow throughput increases with the increase of the CAV penetration rate in the heterogeneous flow.

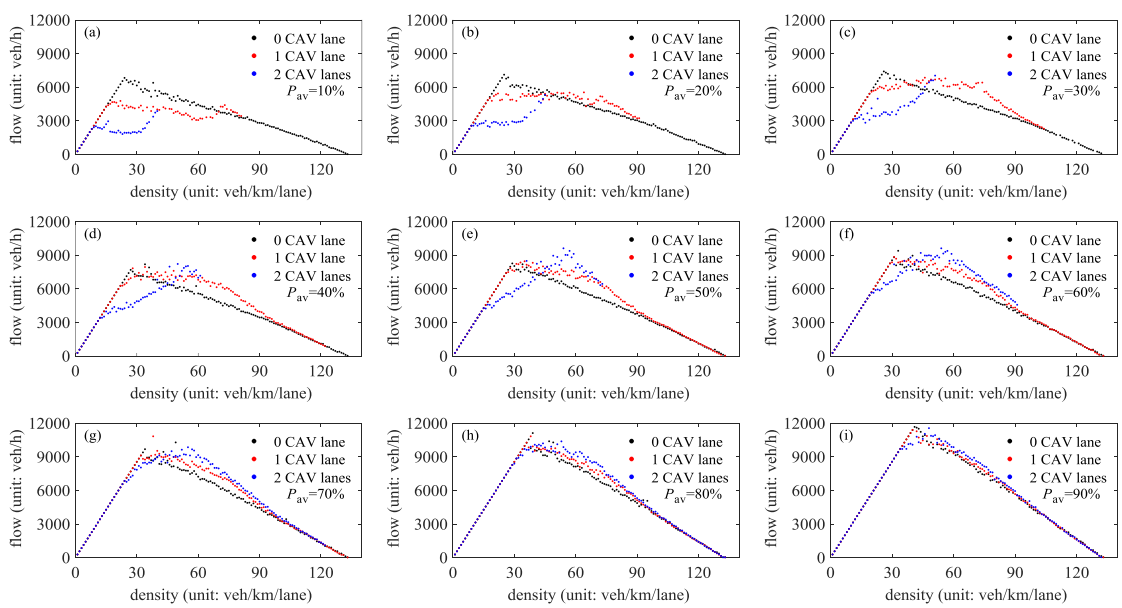


Figure 5.2 Flow-density diagrams under different CAV-dedicated lanes policies with T_{ACC} equals to 0.5 s

The diagrams in scenarios with CAV-dedicated lanes can be roughly divided into three parts: the free flow phase, the congestion phase and the intermediate phase between aforementioned two phases, which is divided by the cross points between diagrams with CAV lane and the mixed flow diagram without CAV lane. In the free flow phase and the congestion phase, traffic flow on all three lanes is free flow and congestion flow. While for the intermediate phase, traffic flow states on different lanes may be different, due to the impact of different lane policies.

For the congestion phase, there is no significant difference among all of the scenarios with different CAV-dedicated lane policies. This is easy to understand because the traffic flow on all of the three lanes is congested. While for the free flow phase and the intermediate phase between free flow phase and the congested flow phase, a considerable difference can be observed easily. In the free flow phase, when density is low enough, the traffic flow on all of the three lanes is free flow, and there is no significant difference even under different CAV-dedicated lane policies. However, the density range of the free flow phase is different among cases with different CAV penetration rates. Namely, in cases with lower CAV penetration rates, the density ranges of free flow phase are shorter than that with a higher CAV penetration rate. This is explained by the fact that CAVs have a better performance than regular vehicles, a larger free flow phase corresponds to a higher capacity.

Even in a case with a fixed CAV penetration rate, the density ranges of free flow under three scenarios with a different number of CAV-dedicated lane are also distinct from each other.

Particularly in cases with a relatively lower CAV penetration rate, the free-flow density range under the scenario with 2 CAV-dedicated lanes is much lower than that with fewer CAV-dedicated lane. This is because there are not enough CAVs on the CAV-dedicated lanes, which result in waste of the road resource. While the normal lanes have to deal with the heavy traffic of regular vehicles, the normal lane will soon be congested, with CAV-dedicated lanes still in free flow state. In Figure 5.2(a), the flow-density diagrams of cases with CAV-dedicated lanes (marked with blue and red points) are lower than that of the case without CAV-dedicated lane (marked with black points). The area between them represents the negative effect of setting CAV-dedicated lane under a CAV penetration rate of 10%. For simplicity, we name it the negative effect area of setting CAV-dedicated lane. The negative effect area in the case with two CAV-dedicated lanes is even larger than that with one CAV-dedicated lane.

