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Impacts of Automated Vehicle Technologies on Future Traffic

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Impacts of Automated Vehicle Technologies on Future Traffic

by

Xiaowei Shi

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Civil Engineering
Department of Civil and Environmental Engineering
College of Engineering
University of South Florida

Major Professor: Xiaopeng Li, Ph.D.
Fred Mannering, Ph.D.
Larry Head, Ph.D.
Xiaobo Qu, Ph.D.
Yujie Hu, Ph.D.

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Keywords: Adaptive Cruise Control, Fundamental Diagram, Car Following Characteristics, Energy Consumption, Empirical Method

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Dedication

This dissertation is wholeheartedly dedicated to my beloved parents and girlfriend, who continuously provide their love, supports, and encouraging words to me. Without these, I could not accomplish the graduation of a Doctor of Philosophy degree.
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I sincerely thank my advisor Dr. Xiaopeng Li for his guidance and assistance during my studies at USF. His earnest research attitude and extensive knowledge inspire me. I am also very thankful for my dissertation committee members Dr. Fred Mannering, Dr. Larry Head, Dr. Xiaobo Qu, and Dr. Yujie Hu for their valuable advice during the preparation of this dissertation. I learned how to systematically investigate a research problem and how to clearly present the results to audiences. The experience I learned during this dissertation is precious to me. Also, thank everyone in the Connected & Autonomous Transportation Systems (CATS) Lab. I cherish the time we spent together.
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Abstract

Recently manufactured commercial vehicles are increasingly equipped with automated driving features. The adaptive cruise control (ACC) system, arguably the most common automated vehicle (AV) driving feature, is available on many new models of commercial vehicles in recent years. The ACC system is composed of a series of onboard sensors (e.g., millimeter-wave radars), computing and control units, which enables the commercial AVs to automatically maintain a safe headway between the subject AV and the lead vehicle by dynamically control the AV speed with real-time sensor information. Note that such commercial AVs are controlled by exact, prescriptive, and fast-responding computer-mechanical dynamic models while human-driven vehicles often exhibit uncertain, unpredictable, and slowly responding driving behaviors. Therefore, the commercial AVs may fundamentally alter traffic flow characteristics as their market penetration keeps increasing rapidly in these years. Due to this, it has a great need to study the impacts of the commercial AVs on future traffic. To investigate the impacts, this dissertation collected high-resolution trajectory data of multiple commercial AVs following one another in a platoon with different headway settings. Then, the impacts of AV technologies on future traffic from both macroscopic and microscopic aspects were studied.

To investigate the impacts of commercial AVs on macroscopic traffic flow, this dissertation proposed a general methodology that combines both empirical experiments and theoretical models to construct a fundamental diagram (FD), i.e., the foundation for traffic flow theory for AV traffic. The field experiment results revealed that the traditional triangular FD structure remains applicable to describe the traffic flow characteristics of AV traffic. Further, by
comparing the FDs between AVs and human-driven vehicles, it was found that although the shortest AV headway setting can significantly improve road capacity, other headway settings may decrease road capacity compared with existing human-driven-vehicle traffic. It was also found that headway settings may affect the stability of traffic flow, which has been revealed by theoretical studies but was first verified by empirical AV data. With these findings, mixed traffic flow FDs were derived by incorporating different headway settings and AV penetration rates. The proposed method, including experiment designs, data collection approaches, traffic flow characteristics analyses, and mixed traffic flow FD construction approaches, can serve as a methodological foundation for studying future mixed traffic flow features with uncertain and evolving AV technologies.

The microscopic impacts of commercial AVs were investigated from the AV car-following characteristics (i.e., ACC system design) and AV energy consumption. To investigate the impacts of car-following characteristics of commercial AVs, parsimonious linear AV-following models that capture the first-order parameters on safety, mobility, and stability aspects were estimated with the data. The estimation results of the key parameters validated several theoretical predictions predicted by Li (2020). Specifically, it was found that as the time lag setting increases, the corresponding safety buffer decreases, indicating that AV safety could be improved with less pursuit of AV mobility or, conversely, AV mobility improvement may come at a cost of more stringent safety requirements. Also, as the time lag setting increases, AV string stability increases, indicating that stop-and-go traffic potentially could be dampened by compromising AV mobility. With this, one possible explanation to the observed string instability of commercial AV following control (i.e., ACC function) is that automakers may prefer to ensure a relatively short headway (and thus better user experience on vehicle mobility) at a cost of compromising string stability. It
was also found that as the time lag increases, the cycle period of traffic oscillations gets longer, and the oscillation amplification gets smaller, which supports the tradeoff between mobility and stability. On the other hand, field experiments revealed issues beyond the predictivity of a simple linear model. That is, vehicle control sensitivity factors vary across different speed and headway settings, and the model estimation results for key parameters are not consistent over different speed ranges. This opens future research needs for investigating nonlinearity and stochasticity in the AV following modeling.

Since AVs are controlled by exact and fast-responding sensors and computers, the driving behavior as well as the driving strategies of AVs are expected to be enhanced compared with those of human-driven vehicles. With this, AVs have a great potential in reducing overall fuel consumption of traffic and consequentially achieving environmental-friendly mobility. To understand this probability, the AVs’ fuel consumption was calculated by several state-of-the-art or classical vehicle fuel consumption models by inputting the collected AV trajectory data. From empirical analyses, we found that as the AV headway setting increases, the corresponding fuel consumption decreases. It indicates that AV energy efficiency could be enhanced with less pursuit of AV mobility. One possible explanation for the tradeoff is that a longer headway may cause more stable AV following behavior and thus yields less fuel consumption. Also, we found that as the speed of AV traffic increases, the impacts of AV headway settings on fuel consumption decrease while the impacts of speed variation settings remain significant. In addition, we compared the fuel consumption of AVs and human-driven vehicles (HVs). We found that for the same experiment settings, the AVs always require less fuel consumption than the HVs. Further, we found that as the AV headway setting increases, the AV string stability increases and thus the overall fuel consumption of the AV string decreases.
Overall, this dissertation systematically investigated the impacts of AV technologies on future traffic from both macroscopic (AV FD) and microscopic (AV car-following characteristics and energy consumption) aspects. Following these findings, a set of managerial insights were provided into the relevant stakeholders for future AV traffic.
Chapter 1: Introduction

Automated vehicle (AV) technology holds great potential to improve traffic safety, comfort, and energy optimization (Li and Li, 2019; Naranjo et al., 2008; Qu et al., 2020; Shi and Li, 2019; Wang et al., 2019) and thus is considered one of the most promising transportation technologies in the near future. To take advantage of this emerging technology, recently manufactured commercial vehicles are increasingly equipped with automated driving features. For example, the adaptive cruise control (ACC) system, arguably the most common automated vehicle (AV) driving feature, is available on many new models of commercial vehicles in recent years. The ACC system is composed of a series of onboard sensors (e.g., millimeter-wave radars), computing and control units (Wang et al., 2019). The ACC system automatically maintains a safe headway between the subject AV and the lead vehicle by dynamically control the AV speed with real-time sensor information. Note that such commercial AVs are controlled by exact, prescriptive, and fast-responding computer-mechanical dynamic models while human-driven vehicles often exhibit uncertain, unpredictable, and slowly responding driving behaviors. Therefore, the commercial AVs may fundamentally alter traffic flow characteristics as their market penetration keeps increasing rapidly in these years (Auld et al., 2018, 2017; Soteropoulos et al., 2019). It was recorded that the market penetration of commercial AVs with ACC operating on highway systems rapidly increases from 2% in 2015 to a projection of over 10% in 2025 (Calvert et al., 2017). It is predicted that half of the vehicles sold and 40% of vehicles on the road will be equipped with

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1 Portions of this chapter has been previously published in Shi and Li (2021a, 2021b). Permission is included in Appendix A.
automated driving features by the 2040s. Thus, it has a great need to study the impacts of the commercial AVs on future traffic. To this end, this dissertation aims to investigate the impacts of AV technologies on future traffic from the following three aspects, such as AV traffic flow fundamental diagram, AV car-following characteristics, and AV energy consumption, which could be further classified into two categories, such as macroscopic aspect (AV FD) and microscopic aspect (AV car-following characteristics and AV energy consumption). The research of each aspect is described as follows.

1.1 AV Traffic Flow Fundamental Diagram

Fundamental diagram (FD) describes a well-defined relation curve for traffic flow rates and density in steady traffic states (Daganzo, 1997; Greenberg, 1959; Newell, 1961). The FD is critical to study traffic flow characteristics and dynamics across various spatial scales with analysis, modeling, and simulation methods (Daganzo and Geroliminis, 2008; Geroliminis and Sun, 2011a; Knoop and Hoogendoorn, 2013; Zhang et al., 2018). A series of studies was conducted on models, properties, and estimation methods of FD (Delis et al., 2018; Nikolos et al., 2015; Qu et al., 2017). For example, Qu et al. (2015) proposed a novel calibration approach for single-regime FD models by using a weighted least squares method that can address the sample selection bias problem in existing single-regime models. Tian et al. (2012) studied the properties of the FD and synchronized flow by incorporating the anticipation rule into the Nagel–Schreckenberg model (Nagel and Schreckenberg, 1992). They found that the proposed model observed the same spatiotemporal dynamics as many of the more complex models. Wang et al. (2013) presented a speed-density model that aims to incorporate stochasticity in FD. Knoop and Daamen (2017) proposed a two-stage method for enhancing the fitting performance of FD with loop detector data. Seo et al. (2019) studied the estimation of the FD with trajectory data collected by probe vehicles. Overall, the FD
is a fundamental concept of traffic flow theory and has been applied to a wide variety of research problems and engineering applications.

Existing studies on macroscopic AV traffic characteristics focused on the impacts of AVs on traffic flow capacity (Arnaout and Arnaout, 2014; Ghiasi et al., 2019, 2017; Liu et al., 2018; Shladover et al., 2012; Van Arem et al., 2006). For example, Arnaout and Arnaout (2014) proposed an agent-based microscopic simulation model to estimate the impacts of AVs on the capacity of a multi-lane highway system. Shladover et al. (2012) examined the effect on highway capacity of varying AV market penetrations by microscopic simulation methods. Despite the successes of these pioneering studies, existing capacity analysis studies mainly focused on the highest throughput, whereas the FD concerns the full spectrum of traffic flow characteristics (e.g., steady state) across all density values (Zhou and Zhu, 2020). Further, most of these studies validated their findings using a simulation-based approach relying on assumptions of AV controls (e.g., extremely short headway and precise vehicle control), which may not be consistent with the behaviors of commercial AVs (Gunter et al., 2019; Milanes et al., 2014; Shi and Li, 2020).

Modeling the full FD for a pure AV or mixed human-driven vehicle and AV traffic is relatively scarce in the literature (Baskar et al., 2009; Bose and Ioannou, 2003; Levin and Boyles, 2016; Yao et al., 2019; Ye and Yamamoto, 2018; Zhou and Zhu, 2020). To generate optimal routing solutions for intelligent vehicle highway systems, Baskar et al. (2009) studied the FD of pure AV traffic by fixing the AV following headway to a small value (i.e., 0.5 seconds). Bose and Ioannou (2003) analyzed the FD of mixed traffic from pure human-driven vehicle traffic to pure AV traffic by assuming that the AVs have a smaller headway than human-driven vehicles due to the use of sensors and actuators. Levin and Boyles (2016) investigated the mixed traffic FD of AVs and human-driven vehicles by proposing a multiclass cell transmission model. Yao et al.
(2019) studied the mixed traffic FD with different AV penetration rates and analyzed the influence factors of the FD. Ye and Yamamoto (2018) proposed a two-lane cellular automaton model to study the mixed traffic FD with different AV penetration rates. The most recent study on the modeling of FD for mixed traffic was Zhou and Zhu (2020). Changes of AV penetration rate and platooning intensity were considered when generating the FD. Despite these successes, the existing studies modeled the FD with simple analysis or pure simulation with very optimistic assumptions of AV controls, which may overestimate the actual performance of existing commercial AVs. Such overestimations or biases from theoretical studies alone may lead to sub-optimal operations (e.g., ineffective platooning operations) and planning (e.g., future roads not reaching expected high capacity, thus causing transportation system breakdowns) decisions in practice when facing emerging AV traffic.

To effectively support informed decisions in the AV traffic era, there is a need to build an FD with real-world AV data. As vehicle motion characteristics of the AV may vary and evolve as the technology develops in the near future, it is imperative to develop a general approach for modeling traffic flow characteristics for the evolving AV traffic.

To this end, the AV FD chapter of this dissertation aims to make the following contributions to the literature:

1) This chapter proposes a general method for constructing the FD for AV traffic, integrating empirical experiments and data analytics. The proposed method, including experiment designs, data collection approaches, traffic flow characteristics analyses, and mixed traffic flow FD construction approaches, can be easily adopted for future traffic despite technology evolutions.

2) To the best of the authors’ knowledge, this chapter is the first research that constructs the FD for AV traffic with empirical data. Some results obtained by this chapter were found that
are consistent with those predicted by theoretical studies, including that (i) the greater the free flow velocity is, the greater the traffic capacity will be (Yao et al., 2019); and (ii) the smaller the following headway is, the larger the capacity is (Levin and Boyles, 2016; Yao et al., 2019; Ye and Yamamoto, 2018).

Although some results are inconsistent with those predicted by the theoretical studies, including (i) AV technologies can significantly improve road capacity (Baskar et al., 2009; Bose and Ioannou, 2003) and (ii) the greater the AV penetration rate is, the greater the traffic capacity will be (Levin and Boyles, 2016; Yao et al., 2019; Ye and Yamamoto, 2018; Zhou and Zhu, 2020).

Based on our findings, only the shortest AV headway setting can significantly improve road capacity, and some other headway settings may even reduce road capacity. Thus, as the AV penetration rate increases, the traffic capacity variation trend is unclear, which is dependent on the enabled AV headway settings.

This chapter also reveals findings that have not been reported in the AV FD literature to date, including (i) the traditional triangular FD structure remains valid to describe AV traffic stationary states, and (ii) AV headway settings may affect the stability of traffic flow. Note that although a series of microscopic studies have verified that AV headway settings will affect traffic stability (Gunter et al., 2019a; Shi and Li, 2021a), none reveal this relationship on the FD. This chapter fulfills this research gap.

Following these findings, managerial insights into effective AV traffic management are drawn: (i) to maximize the utilization of road infrastructures in peak hours, policies could be made to encourage the use of shorter headway settings to mitigate congestions, and (ii) to stabilize traffic oscillation and thus improve the driving experience of passengers, when traffic capacity is
sufficient (e.g., off-peak hours), the use of longer headway settings may be encouraged for a more stable driving experience.

**1.2 AV Car-Following Characteristics**

AV following control, as a fundamental function of AV at all automation levels (SAE, 2020), has significant impacts on road traffic performance, including both stationary (e.g., vehicle-following headway) and dynamics (e.g., traffic oscillation) characteristics. Clear understandings of the impacts of AVs on road traffic provide informative insights into academia and industry, such as traffic simulation, product development, and road traffic management, etc.

In general, a vehicle-following spacing, i.e., the distance between the front bumpers of the two consecutive vehicles, can be decomposed into three components – the preceding vehicle length, a time-lag gap, and a safety buffer, as illustrated in Figure 1.1 (Li, 2020). The time lag is reserved for response delay and driving comfort, and the safety buffer is reserved to absorb the overshoot caused by the following vehicle due to the uncertainty of the preceding vehicle’s movements. Due to the mechanical nature of the AV-following control, the relatively long time-lag gap caused by human drivers was expected to be largely reduced by the control of AV (Karaaslan et al., 1990), and thus the corresponding mobility performance such as road capacity would be significantly improved as well. However, based on state-of-the-art studies in the literature, the road capacity of AV traffic was found comparable or even worse than that of human-driven vehicle traffic under specific headway settings of AV (Shi and Li, 2021a; Shladover et al., 2012). These findings challenged the expected lucrative benefits of AV technology predicted in research (Kesting et al., 2008; Makridis et al., 2020a).
Figure 1.1 Illustration of following spacing components (Source: Li, 2020).

One possible reason for the discrepancy between theoretical predictions and industry practice is that the existing AV-following control design is string unstable. Vehicle string (or asymptotic) stability investigates whether the perturbations of a lead vehicle of a vehicle string get amplified while propagating across multiple following vehicles in the vehicle string. The string instability will cause traffic oscillation and a consequential road capacity drop due to the increased space between vehicles (Chen et al., 2014); e.g., a small speed perturbation of a preceding vehicle will be amplified while propagating across multiple following vehicles and may even lead to stop-and-go traffic. The other potential reason is safety concerns. Due to the uncertainty of the preceding vehicle’s movements, to guarantee a sufficient safety buffer for absorbing the worst-case following AV overshoot considering all possible movements of the preceding vehicle, vehicle makers might set a safety buffer to a relatively conservative value at a cost of compromising AV mobility and decreasing road capacity (Li, 2020; Milanes et al., 2014).

Studies investigating the impacts of AV-following control designs on road traffic performance (i.e., safety, mobility, stability) are abundant (Ghiasi et al., 2017; Jerath and Brennan, 2012; Kesting et al., 2010; Ngoduy, 2013; Seiler et al., 2004; Talebpour and Mahmassani, 2016). For example, Ghiasi et al. (2017) proposed a Markov chain-based traffic capacity model to study the impacts of AVs with different penetration rates on mixed traffic. Kesting et al. (2008) presented an adaptive cruise control strategy in which the driving style can be automatically adjusted
according to traffic scenarios, and the potential impacts of the strategy on traffic were analyzed. However, most of these studies validated their findings by using simulation-based approaches (Lenard, 1970; Treiber and Kesting, 2013), and only a few conducted corresponding field experiments. Due to the lack of empirical validations, some findings obtained with simulation approaches, e.g., AVs can significantly improve traffic stability and road capacity, were inconsistent with those from field experiments (Gunter et al., 2020a; Milanés and Shladover, 2014; Shi and Li, 2020), which highlighted the needs for using field experiments to scrutinize theoretical findings. In the literature, only a few studies (e.g., Ciuffo et al., 2020; Gunter et al., 2019a,b; Knoop et al., 2019; Makridis et al., 2020b; Milanés and Shladover, 2014; Shi and Li, 2020; James et al., 2019) investigated following control designs of commercial AVs (or production vehicles that have automated control features such as adaptive cruise control) with field experiments. These studies showed that existing commercial AVs were string unstable. Despite these successes, none of them investigated the design considerations of the string-unstable design of commercial AV control, e.g., possibly as a compromise with factors such as safety and driving comfort (Eskandarian, 2003; Xiao and Gao, 2010).

Further, note that commercial AVs often offer users to customize the AV-following headway among different levels. Although the impacts of different headway settings on traffic mobility and stability could be significant, this issue was rarely investigated in the literature. To the best of the authors’ knowledge, only Gunter et al. (2019b) and Shi and Li (2021b) are related to this topic. Gunter et al. (2019b) calibrated an optimal velocity relative velocity car-following model with field experiment data and investigated the string stability of the calibrated model with two different headway settings. They found that even the AV-following design is string unstable, and commercial AV platoons of moderate size can dampen disturbances. However, only the results
from two headway settings cannot provide a clear vision to the variation trend of the string stability. Compared with Gunter et al. (2019b), Shi and Li (2021b) studied the impacts of different headway settings on traffic from a macroscopic aspect and constructed a fundamental diagram for AV traffic with four different headway settings based on field experiment data. The results indicated that AV headway settings can affect traffic flow stability. Although Shi and Li (2021b) presented a successful study and revealed insights into the relationship between string stability and AV headway settings, they did not qualitatively analyze the relationship. Moreover, none of them incorporated traffic mobility into their research, which is quite relevant to traffic stability.

A recent study (Li, 2020) analytically explained the tradeoffs among safety, mobility, and stability of the underlying AV control mechanism by proposing a parsimonious linear AV-following model based on the above following spacing decompositions (i.e., preceding vehicle length, time-lag gap, and safety buffer). This study aimed to provide empirical support to the Li (2020) findings with field experiment data. Field experiments with commercial AVs with longitudinal automation were conducted to collect high-resolution AV-following trajectory data. Parameters of the parsimonious linear AV following model were estimated with linear regression using the collected trajectory data. Interestingly, the estimated parameters for the existing commercial AV-following design verify the following theoretical findings in Li (2020):

1) There exists a tradeoff between the time lag gap and the safety buffer that together constitute the AV-following gap and thus determine road capacity. As the time lag gap increases, the corresponding safety buffer decreases, indicating that AV safety could be improved with less pursuit of AV mobility or, conversely, AV mobility improvement may come at a cost of more stringent safety requirements.
2) There exists a relation between the time lag gap and AV string stability. As the time lag gap increases, AV string stability increases, i.e., with a smaller amplification ratio and a longer oscillation period. This indicates that the stop-and-go traffic potentially could be dampened by compromising AV mobility.

3) By theoretically solving the string stable headway setting for the studied AV following design, a possible explanation to the observed string instability of the design (i.e., adaptive cruise control [ACC] function) is that the string-stable headway would be too long to result in superior driving experience (e.g., cut-in lane changes may be induced by long headway). Thus, automakers may opt to design a relatively short headway for the best user experience (which may be directly correlated with users’ vehicle purchase decisions) at a cost of compromising string stability (which could be perceived only when traffic oscillation is amplified across a platoon of vehicles).

Additionally, the estimated parameters reveal the following findings that were beyond what was reported in Li (2020):

1) It was found that the range of the lead vehicle’s acceleration variation that the investigated linear AV control accommodates is rather narrow. When the lead vehicle’s speed variation gets beyond this range, it is likely that the nonlinear control mechanism will be activated, which could largely reduce the needed safety buffer length and thus the linear model prediction becomes too conservative (Li and Ouyang, 2011). This seems also related to the above-speculated automakers’ desire to reduce the needed safety following headway. Nonetheless, this finding indicates that the current commercial AV-following design entrusts much of the safety warranty to nonlinear control mechanisms (e.g., drastic emergency stops) while the linear control dominates only in a relatively narrow acceleration range. The revelation of this design mindset can help researchers understand the AV design components in which AV safety risks likely reside. Further,
it may raise a need to introduce nonlinear AV control models in AV traffic analysis to better reflect AV safety performance; most existing AV traffic simulation studies rely on simplified linear models alone.

2) The estimated vehicle control sensitivity factors vary across different speed and headway settings, again alluding to nonlinear control mechanisms. This indicates that automakers opt to adjust the vehicle control sensitivity to fit different driving environments, possibly for better driving experience and vehicle performance.

Overall, this study validated the theoretical findings in Li (2020) with field experiment data. Also, additional managerial insights into the nonlinearity of existing commercial AV control design were drawn. It will be helpful for transportation stakeholders to better understand how emerging AV technology will impact traffic operations and for automakers to consider further improvements on the existing design.

1.3 AV Energy Consumption

Automated vehicle (AV) is considered to be one of the most promising transportation technologies in the near future (Shi and Li, 2019; Wang et al., 2019). Revealed by Shi and Li (Shi and Li, 2021a), road traffic can be effectively stabilized with an appropriate strategy for following headway setting management. With this, AVs may have a great potential in reducing overall fuel consumption of traffic and consequentially achieving environmental-friendly mobility with optimal motion strategies (Zhang and Cassandras, 2018).

To date, a great number of studies have investigated this potential (Kopelias et al., 2020; Lee et al., 2021; Li et al., 2014; Ligterink and Eijik, 2014; Liu et al., 2019; Plötz et al., 2018; Stern et al., 2018; Yang et al., 2021; Zhou et al., 2017). Qu et al. (2020) developed a car-following model for electric and connected AVs based on reinforcement learning to dampen traffic oscillations and
reduce fuel consumption. Yao et al. (2018) proposed a trajectory smoothing method for connected AVs. In their study, with real-time traffic demand and signal timing information, connected AVs are optimized to run smoothly without any full stop and thus reduce fuel consumption. Li et al. (2017) studied a periodic switching control method for an AV platoon to minimize the overall fuel consumption. Wadud et al. (2016) explored the net effects of AVs on fuel consumption and greenhouse emissions. They found that AVs might plausibly reduce road transport greenhouse gas emissions and energy use, e.g., by nearly half in some scenarios. Despite these successes, most of the studies validated their findings by using simulation-based approaches instead of field experiments and thus the fuel consumption benefits of AVs in practice remain unclear.