In Figure 5.2(b), the CAV penetration rate is 20%, from the flow-density diagram two kinds of areas can be observed, which are divided by a cross point of the flow-density diagrams under three different scenarios, namely around the density of 50 veh/km/lane. For the right part, the flow-density diagrams of cases with CAV-dedicated lanes are above the flow-density diagram in the case without CAV-dedicated lane. It shows that the setting of CAV-dedicated lane is beneficial under a CAV penetration rate of 20% when the density exceeds 50 veh/km/lane. For this kind of area, correspondingly, we name it the positive effect area of setting CAV-dedicated lane.

With further increase in CAV penetration rate, the negative area gradually decreases. When

the CAV penetration rate reaches a rate of 50%, namely in Figure 5.2(e), the negative area of setting 1 CAV-dedicated lane nearly vanishes. The negative area of setting 2 CAV-dedicated lanes continues to decrease until the CAV penetration rate reaches a rate of 80%, then it also nearly vanishes. By comparing these two kinds of areas, the optimal strategy for setting CAV-dedicated lane can be developed. Figure 5.2 reveals the pros and cons of setting CAV-dedicated lane, considering the CAV penetration rate and density. For a three-lane highway, it is beneficial to set 1 CAV-dedicated lane when CAV penetration rate exceeds 40%, and 2 CAV-dedicated lanes when CAV penetration rate exceeds 60% in the considered case.

Figure 5.3 shows the simulation result under a case with a less advanced CAV in ACC performance, in which T_{ACC} is set at 0.8 s. The evolution pattern with regard to P_{av} is similar to that in Figure 5.2. However, the positive areas in Figure 5.3 are smaller than its counterparts in Figure 5.2. This phenomenon indicates that the performance of individual CAV is literally a decisive factor in the performance of CAV-dedicated lanes. A more advanced performance in CAV corresponds to a larger benefit it will attain through the deployment of CAV-dedicated lanes. Moreover, when the CAV penetration rate exceeds 70%, the difference between the scenarios with CAV-dedicated lanes and scenario without CAV-dedicated lane becomes smaller and smaller with further increase in CAV penetration rate. This phenomenon indicates that when CAVs reach a dominant role in the mixed traffic flow, the benefit of setting CAV-dedicated lane also decreases. Compared with the cases in Figure 5.3, we can find that this trend is much more obvious in Figure

5.4 with a less advanced CAV performance.

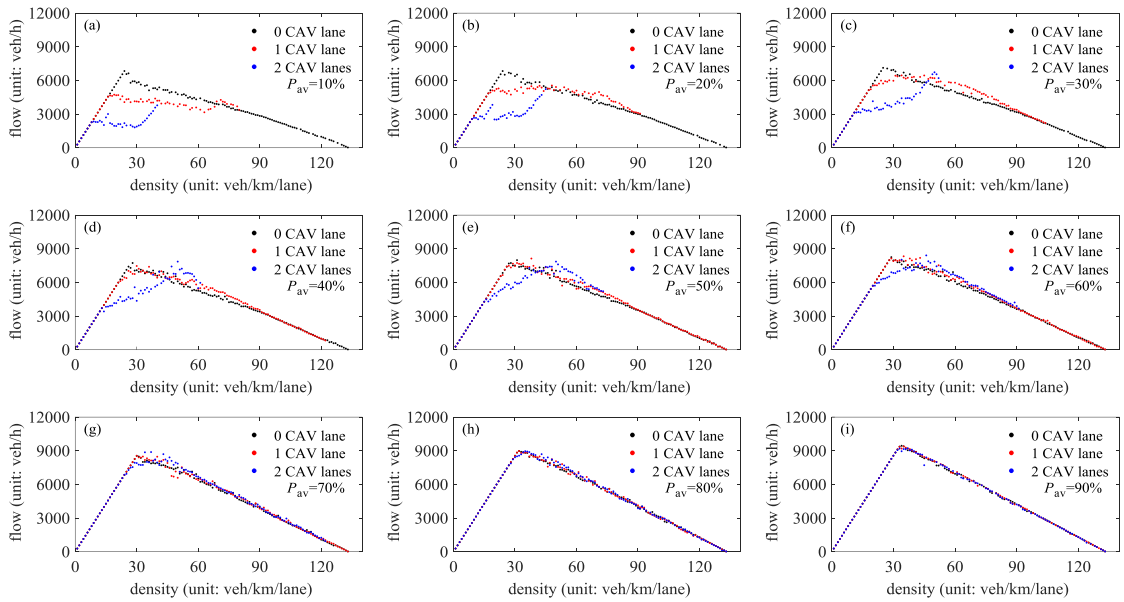


Figure 5.3 Flow-density diagrams under different CAV-dedicated lanes policies with T_{ACC} equals to 0.8 s