There are a few studies that investigated commercial AVs with field experiments (Gunter et al., 2020a, 2019a; Jing et al., 2020; Knoop et al., 2019; Makridis et al., 2020a; Milanés and Shladover, 2014). For example, by calibrating an optimal velocity model with a set of field data of AVs, Gunter et al. (2019a) studied the string stability of the AVs. Shi and Li (2021b) developed traffic flow fundamental diagrams for AVs under different AV penetration rates based on the field experiment data of commercial AVs. Makridis et al. (2020b) conducted a field experiment with five commercial AVs to study the impacts of AVs on traffic flow and string stability. However, one can find that these studies mainly focused on AV car-following behavior modeling, string stability analyses, traffic system impacts, etc. While the AV fuel consumption aspect attracts less attention in the literature.

Further, note that commercial AVs often offer customers a set of options to adjust AV following headways. While the impacts of different headway settings on fuel consumption could be significant, this issue has not been investigated with either theoretical or empirical studies.
To the best of the authors’ knowledge, the study conducted by Victor et al. (2019) is the most relevant study to this chapter. They performed a field experiment with seven commercial AVs driven as a platoon on public roads for a trip of almost 500 km. Then, by utilizing a classical fuel consumption model proposed by Akcelik (1989), they compared the fuel consumption of the first and last vehicles in the platoon and concluded that the vehicle string instability not only causes discomfort but also increases fuel consumption. The analysis in this study reveals interesting phenomena into AV fuel consumption and inspires the investigation of the following research.

Motivated by Victor et al. (2019) and aiming to provide a comprehensive study of the impacts of commercial AVs on fuel consumption, this chapter first collected high-resolution trajectory data of commercial AVs with different operating scenarios, speed ranges, and headway settings. Then, without loss of generality, the AVs’ fuel consumption measurements were calculated by several state-of-the-art or classical vehicle fuel consumption models (Zhou et al., 2016), including (1) VT-Micro model (Ahn, 1998); (2) Microscopic Emission and Fuel consumption (MEF) model (Lei et al., 2010); (3) Vehicle Specific Power (VSP) model (Duarte et al., 2015); and (4) Australian Road Research Board (ARRB) model (Akcelik, 1989). From empirical analysis results, we found that there is a tradeoff between AV mobility and fuel consumption regarding different AV headway settings. As the AV headway setting increases, the corresponding fuel consumption decreases, indicating that AV energy efficiency could be improved with less pursuit of mobility. Thus, one possible explanation for the tradeoff is that the longer headway setting causes more stable AV car-following behavior with less speed standard deviation and thus causes less fuel consumption. Also, we found that the changes of either headway or speed variation settings have significant impacts on fuel consumption when the AV traffic speed is relatively low. However, the impacts of AV headway settings will decrease with the increase of
the AV traffic speed while the impacts of speed variation remain significant. Further, compared with human-driven vehicles (HV), we found for the same experiment settings, the AVs always require less fuel consumption. Moreover, we found that as the AV headway setting increases, the AV string stability increases and thus the overall fuel consumption of the AV string decreases, which reveals an important characteristic of the current AV longitudinal control design. Following these findings, insights into effective AV fuel consumption management and modelling were drawn.

1.4 Research Goal and Scientific Questions

Based on the research gaps revealed in the introduction, this dissertation aims to answer the following scientific questions.

1) What are the impacts of commercial AVs on FD, car-following characteristics, and energy consumption aspects, especially when customers can customize the driving behavior of the AVs (i.e., different AV following headway settings)?

2) What are the impacts of commercial AVs on future traffic with increasing AV penetration rates?

3) How to properly manage future traffic to maximize the benefits of AV technology?

1.5 Dissertation Overview

Figure 1.2 shows the overall structure of the dissertation. Chapter 2 collected high-definition AV trajectory data to support the further investigations and analyses. The detailed experiment settings and plans were described.

Chapter 3 investigated the impacts of commercial AVs on macroscopic traffic flow. We proposed a general methodology that combines both empirical experiments and theoretical models
to construct traffic flow FDs. Mixed traffic flow FDs were derived by incorporating different headway settings and AV penetration rates.

Chapter 4 studied the impacts of car-following characteristics of commercial AVs. Parsimonious linear AV-following models that capture the first-order parameters on safety, mobility, and stability aspects were estimated with the data. The estimation results of the key parameters validated several theoretical predictions predicted by Li (2020).

Chapter 5 explored the impacts of commercial AVs on energy consumption. The AVs’ fuel consumption was calculated by several state-of-the-art or classical vehicle fuel consumption models. We compared the AVs’ fuel consumption with different driving scenarios, speed ranges, and headway settings. The results revealed important implications on overall energy consumption of AV traffic.

Finally, Chapter 6 summarized the major findings and closed this dissertation. A few interesting research directions were pointed out.

Figure 1.2 Summary of dissertation contents.
Chapter 2: AV Trajectory Data Collection

Vehicle trajectories, as the positions of a stream of vehicles over time along a guideway (Daganzo, 1997), can provide informative insights into various traffic-related studies, such as traffic flow theory, traffic simulation modeling, traffic safety measures, and traffic management. To study the impacts of commercial AV on future traffic without loss of generality, this dissertation conducted a series of field experiments to collect real-world commercial AV trajectory data. The rest of this chapter is organized as follows. Section 2.1 describes the sites, facilities, and device for collecting the AV trajectory data. Section 2.2 presents the detailed experiment plans. Section 2.3 concludes the chapter.

2.1 Experiment Settings

2.1.1 Vehicles

The vehicles employed in the field experiments included two AVs equipped with commercially-implemented ACC systems and one regular vehicle equipped with a cruise control system. The AV models were Lincoln MKZs 2016 and 2017 with the same vehicle length (i.e., 4.92 meters) as shown in Figure 2.1; the regular vehicle model was an Audi Q7. The equipped ACC systems of these two AVs were the same – four different following headway settings, indexed from 1 through 4 as the headway increases. Note that the ACC systems in the AVs can also perform speed cruise control such that specified speed profiles can be executed by inputting the desired speed to the ACC systems. Therefore, these two ACC vehicles were used to collect the two-vehicle

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2 Portions of this chapter has been previously published in Shi and Li (2021a, 2021b). Permission is included in Appendix A.
car-following data – one served as the preceding vehicle executing a specified speed profile and the other as the following vehicle. To collect three-vehicle platoon trajectory data, the Audi Q7 served as the leading vehicle and the Lincoln MKZ 2016 and 2017 were the second and third vehicles in the platoon following the leading vehicle in the ACC mode in a single lane. Trajectory data of vehicles during the experiments were recorded for further analysis.

Figure 2.1 Experiment Vehicles.

2.1.2 GPS Device

Real-time GPS positions and speeds of the experiment vehicles were collected at a sampling rate of up to 10Hz by high-accuracy U-blox C066-F9P GPS receivers with antennas affixed to the rear bumpers of the vehicles. The U-blox GPS devices are illustrated in Figure 2.2. Preliminary testing indicated that the GPS receivers had a position accuracy of 0.26 m and a speed accuracy of 0.089 m/s. Thus, the real-time vehicle-following spacing between the two vehicles could be obtained by the distance between the GPS positions of the two vehicles due to the identical lengths of the two vehicles.
2.1.3 Testing Site

As shown in Figure 2.3, the experiments were conducted at a segment of Florida State Rd 56 between Bruce B Downs Blvd and Gall Blvd. The length of the experiment site is around 10 miles. The vehicles circulated between the start and end points and collected the field experiment data. The building density around the experiment site is relatively low, which is ideal for collecting the GPS data.

2.2 Experiment Plans

With this, two types of experiments were conducted, such as car-following and platooning experiments as illustrated in Figure 2.4.
2.2.1 Car-Following Experiment 1

In car-following experiments 1 and 2, AV A (red) always served as the lead vehicle, and AV B (black) enabled ACC system following AV A in a single lane. To study the fuel consumption of the commercial AVs under different speed ranges and headway settings, in car-following experiment 1, ten speed profiles were executed by AV A for each headway setting (i.e., headway settings 1 through 4), as illustrated in Table 2.1. For validation purposes, we conducted each speed profile twice. Therefore, there were twenty tests for each headway setting. The raw car-following data for headway setting 1 are shown in Figure 2.5 to help readers understand the experiment settings. The upper subfigure of Figure 2.5 shows the data of tests 1-5 (denoted by high-speed tests, i.e., 45-55 mph), and the lower subfigure shows the data of tests 6-10 (denoted by low-speed tests, i.e., 35-45 mph).
Table 2.1  Speed profiles for the car following experiment for each headway setting.

<table>
<thead>
<tr>
<th>Speed Profile</th>
<th>0s-30s</th>
<th>30s-60s</th>
<th>60s-90s</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>55 mph</td>
<td>53 mph</td>
<td>55 mph</td>
</tr>
<tr>
<td>2</td>
<td>55 mph</td>
<td>51 mph</td>
<td>55 mph</td>
</tr>
<tr>
<td>3</td>
<td>55 mph</td>
<td>49 mph</td>
<td>55 mph</td>
</tr>
<tr>
<td>4</td>
<td>55 mph</td>
<td>47 mph</td>
<td>55 mph</td>
</tr>
<tr>
<td>5</td>
<td>55 mph</td>
<td>45 mph</td>
<td>55 mph</td>
</tr>
<tr>
<td>6</td>
<td>35 mph</td>
<td>33 mph</td>
<td>35 mph</td>
</tr>
<tr>
<td>7</td>
<td>35 mph</td>
<td>31 mph</td>
<td>35 mph</td>
</tr>
<tr>
<td>8</td>
<td>35 mph</td>
<td>29 mph</td>
<td>35 mph</td>
</tr>
<tr>
<td>9</td>
<td>35 mph</td>
<td>27 mph</td>
<td>35 mph</td>
</tr>
<tr>
<td>10</td>
<td>35 mph</td>
<td>25 mph</td>
<td>35 mph</td>
</tr>
</tbody>
</table>

Figure 2.5  Raw trajectory data for high-speed tests with different headway settings.
2.2.2 Car-Following Experiment 2

In car-following experiment 2, we aim to study the fuel consumption of the commercial AVs under different operating scenarios and speed ranges. Four types of operating scenarios were explored, such as HV follows HV (both AVs disabled the ACC systems and were operated by human drivers, denoted by HV-HV), AV follows HV (HV-AV), HV follows AV (AV-HV), and AV follows AV (AV-AV), as shown in Figure 2.6. For each operating scenario, AV A (operated by either the ACC system or human driver) served as the lead vehicle executing a set of speed profiles with given values (e.g., 30, 40, 50, 60 mph). AV B (operated by either the ACC system or human driver) followed AV A in a single lane. Thus, there were sixteen tests in car-following experiment 2. The AVs circulated at the segment of the testing site to conduct the tests. Once the AVs arrived at the end of the segment, the AVs needed to decelerate to a low speed (or a full stop) to make a U-turn. Then the AVs needed to accelerate to the given speed values to conduct the experiment. To avoid the impacts of the acceleration and deceleration processes on fuel consumption, only the data that both the lead and following vehicles reached the given speed values will be studied in this chapter. Then the raw speed data of AV B of the car-following experiment 1 is shown in Figure 2.6.
2.2.3 Platooning Experiment

To supplement the above data in particular to test oscillation periodicity, a series of three-vehicle platoon tests were conducted, in which the speed of the lead vehicle was changed.
periodically to match the dominating oscillation periods derived for the estimated AV control models (see Table 4.4 for the estimated period values).

As noted, the Audi Q7 was the lead vehicle, and the Lincoln MKZs 2016 and 2017 were the second and third vehicles in the platoon following the lead vehicle in the ACC mode in the same lane. For each headway setting, five different cycle periods were tested – 18, 20, 22, 24, and 26 seconds. Each period was repeated in four cycles to reveal the propagation pattern of the repeated cyclic speed profile while attenuating the impacts of the initial states. Therefore, the duration time for the tests with one headway setting was \((18 + 20 + 22 + 24 + 26) \times 4 = 440\) seconds. The two target speeds of the lead vehicle were set to 55 mph and 50 mph. The lead vehicle’s speed profile was generated by manually setting its cruise control target speed to the corresponding target speed at the beginning of each half cycle, i.e., 50 mph for the first half of a cycle and 55 mph for the second half of a cycle. As a result, the lead vehicle speed decreased from 55 mph to 50 mph in the first half of each cycle and increased from 50 mph to 55 mph in the second half of a cycle. To help readers understand the test settings, the detailed test plan for headway setting 1 with a cycle period equal to 18 seconds is shown in Table 2.2 as an example. Since the cycle period will be repeated four times, the duration time was 72 seconds for the example.

<table>
<thead>
<tr>
<th>Cycle number</th>
<th>Duration (seconds)</th>
<th>Initial speed (mph)</th>
<th>Target speed (mph)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1-9</td>
<td>55</td>
<td>50</td>
</tr>
<tr>
<td>2</td>
<td>10-18</td>
<td>50</td>
<td>55</td>
</tr>
<tr>
<td>2</td>
<td>19-27</td>
<td>55</td>
<td>50</td>
</tr>
<tr>
<td>3</td>
<td>28-36</td>
<td>50</td>
<td>55</td>
</tr>
<tr>
<td>3</td>
<td>37-45</td>
<td>55</td>
<td>50</td>
</tr>
<tr>
<td>4</td>
<td>46-54</td>
<td>50</td>
<td>55</td>
</tr>
<tr>
<td>4</td>
<td>55-63</td>
<td>55</td>
<td>50</td>
</tr>
<tr>
<td>4</td>
<td>64-72</td>
<td>50</td>
<td>55</td>
</tr>
</tbody>
</table>
The obtained raw speed data with different headway settings are shown in Figure 2.7. Analysis of the platoon data is elaborated on in the stability analysis section.

![Figure 2.7 Raw trajectory data for platoon tests with different headway settings.](image)
Chapter 3: AV Traffic Flow Fundamental Diagram

Fundamental diagram (FD) describes a well-defined relation curve for traffic flow rates and density in steady traffic states (Daganzo, 1997; Greenberg, 1959; Newell, 1961). The FD is critical to study traffic flow characteristics and dynamics across various spatial scales with analysis, modeling, and simulation methods. This chapter studied the AV traffic flow FD based on the collected AV trajectory data. The rest of this chapter is organized as follows. Section 3.1 presents the methods to extract traffic flow characteristics from vehicle trajectory datasets. Section 3.2 shows the datasets analyzed in this chapter. Results are discussed in Section 3.3. Section 3.4 describes the mixed traffic flow FD construction approach. Section 3.5 summarizes the section and identifies future research directions.

3.1 Methods for Measuring Traffic Flow Characteristics

This section presents two methods from the macroscopic and microscopic perspectives to measure traffic flow characteristics (i.e., density, flow rate, and speed). The estimated traffic flow characteristics may be used to construct the corresponding FD.

3.1.1 Macroscopic Method

When a stream of trajectory data is available, we can study traffic flow characteristics by the macroscopic method proposed by Edie (1963), known as Edie’s generalized definition of traffic variables. In this dissertation, a vehicle trajectory means the curve of the location of a certain reference point on a vehicle (e.g., mid-point of front bumper) over time. This method deals with a

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3 Portions of this chapter has been previously published in Shi and Li (2021b). Permission is included in Appendix A.
An n-vehicle platoon inside an arbitrary time-space region $A$. Density $k$, flow rate $q$, and speed $v$ in region $A$ can be calculated by (3.1)-(3.3).

\[ k = \sum_{i=1}^{n} \frac{t_i}{|A|}, \]  
(3.1)

\[ q = \sum_{i=1}^{n} \frac{x_i}{|A|}, \]  
(3.2)

\[ v = \frac{q}{k} = \sum_{i=1}^{n} \frac{x_i}{t_i}, \]  
(3.3)

where $|A|$ denotes the area size of region $A$ and $t_i, x_i$ are the $i$th vehicle travel time and distance traveled inside $A$, respectively, as illustrated in Figure 3.1.

Figure 3.1 Illustration of parameters for traffic flow characteristics calculations.

In this dissertation, $A$ is set as a parallelogram region constructed with two sides parallel to the shockwave speed of $w$ and the other two parallel to trajectories, as shown in Figure 3.2. In this way, one maximizes the chances of having stationary conditions inside the region (Laval, 2011).
3.1.2 Microscopic Method

Such trajectory data in a long platoon may not always be available due to limited experiment resources. When a platoon is relatively short (e.g., only a couple of vehicles), it would be difficult to apply the above macroscopic method to construct traffic flow characteristics accurately. To address this issue, we propose a microscopic method to measure the traffic flow characteristics with only two consecutive vehicle trajectories. Note that the FD describes the relationship of the flow rate and density at steady states. Thus, to maximize the possibilities that the calculated flow rate and density can describe steady-state characteristics, only trajectory segments that the two vehicles have relatively constant speed are selected for the following calculations. The microscopic method is described as follows.

For two consecutive trajectories, we consider a time-space region $B$ (as shown in Figure 3.3). Note that the lower and upper sides of the region are the corresponding segments of the two trajectories within the same time window $t$. Density $k$, flow rate $q$, and speed $v$ for region $B$ can be calculated by (3.4)-(3.6).

$$v = \frac{x}{t},$$  \hspace{1cm} (3.4)
\[ k = t / |B|, \]
\[ q = kv = x / |B|, \]

where \( t, x \) denote the following vehicle travel time and distance traveled inside \( B \), and \( |B| \) is the area of region \( B \). What must be emphasized is that the proposed microscopic method arguably is the most efficient way to study the characteristics of traffic flow without much loss of generality when experiment resources are limited; otherwise, the macroscopic method is preferred.

![Figure 3.3 Illustration of generated region for vehicle following trajectories.](image)

With these two methods, by successively moving the region \( A \) or \( B \) throughout the study trajectories, the traffic flow characteristics (e.g., density, flow rate, and speed) are obtained. Then, the FD can be obtained by fitting the characteristic data points in the flow-density diagram.

### 3.2 Dataset

#### 3.2.1 Dataset 1

The first dataset includes three-vehicle platoon trajectory data and two-vehicle car-following data, collected by the proposed data collection method.

#### 3.2.2 Dataset 2

The second dataset was generously shared by Gunter et al. (2019). Two types of trajectory data were included—a five-vehicle platoon trajectory dataset (including one lead autonomous test
vehicle for which control commands can be input from onboard computers and four following commercial AVs), and a two-vehicle car-following trajectory dataset (including one lead CC vehicle and one following commercial AV). The following AVs in the experiments had the same ACC systems with two headway settings, e.g., short and long headway settings. Similarly, the experiments were conducted at two-speed ranges, high (65–75 mph) and low (35–55 mph) speed ranges. In the experiments, the lead vehicle executed a specific pre-defined speed profile (including quick acceleration and deceleration) and the following vehicles (four or one commercial AVs) drove in a single lane followed the lead vehicle by controlling the onboard ACC system. Due to limited experiment resources, the platoon trajectory data were relatively short, so we could not accurately construct traffic flow characteristics using the macroscopic method. Therefore, the car-following trajectory dataset was processed with the proposed microscopic method instead.

3.2.3 Dataset 3

The third dataset was a set of trajectory data of human-driven vehicles in a specified segment of I-75 in Florida, which served as a benchmark to the studied traffic flow characteristics of the commercial AVs. Videos of human-driven vehicle trajectories were taken via helicopter. Then, the trajectory data were extracted from the videos by the video processing method proposed by Shi et al. (2021). Trajectory data can be found at https://github.com/CATS-Lab-USF and will also be available on the official website of the Federal Highway Administration soon. Figure 3.4 illustrates the trajectories of dataset 3.
3.3 Experiment Results and Discussions

We first studied the characteristics of traffic flow for each dataset by using the methods proposed in Section 3.1. Based on the trends of the characteristics, the triangular FD was adopted to interpret the relationships among the traffic flow characteristics. Then, comparisons of traffic flow characteristics between the AVs and human-driven vehicles were conducted to provide insights into the impacts of AVs on traffic flow.

3.3.1 Experiment Results and Analyses

Figure 3.5 (a)–(c) shows scatter plots of traffic flow characteristics generated by dataset 1. To differentiate the data from different experiment settings, the points from high-speed, mid-speed,
and low-speed tests are marked with triangles, circles, and diamonds, respectively. The points of headway settings 1–4 are red, green, blue, and pink, respectively.

Figure 3.5 Density-flow rate, density-speed, flow rate-speed scatter plots for Dataset 1.
Figure 3.5 (a) plots the flow rates over the density of the studied dataset. It can be seen that all data points are in the congested regime of the FD. This is because all data points were associated with the car-following mode, whereas the free-flow regime of the FD (left side of congestion) corresponds to all AVs cruising at free-flow speed without downstream impedance. Thus, even without data points, the free-flow regime can be easily estimated with a straight line from the origin point with a slope of the given free-flow speed (often depending on the road speed limit). Therefore, in engineering applications, the free-flow regime is often trivial, and the congestion regime is often the focus. Thus, we focused on the congestion regime in the following analysis. Next, it can be found in Figure 3.5 (a) that as density increases, the flow rate exhibits a decreasing trend, and the longer the headway is, the lower the flow rate is, and the slower the decreasing slope is. This indicates that the road capacity (i.e., maximum flow rate across all density) decreases as the AV headway setting increases. For the longest headway setting (#4), the road capacity is only around 1500 vehicles/hour, which is about half of that for the shortest headway setting, i.e., around 2900 vehicles/hour. This empirical finding is informative to future road traffic management by relevant stakeholders. For example, to maximize the utilization of road infrastructures in peak hours, policies could be made to encourage the use of shorter headway settings to mitigate congestion.

The classic triangular FD has many merits in traffic flow studies, such as the fixed free flow rate and shock wave speed. Thus, this structure indicates that the flow-density relationship in the congestion regime can be captured by a linear function. We fitted a linear function to the points in Figure 3.5 (a) of each headway setting. The fitting parameters of the linear function for each headway setting, including flow rate capacity, shock wave speed, jam density, and fitness results such as the adjusted $R^2$, are shown in Table 3.1. It was found that the fitted straight lines had
relatively good fitness, indicating that the triangular FD structure remains applicable to describe the characteristics of AV traffic.

Table 3.1 Fitting parameters of triangular FDs.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Headway setting</th>
<th>Road capacity (vehicles/h)</th>
<th>Shock wave speed (km/h)</th>
<th>Jam density (vehicles/km)</th>
<th>Adjusted $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>2900</td>
<td>61.1</td>
<td>80.77</td>
<td>0.50</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>2250</td>
<td>47.2</td>
<td>74.96</td>
<td>0.64</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>1850</td>
<td>28.4</td>
<td>86.11</td>
<td>0.75</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>1500</td>
<td>20.0</td>
<td>90.77</td>
<td>0.67</td>
</tr>
<tr>
<td>2</td>
<td>Short</td>
<td>2550</td>
<td>64.4</td>
<td>62.00</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
<td>Long</td>
<td>1480</td>
<td>30.0</td>
<td>60.91</td>
<td>0.22</td>
</tr>
<tr>
<td>3 (Human-driven)</td>
<td>2000</td>
<td>30.5</td>
<td>94.40</td>
<td>0.79</td>
<td></td>
</tr>
</tbody>
</table>

Note that the adjusted $R^2$ values of headways 3 and 4 are better than those of headways 1 and 2, which indicates that a longer headway setting tends to yield more steady traffic. This indication can also be verified by the widespread data points of headways 3 and 4 in Figure 3.5 (a). This result provides empirical support to the trade-off between traffic stability and AV headway settings—a longer AV headway, though decreasing traffic capacity, may help stabilize traffic oscillation. The implication to policymaking is that when traffic capacity is sufficient (e.g., off-peak hours), the use of longer headway settings may be encouraged.

Further, we observed that the fitted straight lines intersect with the horizontal axis (i.e., density axis) in Figure 3.5 (a). Each intersection indicates the jam density for the corresponding headway setting—once the traffic flow stops completely, how many vehicles can be accommodated by the road in one kilometer. The results show that the jam density values across different headway settings are approximately identical, at around 85 vehicles/km.