Figure 5.4 shows the results of the relationship between the traffic flow with respect to the density. In which case the T_{ACC} is set as 1.1 s. At the early stage, when CAV penetration rate and density is relatively small, setting CAV-dedicated lane only deteriorates the overall throughput performance, since there are not enough CAVs on the road and CAV lanes are underused. With the increase in CAV penetration rate, the negative impact eased gradually. However, no positive effect can be observed in this case due to a less advanced level in the ACC performance.

Under some extreme cases, the lane policy is not always obeyed strictly. Such as in Figure 5.4 (a), in which case the CAV penetration rate is only 10% while there are two CAV-dedicated lane is set among the total three lanes. With the increase in density, some regular vehicles may fail to

change to the normal lane, due to the severe congestion caused by the improper setting of the CAV-dedicated lanes. Under such cases, the normal lane will first reach the congestion phase, with other two CAV-dedicated lanes still in free flow phase. And the CAV-dedicated lane adjacent to the normal lane will be occupied by the heterogeneous flow. With further increase in density, it will soon reach the congestion phase. The similar situation will occur in the last CAV-dedicated lane. This explains the intermittent curve shown in the case of setting 2 CAV lanes.

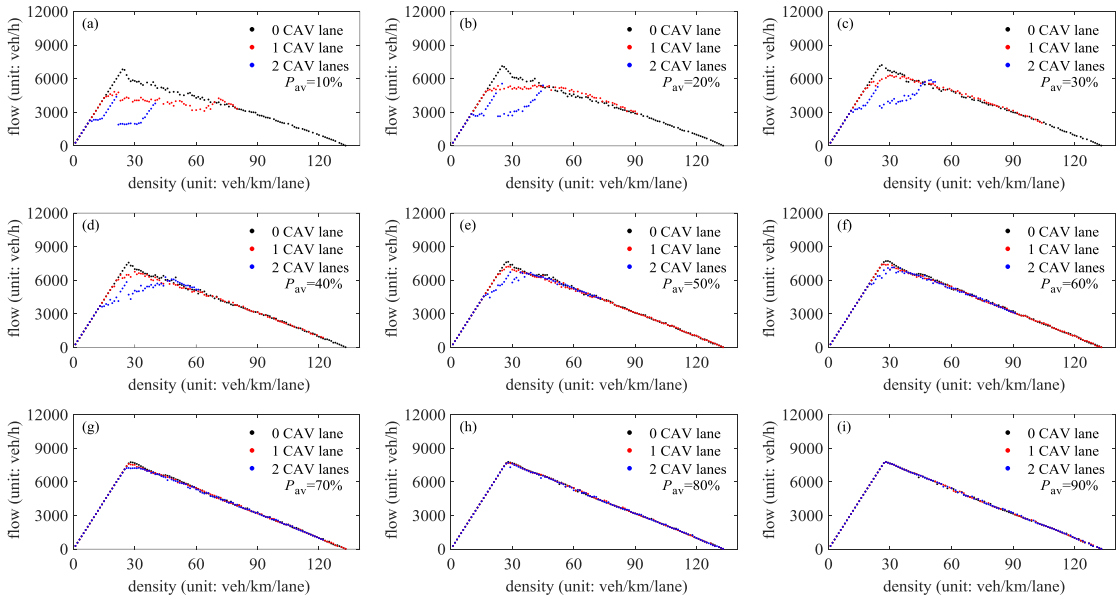


Figure 5.4 Flow-density diagrams under different CAV-dedicated lanes policies with T_{ACC} equals to 1.1 s

Figure 5.5 shows the results of the case in which the maximum speed of CAV on the CAV-dedicated lanes is 120 km/h, while the maximum speed for all vehicles on normal lanes is 95 km/h. Each subplot corresponds to a CAV penetration rate P_{av}, which increase from 10% to 90%, T_{ACC} = 0.5 s. Compared with Figure 5.2, we can find that the benefit areas is larger than its counterparts in Figure 5.2. This phenomenon indicates that the performance of CAV-dedicated lane can be

improved by setting a higher speed limit for CAVs on the dedicated lane.