To provide different perspectives of the traffic flow characteristics, Figure 3.5 (b) and (c) plot the density-speed and flow rate-speed relationships from the observed data points, respectively. In the density-speed figure (Figure 3.5 (b)), as density increases, speed exhibits a decreasing trend.
In the flow rate-speed figure (Figure 3.5 (c)), as the flow rate increases, speed exhibits an increasing trend. Further, the data points across different headway settings seem to all converge at the origin with proper extrapolation, which verifies that when the speed drops to 0, the flow rate is also 0. These trends are the same as those described by the congestion regime of the triangular FD, which further validates the suitability of the triangular FD structure in analyzing these data.

Figure 3.6 (a)-(c) show the scatter plots of traffic flow characteristics generated by dataset 2. Similarly, all data points are in the congested regime of FD. Also, significant correlations among the traffic density, flow rate, and speed are shown in the figure. For consistency, the points of the long headway setting are pink and those of the short headway setting are red. The points from high-speed tests are marked with triangles and those from low-speed tests are marked with circles.

Figure 3.6 Density-flow rate, density-speed, flow rate-speed scatter plots of Dataset 2.
Figure 3.6 (a) plots the flow rates over the density of dataset 2. It was found that as density increases, the flow rate exhibits a decreasing trend, and the long headway setting has lower values of the flow rate and decreasing slope than the short headway setting. The road capacity for the short and long headway settings of dataset 2 is approximately 2550 and 1480 vehicles/hour, respectively.

By fitting a linear function to the data points in Figure 3.6 (a) of each headway setting, the fitting parameters of the linear function of dataset 2 are shown in Table 3.1. The values of adjusted $R^2$ shown in Table 3.1, indicating that the model fitness is significantly different from Datasets 1 and 2. Although the data points of headways 1 and 2 in dataset 1 are dispersed, as shown in Figure 3.6 (a), the average value of adjusted $R^2$ of dataset 1 over the four headway settings is 0.64. However, the average value of adjusted $R^2$ of dataset 2 over the two headway settings is 0.16. The main reason for this difference may be because of the pertinent experiment design described in Section 3. That is, the experiment design proposed herein includes more traffic flow steady states than that proposed in Gunter et al. (2019). Therefore, the data points of dataset 1 shown in Figure 3.5 are more aggregated than those of dataset 2 shown in Figure 3.6. Moreover, the jam density values across different headway settings for dataset 2 are approximately identical, around 60 vehicles/km.

Figure 3.6 (b) and (c) plot the density-speed and flow rate-speed relationships of dataset 2, respectively. The relationships follow the same trends as those of dataset 1. In the density-speed figure (Figure 3.6 (b)), as the density increases, the speed exhibits a decreasing trend. In the flow rate-speed figure (Figure 3.6 (c)), as the flow rate increases, the speed exhibits an increasing trend.

Figure 3.7 plots the flow rates over the density of dataset 3 (i.e., human-driven data). Due to the available data points in the free-flow regime, both the free-flow and congested regimes can
be found in Figure 3.7. We fit a linear function to the data points at the congested regime in Figure 3.7, and the fitting parameters of the linear function is shown in Table 3.1. Note that the traffic flow FD of human-driven vehicles has been well investigated by existing studies (Gayah et al., 2014; Geroliminis and Sun, 2011b; Knoop and Hoogendoorn, 2013), and the obtained fitting parameters of dataset 3 are consistent with the previous studies’ findings. The estimated free-flow speed of the dataset is about 70 km/h. The value of the adjusted $R^2$ of the fitness is 0.79, indicating a relatively good fitness of the triangular FD.

![Figure 3.7 FD plots of dataset 3.](image.png)

3.3.2 Comparisons and Discussions

The above sections present the traffic flow characteristics and the FDs of the three datasets. In this section, traffic flow characteristics among the three datasets are compared and discussed to draw insights into the impacts of AVs on traffic flow.

Compared the results of the AV datasets (datasets 1 and 2) in Table 3.1, the estimated road capacity is almost consistent over the two datasets. The maximum and minimum road capacity obtained from dataset 2 is 2550 vehicles/hour and 1480 vehicles/hour, respectively. These values are on the same order of magnitude with the maximum (2900 vehicles/hour) and minimum (1500 vehicles/hour)
vehicles/hour) road capacity obtained from dataset 1, whereas the actual values are slightly smaller than those in dataset 1. The consistency indicates that different automakers may follow similar general principles in designing ACC control, which enables our FD method to generally apply across different vehicle technologies. This slight difference may be due to different ACC configurations and vehicle dynamics between different vehicle vendors and other heterogeneous exogenous factors while conducting the experiments (e.g., speed limit, road conditions, etc.).

Table 3.1 shows the fitting parameters across the six headway settings of the two AV datasets (i.e., four headway settings of dataset 1 and two headway settings of dataset 2). As shown, as the headway increases in both datasets, road capacity decreases and the shockwave speed decreases, whereas the jam density does not change much. This indicates that different headway settings will mainly affect traffic throughput when traffic is mildly congested but may have fewer impacts in highly congested traffic. We also see that the jam density value of dataset 2 (60 veh/km) is smaller than that of dataset 1 (85 veh/km). One possible explanation is that the ACC system design in dataset 2 is more conservative than the ACC system in dataset 1 when traffic is highly congested. Thus, when traffic flow stops completely, a smaller number of vehicles can be accommodated by the road in one kilometer with the ACC system in dataset 2 compared with that in dataset 1.

Overall, in both AV datasets, the impacts of AVs on traffic flow are related to the enabled headway settings—a shorter headway setting improves road capacity. Further, the values of the minimum and maximum capacity across different AV vendors are consistent despite some minor discrepancies. This finding verifies the potential transferability of the proposed AV FD modeling framework across different AV technologies for engineering applications that may tolerate certain
errors. However, if more accurate measures are needed, the heterogeneity of AV traffic flow may need to be taken into consideration in future studies.

Note that the estimated parameters of the FDs are different across the different datasets, as shown in Table 3.1. The road capacity of the human-driven vehicles is about 2000 veh/hour, which is between the highest capacity (with the shortest headway) and the lowest capacity (with the longest headway) of AV datasets 1 and 2. This result draws the following insights into existing commercial AV following designs. First, it suggests that vehicle vendors may design AV following algorithms in accordance with the traffic flow characteristics of human-driven vehicles. AV headway settings are comparable to the average following headway of human drivers while allowing some variation range to suit preferences from heterogeneous individual drivers. Second, the merits of AVs proposed by previous studies that AV technologies can significantly improve the road capacity may be too optimistic. Based on the estimated results of this study, only the shortest headway setting can significantly improve road capacity (from 2000 veh/hour to 2900 or 2550 veh/hour dependent on the result of which dataset is adopted), whereas some other headway settings may even reduce the road capacity.

Further, it is worth mentioning that although we found that a shorter headway setting improves road capacity, safety concerns will be raised once the headway setting is too short (Robbins et al., 2018). Also, headway settings may affect the stability of the traffic flow. Once the enabled headway setting is too short, traffic flow becomes less stable, and road capacity may drop (Li, 2020; Shi and Li, 2020).

3.4 Mixed Traffic Flow Fundamental Diagram

As the AV feature (ACC system) is equipped on only a relatively small subset of vehicles currently, pure AV traffic flow is still far from reality. Instead, it is likely that mixed traffic flow
containing both AVs and human-driven vehicles will dominate road traffic for a long time. Investigations of mixed traffic flow characteristics are essential for the analysis, modeling, and simulation of future traffic as AV penetration rates increase. Extended from the analytical methods for mixed traffic flow characteristics proposed by Ghiasi et al. (2017) and Qian et al. (2017), we propose a general and parsimonious method to formulate a mixed traffic FD function, i.e., mixed traffic flow rate over density, based on the above pure AV/human-driven vehicle FDs in the following analysis.

Consider a set of different vehicle types, denoted by $J$, e.g., including human-driven vehicles, AVs with headway settings 1, 2, 3 and 4, etc. Note that if platooning with connected vehicles are considered, vehicle following behaviors may depend not only on the subject vehicle but also the preceding vehicle (e.g., an AV following a human-driven vehicle may have different following behaviors as opposed to an AV following another AV that is platooned with a shorter headway; see Ghiasi et al. (2017)). Assume that the pure traffic with type-$j$ vehicles follows the following FD equation:

$$
q_j(k) := \begin{cases} 
\bar{v} k, & k \in [0, q_j^0/(\bar{v} + w_j)]; \\
-w_j k + q_j^0, & k \in [q_j^0/(\bar{v} + w_j), q_j^0/w_j], 
\end{cases}
$$

(3.7)

where $\bar{v}$ is the speed limit of the studied road (we assume all vehicle types share the same speed limit on the same road), $-w_j$ is the FD slope of the congestion regime (or the corresponding backward shockwave speed), and $q_j^0$ is the intercept of the congested-regime FD branch and the flow rate axis. These parameters are illustrated in Figure 3.8. Note that each regressed curve in Figure 3.5 (a), Figure 3.6 (a), and Figure 3.7 is such a pure traffic FD (or the congested regime of it).
In the investigated mixed traffic, let \( \alpha_i \) denote the penetration rate of type-\( j \) vehicles \( \forall j \in \mathcal{J} \), and let \( k \) denote the total mixed traffic density. Then \( k_j := k \alpha_j \) is the density of type-\( j \) vehicles in mixed traffic. When \( \sum_{j \in \mathcal{J}} (\bar{v} + w_j) k_j / q_j^0 \leq 1 \) (or \( k \leq 1 / (\sum_{j \in \mathcal{J}} (\bar{v} + w_j) \alpha_j / q_j^0) \)), the occupancy for each type of vehicles is sufficiently low to maintain their vehicle speed at speed limit \( \bar{v} \), and the mixed traffic’s state is in the free-flow regime. In this case, the mixed traffic flow \( q(k) \) is simply identical to \( \bar{v} k \). Otherwise, when \( \sum_{j \in \mathcal{J}} (\bar{v} + w_j) k_j / q_j^0 > 1 \), congestion takes place, and all vehicles will drive at a speed \( v \) less than \( \bar{v} \). We will solve speed \( v \) as follows. At speed \( v \), based on Equation (7), we can obtain the corresponding pure traffic density for type-\( j \) vehicles as \( \bar{k}_j(v) := q_j^0 / (v + w_j) \). Given type-\( j \) vehicles density \( k_j \), then we can obtain that the occupancy of type-\( j \) vehicles in the mixed traffic is \( k_j / \bar{k}_j(v) = (v + w_j) k_j / q_j^0 \). In congested traffic, the summation of the occupancies of all vehicle types should be identical to 100\%, which yields

\[
v = \frac{1 - \sum_{j \in \mathcal{J}} w_j k_j / q_j^0}{\sum_{j \in \mathcal{J}} k_j / q_j^0}.
\]
The corresponding flow rate can be obtained as with the following equation.

\[ q(k) = kv = \frac{1 - k \sum_{j \in J} w_j \alpha_j / q_j^0}{\sum_{j \in J} \alpha_j / q_j^0}. \]

Combining the results for both free-flow and congested regimes, we obtain the mixed traffic FD as

\[ q(k) = \begin{cases} \bar{v}k, & k \in [0, R]; \\ \frac{1 - k \sum_{j \in J} w_j \alpha_j / q_j^0}{\sum_{j \in J} \alpha_j / q_j^0}, & k \in [R, 1]; \end{cases} \]

where \( R = 1/(\sum_{j \in J}(\bar{v} + w_j)\alpha_j / q_j^0) \).

Next, we illustrate how to apply the above formula with the pure FDs from dataset 1 (for the AV types) and dataset 3 (for the human-driven vehicle type). Figure 3.9 (a)-(d) show the FDs with different headway settings as the AV market penetration rate increases. It can be observed in Figure 3.9 (a) that as the AV market penetration rate increases, AVs with the shortest headway setting (headway 1) significantly improve the mixed traffic flow road capacity and shockwave speed, while the jam density does not change much. For the second shortest headway setting (headway 2) shown in Figure 3.9 (b), as the AV market penetration rate increases, the road capacity and shockwave speed slightly increase. Nevertheless, for headways 3 and 4 (Figure 3.9 (c) and (d)), the values of road capacity, shockwave speed, and jam density are found even smaller than that of human-driven vehicle traffic as the AV market penetration rate increases. These results further verify our findings that the results from the previous studies might be too optimistic to be applied to existing commercial AVs.