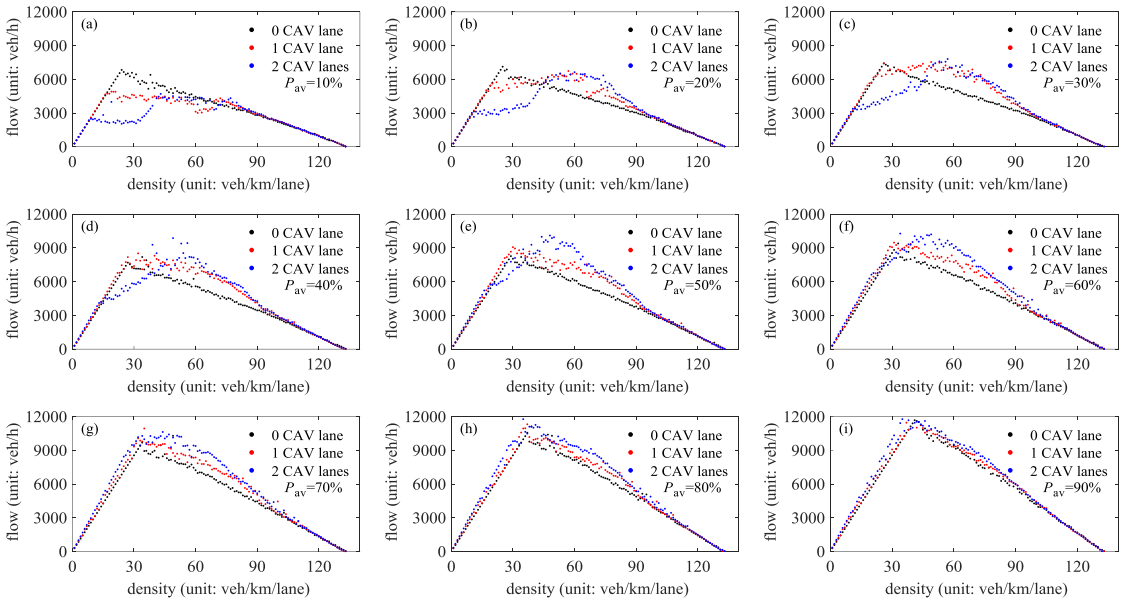


Figure 5.5 Flow-density diagrams with a higher maximum speed on CAV-dedicated lanes

In this case, for a three-lane highway, it is beneficial to set 1 CAV-dedicated lane when CAV penetration rate exceeds 30%. When CAV penetration rate exceeds 50%, setting 2 CAV-dedicated lanes can attain greater benefit than setting 1 CAV-dedicated lane. These findings are qualitatively consistent with findings of previous work. It was found that setting a CAV-dedicated lane is only advantageous at CAV penetration rates above 50% for a two-lane highway, and 30% for a four-lane highway (Talebpour et al. 2017). In addition to CAV penetration rate, we further clarify the dynamic relationship between several factors in this problem, including traffic density, CAV performance, and maximum speed. Each of them has a direct impact on the throughput results. This work provided a much more comprehensive understanding of the CAV-dedicated lane problem than previous works.

5.2 Summery and conclusions

In this chapter, the impact of CAV-dedicated lane on the overall traffic flow throughput was investigated using a three-lane heterogeneous flow model. A fundamental diagram approach was introduced which is able to reveal the pros and cons of setting dedicated lanes for CAVs under various CAV penetration rates. Relations of overall flow throughput under different scenarios with regard to density are numerally investigated. The performance of traffic flow under a different number of CAV-dedicated lanes is compared with mixed flow situation. The simulation results indicate that the capability of CAV plays a key role in the performance of CAV-dedicated lanes. The higher level performance CAVs can achieve, the greater benefit will be through the deployment of CAV lanes. The performance of CAV-dedicated lanes also varies under different CAV penetration rates. At a relatively low CAV penetration rate, the introduction of CAV-dedicated lane has a negative impact on the overall throughput, particularly under low demand level. The negative effect will be eased with the increase in CAV penetration rate. When CAVs reach a dominant role in the traffic flow, the positive effect of introducing CAV-dedicated lanes also decrease. The benefit of setting CAV-dedicated lane can only be obtained within a medium density range. Besides, the performance of CAV-dedicated lane can be improved by setting a higher speed limit for CAVs on the dedicated lane than vehicles on other normal lanes.

The dynamic relationship between CAV-dedicated lane performance, CAV performance, CAV penetration rate and density was revealed, which is helpful in deciding the optimal number

of lanes to be allocated to CAVs. The model can be easily extended to various multi-lane models based on specific scenarios, indicating great practical potentiality for CAV lane management in the near future.

CHAPTER 6

Conclusions and Future Work

6.1 Summary

The gradual adoption of CAVs in current traffic system indicates a mixed traffic flow consists of both conventional vehicles and CAVs will last a long period. During this transition period, great uncertainty exists. A proper understanding on how would CAVs affect current traffic system is essential for a successful deployment of this emerging technology. This dissertation studied the problem concerning CAVs in heterogeneous traffic flow. Three aspects including modeling, evaluation, and management were addressed using a microscopic modeling approach. The contribution of this study can be summarized as follows.

Firstly, an extended CA model was established incorporating the CAVs in the heterogeneous traffic flow. Operation rules for CAVs are proposed considering the new characteristics of this emerging technology. Autonomous driving and vehicle connection were both considered in the process of modeling CAVs. In order to investigate the potential impact of CAVs on various aspects of the traffic system, several assessment models and methods were integrated into the established heterogeneous flow model. Based on the proposed microscopic modeling framework, the mixed

traffic flow with both conventional vehicles and CAVs was simulated and studied.

Secondly, the impact of CAVs on capacity, safety, and fuel consumption under various penetration rates was evaluated. The possible impact of the CAVs on the road capacity under different penetration rates was numerally investigated via the fundamental diagrams. The simulation results indicate that the introduction of CAVs changes the traffic-flow dynamics, increasing the road capacity along with the increase in the CAV-penetration rate within the heterogeneous flow. Before the CAV-penetration rate reaches 30%, the increase in the road capacity; moreover, the effect of the difference in the CAV capability on the growth rate is insignificant. When the CAV-penetration rates exceed 30%, the growth rate is to a great extent decided by the CAV capability on the desired net time gap. Higher capability corresponds to a higher capacity growth rate.

The frequency of dangerous situations, the value of time-to-collision, acceleration rate and velocity difference distributions of the mixed traffic flow were presented as indicators of CAV's impact on traffic safety. The frequency of dangerous situations in the mixed flow under different CAV penetration rates indicates that the condition of traffic safety would be greatly improved with the increase in the CAV penetration rate. The more cautious car-following strategy of CAV would contribute to a greater benefit on traffic safety, though less gain in capacity. Acceleration rate and velocity difference distributions of the mixed traffic flow indicate that the introduction of CAV would contribute to a higher portion of smooth driving in the mixed traffic flow. The velocity

difference between vehicles is decreased and traffic flow is greatly smoothed. Stop-and-go traffic will be eased.

The impact of CAVs on fuel consumption was studied by integrating the fuel consumption and dissipation models. Relationship between CAV penetration rate and energy consumption was revealed under the full density region. Simulation results suggest that the introduction of CAVs will improve the fuel efficiency of the entire traffic system. With the increase in CAV penetration rate, the fuel dissipation rate is reduced. The fuel rate for traveling a unit distance is reduced, typically in the congested traffic flow. However, such effects diminish in free traffic flow.

Thirdly, the impact of CAV-dedicated lane on the overall traffic flow throughput was investigated using a three-lane heterogeneous flow model. A fundamental diagram approach was introduced which is able to reveal the pros and cons of setting dedicated lanes for CAVs under various CAV penetration rates. Relations of overall flow throughput under different scenarios with regard to density are numerally investigated. The performance of traffic flow under a different number of CAV-dedicated lanes is compared with mixed flow situation. The simulation results indicate that the capability of CAV plays a critical role in the performance of CAV-dedicated lanes. The higher level performance CAVs can achieve, the greater benefit will be through the deployment of CAV lanes. The performance of CAV-dedicated lanes also varies under different CAV penetration rates. At a relatively low CAV penetration rate, the introduction of CAV-dedicated lane has a negative impact on the overall throughput, particularly under low demand

level. The negative effect will be eased with the increase in CAV penetration rate. When CAVs reach a dominant role in the traffic flow, the positive effect of introducing CAV-dedicated lanes also decrease. The benefit of setting CAV-dedicated lane can only be obtained within a medium density range. Besides, the performance of CAV-dedicated lane can be improved by setting a higher speed limit for CAVs on the dedicated lane than vehicles on other normal lanes. The dynamic relationship between CAV-dedicated lane performance, CAV performance, CAV penetration rate, and density was revealed, which is helpful in deciding the optimal number of lanes to be allocated to CAVs. The model can be easily extended to various multi-lane models based on specific scenarios, indicating great practical potentiality for CAV lane management in the near future.