Together with the previous findings that a short headway setting can improve the traffic flow capacity at the cost of compromising traffic safety and stability, it is intriguing to
appropriately manage the AV headway settings in future mixed traffic to balance the road capacity and traffic stability.

![Figure 3.9 FDs with different AV penetration rates and headway settings.](image)

**3.5 Chapter Summary**

Increasing the number of commercial AVs may lead to significantly different car-following behaviors compared with those of human-driven vehicles, which challenges the applicability of classic traffic flow theory. To help understand the impacts of commercial AVs on traffic flow, this chapter proposed a general method that combines both empirical experiments and theoretical models to construct an FD for AV traffic. High-resolution trajectory data with multiple commercial
AVs following one another in a platoon with different headway settings were collected to study the AV traffic flow characteristics. Data analysis results revealed that the traditional triangular FD structure remains applicable to describe the traffic flow characteristics of AV traffic. The comparisons and discussions among the FD results of AVs and human-driven vehicles indicated that though the shortest AV headway setting can significantly improve the road capacity, other headway settings may decrease the road capacity compared with existing human-driven-vehicle traffic. Further, this chapter empirically verified that AV headway settings may affect the stability of the traffic flow. A mixed traffic FD construction approach was proposed to provide the basis for analysis, modeling, and simulation of future mixed traffic and draw managerial insights. The proposed general FD modeling approaches, which may be easily calibrated despite uncertainties and evolutions of the AV technologies, can serve as a methodological foundation for future mixed traffic flow studies.
Chapter 4: AV Car-Following Characteristics  

Vehicle following, as a fundamental function of AV longitudinal operation at all different automation levels, has significant impacts on road traffic, including safety, mobility, and stability. To understand the design mechanism of commercial AV car-following function (ACC system), this chapter investigated the AV car-following characteristics through a linear AV-following model proposed in Li (2020). The rest of this chapter is organized as follows. Section 4.1 introduces the linear AV-following model proposed in Li (2020) to be estimated with the collected data. Section 4.2 examines the relationships among the estimated parameters of the AV-following model to verify the tradeoffs between safety, mobility and stability and draw additional managerial insights. Section 4.3 concludes the chapter and points out the directions for future research.

4.1 Car-Following Model

This study adopted the parsimonious linear AV following model proposed in Li (2020) for estimating associated AV control parameters in different settings. This model was formulated as shown in model (4.1)

$$\ddot{y}(t) = k[x(t) - l - \Delta - y(t) - \tau \dot{y}(t)],$$  \hspace{1cm} (4.1)

where $x(t)$ and $y(t)$ are the locations (of the front bumpers) of the preceding and following vehicles at time $t$, $k > 0$ is the control sensitivity factors, $\Delta \geq 0$ is the safety buffer, $\tau \geq 0$ is the time lag, $l > 0$ is the fixed preceding vehicle’s length, and the dot and double dot operators are the first- and second-order derivatives, respectively.

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4 Portions of this chapter has been previously published in Shi and Li (2021a). Permission is included in Appendix A.
The above model is actually the linearized form of the optimal-velocity car-following model proposed to explain periodic traffic oscillation (Bando et al., 1995). As argued in Li et al. (2012), the above linear structure was adopted for the following reasons. First, a linear structure well describes vehicle-following behavior when vehicle speed oscillation is relatively small. Secondly, the performance of a linear AV control model was verified by several field experiments (Gunter et al., 2020a; Milanés and Shladover, 2014). Further, the proposed linear structure is arguably the simplest form that captures all safety (with $\Delta$), mobility (with the following spacing $x(t) - l - \Delta - y(t) - \tau y(t)$) and stability (e.g., as a second-order feed-back control with sensitivity factors $k$) aspects in a physically meaningful way (Li, 2020).

The above simple linear model has certain limitations. First, the linear model may not capture possible nonlinear effects in AV control. Further, the model does not contain the speed difference term compared with the general second-order linear model used in describing AV-following behavior. However, it may still be valuable to conduct an analysis with these limitations. Li and Ouyang (2010) showed that a linear model likely overestimates actual speed oscillation and, thus, the safety buffer obtained from a linear model tends to be on the conservative side and actually provides an upper bound of the actually needed safety buffer, which is acceptable for safety analysis. Further, the data fitness result in Section 4.1 suggests that the impacts on model predictability of dropping the speed difference term are minor in terms of the adjusted $R^2$. Separate numerical tests also showed that dropping this term does not much affect the control overshoot that determines the safety buffer value. Thus, dropping the speed difference term does not lose much generality for this study.
4.2 Field Data Fitness Results and Analyses

This section estimates the parameter values of the AV control model (I) with the experiment data collected in Chapter 2. The relationships between the estimated parameters in different settings are discussed to test the theoretical findings in Li (2020) and draw additional insights. Section 4.2.1 presents the estimated parameters. Sections 4.2.2 and 4.2.3 analyze the mobility and string stability implications of the AV following design, respectively. Section 4.2.4 provides discussion beyond the theoretical predictions of Li (2020). Section 4.2.5 verifies the relations among the estimated parameters by experiment data collected by Gunter et al. (2019). To avoid term confusion, some terms are defined before the analyses. In this chapter, “headway” refers to the time separation between two consecutive vehicles’ front bumpers, “gap headway” refers to the time separation between the leading vehicle’s rear bumper to the following vehicle’s front bumper, “spacing” refers to the distance between two consecutive vehicles’ front bumpers, and “spacing gap” refers to the distance between the leading vehicle’s rear bumper and the following vehicle’s front bumper.

4.2.1 Data Fitness Results

The simple moving average method with a window of 5 seconds was used to denoise the collected data before parameter estimations. By fitting each set (for each headway setting at one speed range) of the two-vehicle car-following data, such as \(x(t), y(t), \dot{y}(t)\) and \(\ddot{y}(t)\), to model (I) with linear regression that aims to maximize the adjusted \(R^2\) value, a total of eight sets of estimation results are obtained as shown in Table 4.1. To verify that the proposed parsimonious linear AV-following model can capture the vehicle following behavior without much loss of predictability, the adjusted \(R^2\) value of the general second-order linear AV control model with the
speed difference term is also provided as a benchmark in Table 4.1 (BM. $R^2_{adj}$). The benchmark model is formulated in model (4.2).

$$\ddot{y}(t) = k_1[x(t) - l - \Delta - y(t) - \tau \dot{y}(t)] + k_2[\dot{x}(t) - \dot{y}(t)],$$

(4.2)

where $k_1, k_2 > 0$ are the control sensitivity factors, and the definitions of the other parameters are the same as those in parsimonious model (4.1).

Comparing the adjusted $R^2$ of the two models shows that the impacts on the model predictability of dropping the speed difference term from the benchmark model are minor. We see that the adjusted $R^2$ values for parsimonious model (4.1) across all the settings are above 0.82, which indicates a fairly good predictability of this model. Further, the improvements of the adjusted $R^2$ from parsimonious model (4.1) to benchmark model (4.2) are not significant. Thus, it does not lose much of the generality to use parsimonious control model (4.1) in the analysis instead of the general second-order control model (4.2).

Table 4.1 Data Fitness Results for Proposed Parsimonious Model and Benchmark Model.

<table>
<thead>
<tr>
<th></th>
<th>$\tau$ (s)</th>
<th>$k$</th>
<th>$\Delta$ (m)</th>
<th>$R^2_{adj}$</th>
<th>BM. $R^2_{adj}$</th>
<th>[(v, V)] (m/s)</th>
<th>([-\bar{a}, \bar{a}]) (m/s²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Speed-Headway Setting 1</td>
<td>0.83</td>
<td>0.10</td>
<td>4.83</td>
<td>0.87</td>
<td>0.90</td>
<td>[8.94, 24.59]</td>
<td>[-0.46, 0.46]</td>
</tr>
<tr>
<td>High Speed-Headway Setting 2</td>
<td>1.21</td>
<td>0.10</td>
<td>4.40</td>
<td>0.95</td>
<td>0.96</td>
<td></td>
<td></td>
</tr>
<tr>
<td>High Speed-Headway Setting 3</td>
<td>1.61</td>
<td>0.09</td>
<td>3.31</td>
<td>0.92</td>
<td>0.93</td>
<td></td>
<td></td>
</tr>
<tr>
<td>High Speed-Headway Setting 4</td>
<td>2.17</td>
<td>0.07</td>
<td>0.66</td>
<td>0.84</td>
<td>0.86</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low Speed-Headway Setting 1</td>
<td>0.79</td>
<td>0.12</td>
<td>7.28</td>
<td>0.92</td>
<td>0.93</td>
<td>[8.94, 15.65]</td>
<td>[-0.53, 0.53]</td>
</tr>
<tr>
<td>Low Speed-Headway Setting 2</td>
<td>1.14</td>
<td>0.09</td>
<td>6.36</td>
<td>0.90</td>
<td>0.92</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low Speed-Headway Setting 3</td>
<td>1.52</td>
<td>0.08</td>
<td>5.92</td>
<td>0.83</td>
<td>0.86</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low Speed-Headway Setting 4</td>
<td>2.09</td>
<td>0.08</td>
<td>4.97</td>
<td>0.82</td>
<td>0.82</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

With the estimated parameter values (i.e., $\tau$, $k$, and $\Delta$), the acceleration ranges (denoted by \([-\bar{a}, \bar{a}]\)) for the studied AV following design were calculated by plugging the estimated parameter and the speed variation ranges (denoted by \([v, V]\), $v$=8.94 m/s for the studied AV following design, and $V$=24.59 m/s or 15.65 m/s that is dependent on the experiment settings) into the equation.
proposed in Li (2020) (i.e., Equation [16] in Li (2020)), and the results are summarized in Table 4.1.

It can be observed in Table 4.1 that the calculated acceleration ranges are very narrow. The average acceleration range over the eight estimations is [-0.495, 0.495] m/s². This means that for the studied AV-following design, the proposed linear model can well interpret the AV following behavior only when the acceleration is within [-0.495, 0.495] m/s². This result indicates that the current commercial AV following design entrusts much of safety warranty to nonlinear control mechanisms (e.g., drastic emergency stops) while the linear control only dominates in a relatively narrow acceleration range. This finding raises cautions of using linear models to describe ACC behavior in simulation, which is pretty much most traffic simulation does.

4.2.2 Mobility and Safety Analysis

This section interprets the parameter estimation results obtained in Table 4.1 from the mobility and safety perspectives and verifies the corresponding theoretical predictions in Li (2020). HS refers to short of the high-speed results and LS refers to short of the low-speed results in the following figures. Figure 4.1 (a) plots the estimated \( \tau \) values over the headway settings. By fitting the scatters to a simple linear regression model, it is clear that the headway settings are highly correlated with the estimated time lags in a linear relationship. The \( R^2 \) of the fitted straight lines for both the high-speed and low-speed settings are over 0.985, indicating very good fitness. The results are consistent with the expectation that the corresponding time lag gap of the commercial ACC system increases linearly with the headway settings. However, of note is that although it was found that there is a linear relationship between the time lag gap and headway settings for the studied ACC system (Lincoln brand), the time lag gap may not necessarily be a linear scaling from the headway settings 1-4. Different vehicle vendors can have different design strategies for the headway settings while the linear relationship perhaps is the simplest strategy. Further, the results
between the high-speed and low-speed settings are consistent, indicating that the time lag is relatively fixed at the same headway setting across all speed ranges. Based on the following gap decompositions as shown in Figure 1.1, \( g(t) = \tau + \Delta/\dot{y}(t) \), where \( g(t) \) and \( \dot{y}(t) \) are the following gap headway (inter-gap headway) and following vehicle speed at time \( t \), respectively.