6.2 Future Work

First and foremost, in order to more accurately model the impact of CAVs on current traffic system, more accurate empirical data regarding the CAVs are needed. In terms of connectivity, the inter-vehicle connection via short-range communication is only used to enlarge the range of the distance sensor. Only the response to the immediate leader is considered; i.e., no "multi-anticipation" is applied. This work adopted relatively ideal technically assumptions in the process of modeling the CAVs. Extending the analysis to multi-anticipation will be a research direction in future studies. The problem of lacking empirical data of CAVs can be solved as and when related data is published along with the development of this emerging technology.

Secondly, a proper understanding of possible interaction between CAVs and human drivers is vital for better modeling the heterogeneous traffic flow dynamics. This will require further data collection in future field experiments. This study was limited to the freeway condition, extending the study to various scenarios such as arterial road and on-ramp section is needed. Moreover, when extending the study to the urban road with signalized intersections, the interaction between CAVs, human drivers, and intersection based V2X infrastructures, will be much more sophisticated. A proper understanding of the heterogeneous traffic flow dynamics at a signalized intersection will be a challenging task.

Additionally, vehicle platooning is a promising technology with the gradual deployment of CAVs. Although there have been a few studies analyzing the impact of vehicle platooning on road capacity and energy saving, how would the formation and dissipation of a platoon of CAVs affect traffic flow has rarely been studied in the existing literature. Future study will be conducted in order to get a better understanding of the traffic system incorporating these emerging technologies.

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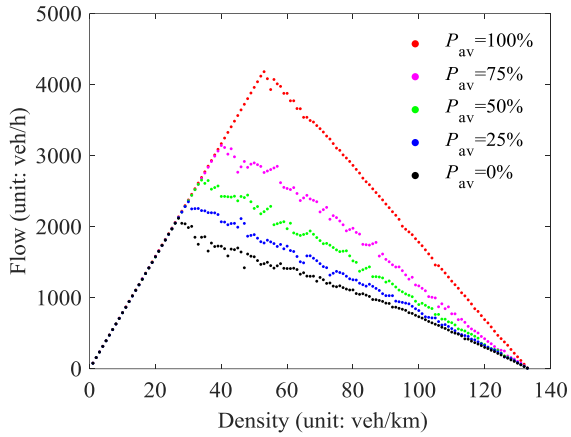
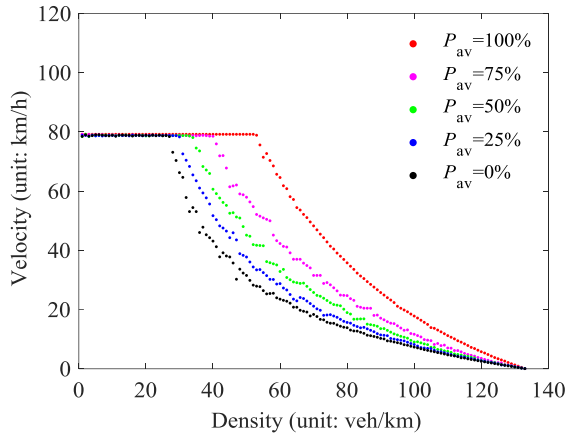
APPENDIX

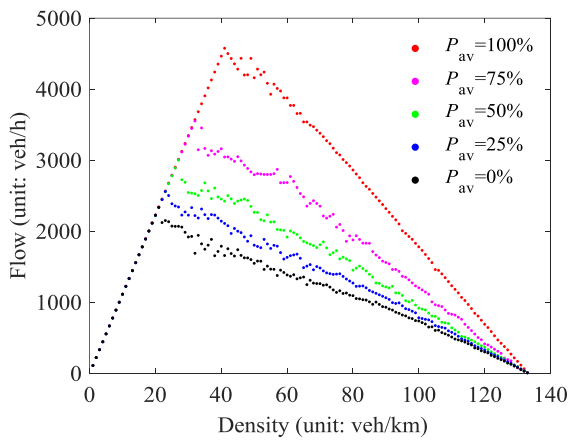
A. Sensitivity analysis regarding *DR*, T_{ACC} = 0.5 s, *CR*=300 m



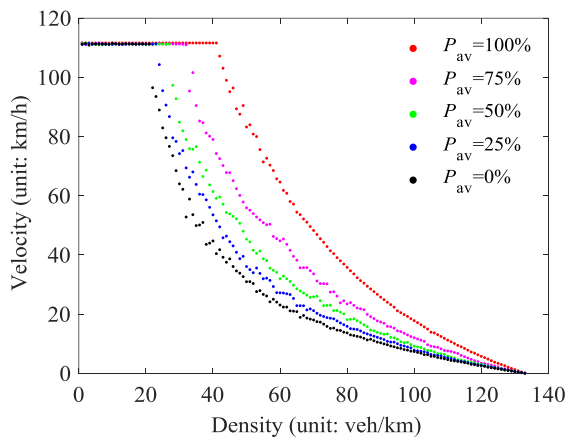
(a) Flow-density diagram with *DR*=80 m



(b) Velocity-density diagram with *DR*=80 m

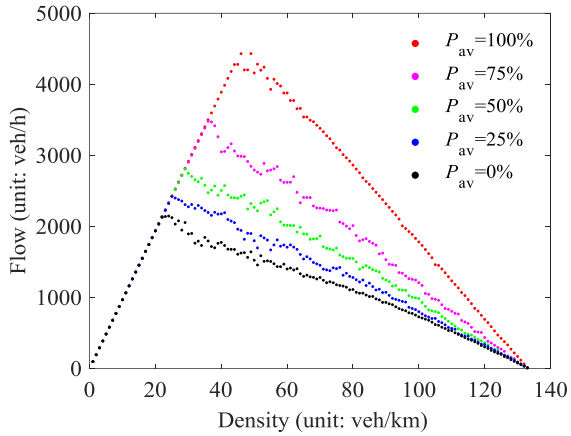


(c) Flow-density diagram with *DR*=160 m

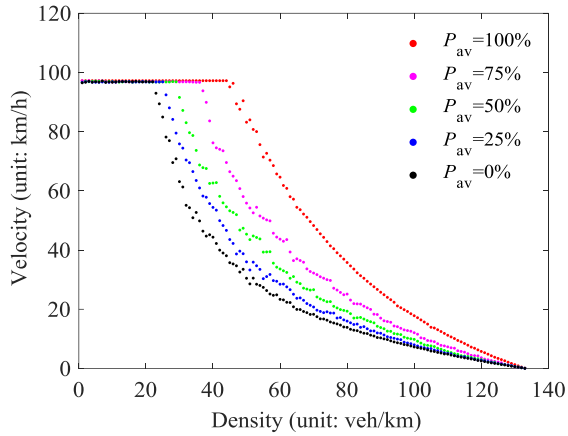


(d) Velocity-density diagram with *DR*=160 m

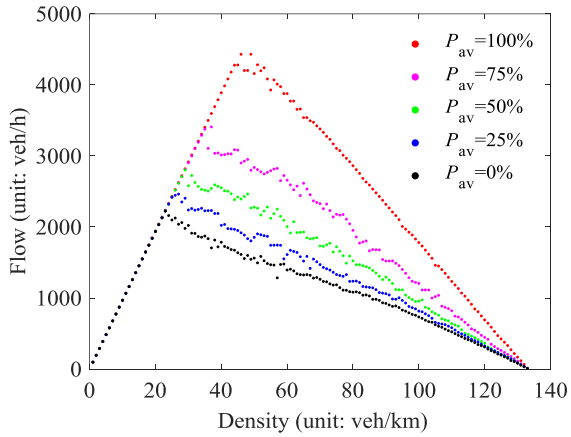
B. Sensitivity analysis regarding *CR*, T_{ACC} = 0.5 s, *DR*=120 m