Figure 4.1 (b) shows the values of the average following gap headway (calculated by averaging the measured following gap headway across all time intervals in an experiment setting, i.e., \( \sum_{t=1}^{T} g(t) / T \), where \( T \) is the number of time intervals) over the headway settings. It can be found that there is also a linear relationship between the values of average following gap headway and the headway settings. Moreover, the fitted line for low-speed settings is slightly higher than the fitted line for high-speed settings as shown in Figure 4.1 (b). Since the values of the time lag (i.e., \( \tau \)) are relatively fixed, it indicates that the safety buffer headway (\( \Delta/\dot{y}(t) \)) for the low-speed settings are greater than that of the high-speed settings, which is consistent with the estimated results in Table 4.1.

![Figure 4.1(a) Scatter plot of \( \tau \) vs headway setting.](image)

Figure 4.1(a) Scatter plot of \( \tau \) vs headway setting.
Figure 4.1(b) scatter plot of following gap headway \( g(t) \) vs headway setting.

Figure 4.2 shows how \( \Delta \) (i.e., safety buffer) varies with \( \tau \). It can be observed in Figure 4.2 that as \( \tau \) increases, \( \Delta \) always decreases for both high-speed and low-speed settings. This suggests that a shorter time-lag gap (i.e., \( \tau \)) demands a longer safety spacing buffer (i.e., \( \Delta \)) to absorb a higher overshoot from the target trajectory in the vehicle following control. This verifies the theoretical finding proposed in Li (2020) that there exists a tradeoff between the time lag gap and the safety buffer. In addition, it was found that the slope of the fitted lines of the high-speed settings is steeper than that of the low-speed settings, which indicates that for the studied ACC design, the variations of \( \Delta \) regarding \( \tau \) at high-speed conditions are more sensitive than that at the low-speed conditions. An interesting finding regarding Figure 4.2 is that the average \( \Delta \) for the low-speed settings is greater than that for the high-speed settings. It means that the overshoot of the vehicle following at high-speed conditions is less than that at low-speed conditions, indicating certain nonlinearity of the AV following control.
Moreover, the tradeoff between safety buffer $\Delta$ and time lag $\tau$ shown in Figure 4.2 also has an implication on road capacity. Consider a one-lane road with pure AVs following the vehicle control model specified by model (4.1); it is easy to see that the minimum headway or equivalently the maximum traffic throughput occurs when the traffic is at the following optimal equilibrium state, i.e., all vehicles driving at the speed limit, $V$, with a minimum following spacing gap of $\tau V + \Delta$. The value of $V$ is set to the maximum speed for each experiment setting. Let $\tau^*$, $\Delta^*$, and $g^*$ denote the optimal time lag, safety buffer, and following gap headway to the minimum headway or the maximum traffic, where $g^* := \tau^* + \Delta^*/V$. Then, $\tau^*$, $\Delta^*$, and $g^*$ can be theoretically solved by the equation and a bisecting search method proposed in Li (2020) (Equation (16) in Li (2020)). Table 4.2 shows the key parameters of the minimum headway settings and those of the studied AV following design. A smaller headway setting reduces the time lag (i.e., $\tau^*$) but increases the safety buffer (i.e., $\Delta^*$) to achieve shorter following gap headways (i.e., $g^*$) as well as higher traffic capacity compared with the studied AV following design.
Table 4.2 Key Parameter Comparisons Among Studied AV Following Design, Minimum Headway Settings, and String Stable Headway Settings.

<table>
<thead>
<tr>
<th>$V$ (m/s)</th>
<th>Studied AV following design</th>
<th>Minimum headway setting</th>
<th>String stable headway setting</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\Delta$ (m)</td>
<td>$\tau$ (s)</td>
<td>$g$ (s)</td>
</tr>
<tr>
<td>24.45</td>
<td>4.83</td>
<td>0.83</td>
<td>1.02</td>
</tr>
<tr>
<td>24.47</td>
<td>4.40</td>
<td>1.21</td>
<td>1.38</td>
</tr>
<tr>
<td>24.48</td>
<td>3.31</td>
<td>1.61</td>
<td>1.74</td>
</tr>
<tr>
<td>24.54</td>
<td>0.66</td>
<td>2.17</td>
<td>2.20</td>
</tr>
<tr>
<td>15.49</td>
<td>7.28</td>
<td>0.79</td>
<td>1.24</td>
</tr>
<tr>
<td>15.38</td>
<td>6.36</td>
<td>1.14</td>
<td>1.54</td>
</tr>
<tr>
<td>15.43</td>
<td>5.92</td>
<td>1.52</td>
<td>1.89</td>
</tr>
<tr>
<td>15.43</td>
<td>4.97</td>
<td>2.09</td>
<td>2.40</td>
</tr>
</tbody>
</table>

4.2.3 Stability Analysis

Unstable AV-following design may easily cause traffic oscillation and, consequentially, road capacity may drop, which reduces the service level of the road. To determine whether the estimated models for the studied AV following design are stable or not, this section investigates the stability of the estimated AV following models based on the formulation (i.e., model (4.1)).

Note that this study particularly focused on the empirical analyses, and the following theoretical analyses are a brief revisitation of Section 6 of Li (2020). By applying the Laplace transform to model (4.1), we obtain

$$\frac{Y(s)}{X(s)} = \frac{k}{s^2 + k\tau s + k}, \forall s \in \mathbb{C},$$

where $X(s) := \int_{0}^{\infty} x(t)e^{-st}dt$, $Y(s) := \int_{0}^{\infty} y(t)e^{-st}dt$, and $\mathbb{C}$ is the set of complex numbers. The roots of the above equation are $(-k\tau \pm \sqrt{k^2\tau^2 - 4k})/2$. With this, if $k\tau^2 < 4$, model (4.1) is a local stable AV following model. Based on the data fitness results as shown in Table 4.1, we conclude that all estimated model results are locally stable and thus the studied AV following design is locally stable.
By applying the Fourier transform to model (I), we obtain
\[ TF(w) := \frac{Y(jw)}{X(jw)} = \frac{k}{-w^2 + k + ik\tau w}, \forall w \in \mathbb{R}^+, \]
where \( j := \sqrt{-1}. \) Then we obtain
\[ TF^* := \max_{w \in \mathbb{R}^+} |TF(w)| = \begin{cases} \sqrt{\frac{4}{4k\tau^2 - k^2\tau^4}} > 1, & \text{if } k\tau^2 < 2; \\ 1, & \text{if } k\tau^2 \geq 2, \end{cases} \]
with the maximizer angular frequency
\[ w^* := \begin{cases} \sqrt{4k - 2k^2\tau^2}/2, & \text{if } k\tau^2 < 2; \\ 0, & \text{if } k\tau^2 \geq 2. \end{cases} \]

Based on the analysis in Li (2020), if the value of \( k\tau^2 < 2, \) the perturbations of a preceding vehicle get amplified while propagating across multiple following vehicles; Otherwise, the perturbations of the preceding vehicle will be dampened across upstream and thus the AV following model is string stable. Note that if the model is string-unstable, small speed perturbations at the preceding vehicle will be amplified to cyclic speed oscillations with angular frequency \( w^* := \sqrt{4k - 2k^2\tau^2}/2 \) (or cycle period \( T^* := 2\pi/w^* \)) at the downstream following vehicles. With this, the parameters related to the stability of the fitted models are calculated as shown in Table 4.3.

<table>
<thead>
<tr>
<th>Model Stability Related Parameters.</th>
<th>( k\tau^2 )</th>
<th>( w^* )</th>
<th>( T^* ) (s)</th>
<th>Stability</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Speed-Headway Setting 1</td>
<td>0.07</td>
<td>0.31</td>
<td>19.99</td>
<td>Unstable</td>
</tr>
<tr>
<td>High Speed-Headway Setting 2</td>
<td>0.15</td>
<td>0.31</td>
<td>20.58</td>
<td>Unstable</td>
</tr>
<tr>
<td>High Speed-Headway Setting 3</td>
<td>0.24</td>
<td>0.29</td>
<td>22.04</td>
<td>Unstable</td>
</tr>
<tr>
<td>High Speed-Headway Setting 4</td>
<td>0.35</td>
<td>0.25</td>
<td>25.39</td>
<td>Unstable</td>
</tr>
<tr>
<td>Low Speed-Headway Setting 1</td>
<td>0.07</td>
<td>0.34</td>
<td>18.62</td>
<td>Unstable</td>
</tr>
<tr>
<td>Low Speed-Headway Setting 2</td>
<td>0.11</td>
<td>0.29</td>
<td>21.78</td>
<td>Unstable</td>
</tr>
<tr>
<td>Low Speed-Headway Setting 3</td>
<td>0.19</td>
<td>0.28</td>
<td>22.77</td>
<td>Unstable</td>
</tr>
<tr>
<td>Low Speed-Headway Setting 4</td>
<td>0.37</td>
<td>0.26</td>
<td>23.90</td>
<td>Unstable</td>
</tr>
</tbody>
</table>

It was found that the values of \( k\tau^2 \) of all estimated results were less than 2, which indicates that the estimated AV following models are string unstable. This result is consistent with the
previous studies’ findings (Gunter et al., 2020a; Milanés and Shladover, 2014). However, it was found that as the headway settings (i.e., $\tau$) increase, the values of $k\tau^2$ increase as well and thus lead the increases of cycle periods, which implicate that a higher $\tau$ value, even if still resulting in string-unstable control, will increase the oscillation cycle period.

To support this implication, we designed an experiment as introduced in Section 2 to obtain the oscillation cycle period and amplification of the studied AV following design. Since each following vehicle will amplify its immediately preceding vehicle’s frequency components in the neighborhood of $w^*$ (or cycle period $T^*$), the most-amplified preceding trajectory will have a sinusoidal speed profile with an angular frequency of $w^*$. Thus, the oscillation cycle periods of the studied AV following design can be obtained by $T$ that has the largest oscillation amplification. As introduced, a series of three-vehicle platoon trajectory data are collected as shown in Figure 2.7. For each headway setting of the AV, based on the calculated $T^*$ shown in Table 4.4, five cycle periods were tested, such as $T = 18, 20, 22, 24,$ and $26$ seconds.

The speed standard deviation ratio with different headway settings and cycle periods (i.e., $T$) that reflects the oscillation amplification for the third vehicle is shown in Table 4.4. The speed standard deviation ratio was calculated by the speed standard deviation of the third vehicle in the platoon dividing the speed standard deviation of the leading vehicle. Detailed theoretical analysis about this term can be found in the stability analysis section of Li (2020).

<table>
<thead>
<tr>
<th>Headway</th>
<th>$T=18$ s</th>
<th>$T=20$ s</th>
<th>$T=22$ s</th>
<th>$T=24$ s</th>
<th>$T=26$ s</th>
</tr>
</thead>
<tbody>
<tr>
<td>Headway 1</td>
<td>1.304</td>
<td>1.553</td>
<td>1.505</td>
<td>1.515</td>
<td>1.478</td>
</tr>
<tr>
<td>Headway 2</td>
<td>1.378</td>
<td>1.460</td>
<td>1.403</td>
<td>1.446</td>
<td>1.424</td>
</tr>
<tr>
<td>Headway 3</td>
<td>1.270</td>
<td>1.215</td>
<td>1.440</td>
<td>1.253</td>
<td>1.352</td>
</tr>
<tr>
<td>Headway 4</td>
<td>1.142</td>
<td>1.199</td>
<td>1.201</td>
<td>1.148</td>
<td>1.208</td>
</tr>
</tbody>
</table>

As shown in Table 4.4 that for headways 1–4, the largest speed standard deviation ratios of the third vehicle appear at $T = 20$ s, 20 s, 22 s, and 26 s, respectively, which indicate that the
$T^*$ (i.e., speed oscillation cycle period) for each highway setting under high-speed condition is in the neighborhood of the obtained $T$. Also shown in Table 4.3, the high speed $T^*$ for headways 1-4 respectively are 19.99 s, 20.58 s, 22.04 s, 25.39 s. This consistency between the practice results obtained from three-vehicle platoon data and the theoretical results obtained from two-vehicle car-following data support the above implication that as $\tau$ increases, the oscillation cycle period $T^*$ increases. Also, as observed in Table 4.4, the average speed standard deviation ratios decrease as the headway settings increase. This means that as $\tau$ increases, the oscillation amplifications decrease, which also can be observed in Figure 2.7. Therefore, we can further extend our finding that although the AV following design in the existing commercial vehicle is string-unstable, as $\tau$ (i.e., headway setting) increases, the AV string stability increases in terms of the oscillation amplification and cycle periods.