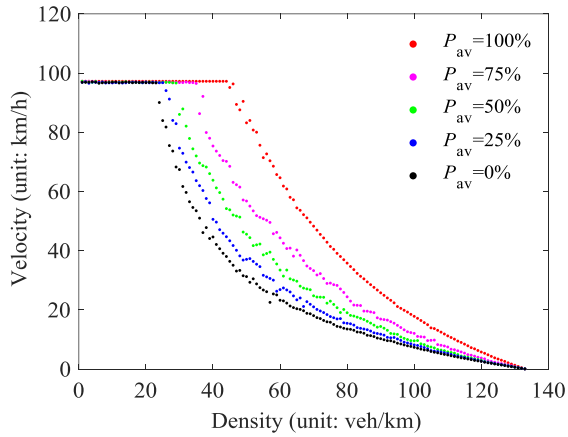
(a) Flow-density diagram with *CR*=200 m



(b) Velocity-density diagram with *CR*=200 m

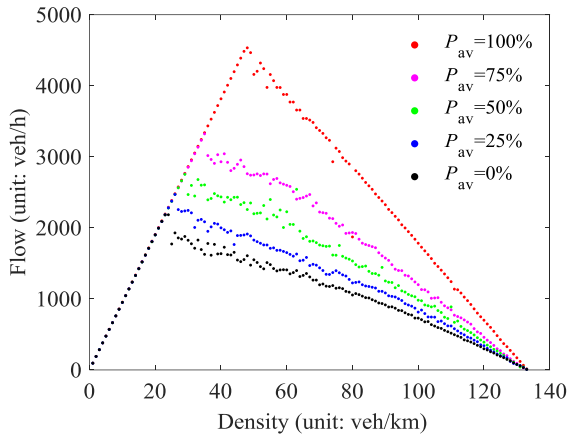


(c) Flow-density diagram with *CR*=400 m

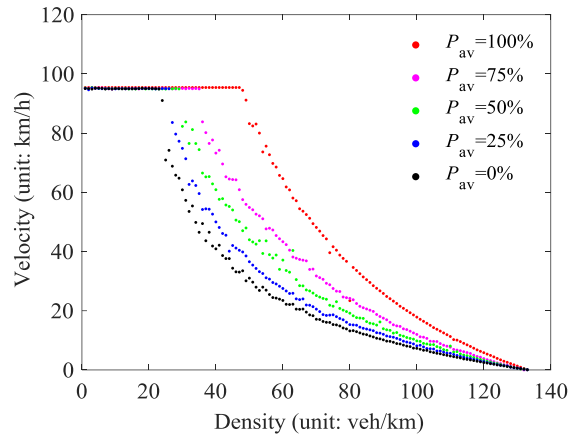


(d) Velocity-density diagram with *CR*=400 m

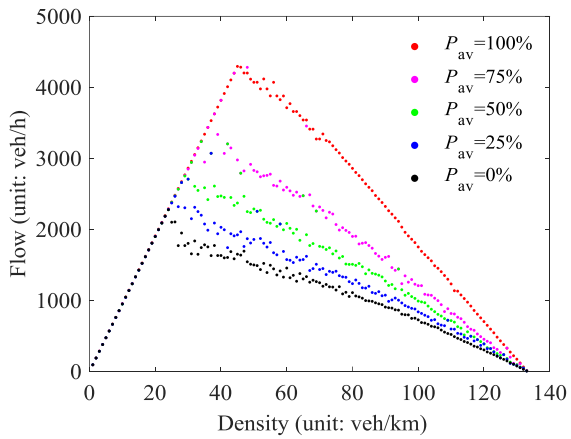
C. Comparison of simulation results of two different runs with the same simulation setting, with T_{ACC} = 0.5 s, *DR*=120 m, *CR*=300 m



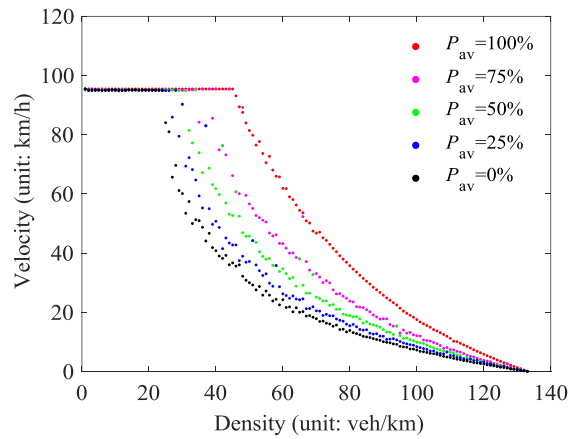
(a) Flow-density diagram of first simulation



(b) Velocity-density diagram of first simulation



(c) Flow-density diagram of second simulation



(d) Velocity-density diagram of second simulation