As proposed in Li (2020), when $\tau^2k < 4$, the riskiest cycle period $\bar{T}$ of stop-and-go traffic that causes minimum gaps between two continuous vehicles is close to $2\pi/\phi$, where $\phi$ is the angular frequency for the riskiest traffic, and $\phi = \sqrt{4k - k^2\tau^2}/2$. The platoon data is also used to check this finding. By plugging $k$ and $\tau$ in Table 4.1 into the equation of $\phi$, the riskiest cycle period for headway settings 1 to 4 under high-speed conditions are 0.31, 0.31, 0.29, and 0.25, which are the same with $w^*$ because the values of $k^2\tau^2$ are too small to cause differences between $\bar{T}$ and $T^*$, and thus $\bar{T} = T^*$. Table 4.5 shows the 95% percentile shortest gaps between leading and second vehicles, and second and third vehicles with different headway settings and cycle periods. Note that the shortest gap for the gaps over five cycle periods (i.e., $T = 18, 20, 22, 24, 26$ s) is marked with “*”.
Table 4.5 95% Percentile Shortest Gaps Between Leading and Second Vehicles and Second and Third Vehicles with Different Headway Settings and Cycle Periods.

<table>
<thead>
<tr>
<th>Headway</th>
<th>T = 18 s</th>
<th>T = 20 s</th>
<th>T = 22 s</th>
<th>T = 24 s</th>
<th>T = 26 s</th>
<th>T = 18 s</th>
<th>T = 20 s</th>
<th>T = 22 s</th>
<th>T = 24 s</th>
<th>T = 26 s</th>
</tr>
</thead>
<tbody>
<tr>
<td>Headway 1</td>
<td>24.48</td>
<td>20.50*</td>
<td>21.54</td>
<td>23.52</td>
<td>20.56</td>
<td>16.85</td>
<td>15.99*</td>
<td>17.57</td>
<td>18.71</td>
<td>16.48</td>
</tr>
<tr>
<td>Headway 2</td>
<td>30.25</td>
<td>30.57</td>
<td>27.89*</td>
<td>28.55</td>
<td>29.32</td>
<td>26.18</td>
<td>26.46</td>
<td>23.77*</td>
<td>26.46</td>
<td>24.68</td>
</tr>
<tr>
<td>Headway 3</td>
<td>39.19</td>
<td>38.23</td>
<td>38.21*</td>
<td>38.25</td>
<td>38.39</td>
<td>36.24</td>
<td>34.72</td>
<td>35.51</td>
<td>33.12*</td>
<td>35.19</td>
</tr>
<tr>
<td>Headway 4</td>
<td>48.33</td>
<td>49.52</td>
<td>49.54</td>
<td>49.97</td>
<td>47.83*</td>
<td>46.87</td>
<td>46.48</td>
<td>46.69</td>
<td>47.56</td>
<td>40.91*</td>
</tr>
</tbody>
</table>

As shown in Table 4.5, most of the shortest gaps for headway settings occur when $T$ is in the neighborhood of $\bar{T}$. This result supports the finding that if the cycle period of stop-and-go traffic is close to $2\pi/\phi$, the gap between the AV and preceding vehicle can reach the shortest gaps and thus the AV control is subject to relatively high safety risks.

Additionally, Li (2020) proposed the equation to analytically solve the parameter settings of a string stable headway (i.e., time lag $\tau$, safety buffer $\Delta$, and following gap headway $g$) based on the estimated parameters of the AV following design (i.e., $k$). Table 4.2 compares the key parameters of the string stable headway settings and those of the studied AV following design. It can be seen in Table 4.2 that the following gap headways of string stable headway settings (i.e., $g$) are much greater than those of the studied AV following design (i.e., $g$). Together with the results of the minimum headway settings (i.e., $\tau^*$, $\Delta^*$, and $g^*$), we see that there is a significant difference between the minimum headway settings and string stable headway settings that require much longer following gap headway and time lag but less safety buffer. This result indicates that string stability achieves at a cost of longer minimum headway. This explains why the existing commercial AV-following designs are not string stable. Incorporating string stability into the AV-following design will lead to an over-long following gap headway and thus degrades the driving experience as well as the traffic capacity. A balance point between the string stable headway settings and minimum headway settings, which is closer to the minimum headway settings...
according to the results, is chosen by vehicle makers to compromise the effects of string instability and traffic capacity.

4.2.4 Discussions Beyond Theoretical Predictions

Based on the estimated parameters shown in Table 4.1, Figure 4.3 shows how $\tau$ (i.e., time lag) varies with $k$ (i.e., control sensitivity factor). As shown in Figure 4.3, as $\tau$ increases, $k$ appears decreasing trends for both high speed and low-speed tests. Although the fitted lines for high-speed and low-speed tests almost overlap with each other, the estimation results of $k$ are not consistent over different speed conditions. This finding may indicate that the studied ACC system automatically adjusts the vehicle control sensitivity to fit different driving environments, which have not been reported in the literature. There are two possible reasons for this finding – one is that a shorter time-lag gap (i.e., $\tau$) requires a stronger control sensitivity (i.e., $k$) to avoid the following vehicle getting too close to the preceding vehicle, and the other is that since a simple linear AV-following model was adopted by this study, the following behaviors may exceed the predictivity of the model, which opens up future research needs for investigating nonlinearity and stochasticity in AV following modeling.
It was also found in Table 4.1 that the estimated results for key parameters of the AV following design are not always consistent over different speed ranges; i.e., for the same headway setting, the values of the estimated $\Delta$ for the high-speed range are greater than those for the low-speed range. This inconsistency may be because that the linear model likely overestimates actual speed oscillation response particularly when the oscillation magnitude gets high (Li and Ouyang, 2011). It indicates that the following behaviors of the studied AV design exceed the predictivity of the adopted simple linear model and thus suggests the needs of a nonlinear AV following model.

4.2.5 Finding Verifications

The AV-following data shared by Gunter et al. (2019) offered an opportunity to verify the generality of the major findings in the commercial AV following control design. Gunter et al. (2019) conducted the AV-following trajectory data collection by seven commercial AVs from two types of vehicle makers (e.g., makers 1 and 2), and two headway settings (e.g., long and short) for each AV were tested in the experiment. With this, the following data of one AV from each type
of vehicle maker was selected, and a total of two sets of AV-following data were used to fit the AV-following model (I). Similarly, the simple moving average method with a window of 5 seconds was adopted to denoise the trajectory data before parameter estimations. Estimation results are shown in Table 4.6.

Table 4.6 Estimation Results of Data.

<table>
<thead>
<tr>
<th>Maker 1</th>
<th>Maker 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Headway Setting Long</td>
<td>Headway Setting Short</td>
</tr>
<tr>
<td>( \tau ) (s)</td>
<td>2.57</td>
</tr>
<tr>
<td>( k )</td>
<td>0.03</td>
</tr>
<tr>
<td>( \Delta ) (m)</td>
<td>2.99</td>
</tr>
<tr>
<td>( k\tau^2 )</td>
<td>0.62</td>
</tr>
<tr>
<td>( R_{adj}^2 )</td>
<td>0.23</td>
</tr>
<tr>
<td>( \tau ) (s)</td>
<td>2.11</td>
</tr>
<tr>
<td>( k )</td>
<td>0.08</td>
</tr>
<tr>
<td>( \Delta ) (m)</td>
<td>3.42</td>
</tr>
<tr>
<td>( k\tau^2 )</td>
<td>0.60</td>
</tr>
<tr>
<td>( R_{adj}^2 )</td>
<td>0.36</td>
</tr>
</tbody>
</table>

Table 4.6 shows that for each vehicle maker, the values of \( \Delta \) increase as \( \tau \) decrease, which verifies the tradeoff between the time lag gap and the safety buffer. Also, the values of \( k\tau^2 \) of all estimations are less than 2, indicating that the studied AV following designs still are string unstable. However, as the headway settings (i.e., \( \tau \)) increase, the values of \( k\tau^2 \) increase as well and thus the AV string stability increases, verifying the relationship between the time lag gap and AV string stability. Moreover, the estimated vehicle control sensitivity factors (i.e., \( k \)) also vary across different headway settings, which implicate the need for investigating nonlinearity and stochasticity in AV following modeling. Further, the estimated factors for the three AV-following designs (Lincoln, maker 1, and maker 2) are different, suggesting that the AV-following designs produced by different vehicle makers are inconsistent and thus the traffic flow of pure AVs should still be studied heterogeneously (Shi and Li, 2021a).

4.3 Chapter Summary

To verify theoretical findings in Li (2020) and study the vehicle following behaviors of commercial AV control design, this study collected field experiment data for AVs. Parameters of the parsimonious linear AV-following model proposed in Li (2020) were estimated with linear regression using the collected trajectory data. Based on the relationship analysis among the
estimated parameters (i.e., $k$, $\Delta$, $\tau$) and the stability analysis, the following theoretical findings were verified:

1) There exists a tradeoff between the time lag gap and the safety buffer.

2) There exists a relation between the time lag gap and AV string stability.

3) A possible explanation to the observed string instability of the AV following design is that a relatively short headway (and thus better user experience on vehicle mobility) is set by automakers at a cost of compromising string stability.

4) The tradeoff between the mobility and stability can be observed that as the time lag increases, the oscillation period gets longer, and the oscillation amplification gets smaller.

Moreover, the estimated parameters with the field experiment data reveal the following findings beyond that reported in Li (2020):

1) The estimated vehicle control sensitivity factors vary across different speed and headway settings.

2) The estimated results for key parameters of the AV following design are not consistent over different speed conditions.

One possible reason to this inconsistency is that the following behaviors of the design cannot be fully interpreted by the proposed simple linear model due to the intrinsic limitations of the linear model. Thus, there is a need to investigate nonlinearity and stochasticity in AV following modeling. This inconsistency also reveals that the commercial AV-following design puts much of the safety into the nonlinear control side while the linear control only dominates in a very small speed variation range.
Overall, these findings provide managerial insights into future AV traffic management, and it will be helpful for transportation stakeholders to realize the tradeoffs to better understand the limits and challenges faced in using AV technology to improve traffic performance.
Chapter 5: AV Energy Consumption

Since AVs are controlled by exact and fast-responding sensors and computers, the driving behavior as well as the driving strategies of AVs are expected to be enhanced compared with those of human-driven vehicles. With this, AVs have a great potential in reducing overall fuel consumption of traffic and consequentially achieving environmental-friendly mobility. To understand this probability, this chapter study AV energy consumption with the collected AV trajectory data from the individual vehicle perspective. The rest of this chapter is organized as follows. Section 5.1 describes the adopted fuel consumption models. Section 5.2 analyzes the empirical results. Section 5.3 concludes the chapter and identifies future research directions.

5.1 Fuel Consumption Models

In this section, several state-of-the-art or classical vehicle fuel consumption models are introduced, including the VT-micro model, MEP model, VSP model, and ARRB model. The reasons that we studied the AV fuel consumption by theoretical models instead of empirical data are twofold: the first is that the speeds of the optimal fuel consumption efficiency are different from vehicle to vehicle. The empirical fuel consumption data can only represent the results of the test vehicles while the significance of the findings on general commercial AVs will be degraded (Howey et al., 2011); the second is that different AV vendors have different energy utilization strategies, e.g., the collection and utilization of the regenerative braking energy, which significantly affects the overall performance of the fuel consumption (Orecchini et al., 2018). Thus, to reveal the impacts of general commercial AVs on fuel consumption, this dissertation calculates the AV fuel consumption by the theoretical models that have been verified by a bunch of studies.
(Chen et al., 2017; Edwardes and Rakha, 2014; Rakha et al., 2004). Although the calculated fuel consumption values from the different models are slightly different, the consistent variation trends validate the findings of this chapter, which will be detailed in Section 5.2. The unit of the instantaneous fuel consumption adopted in this chapter is Liter per hour (L/h).

5.1.1 VT-Micro Model

VT-micro model was developed by Ahn et al. (Ahn, 1998) in 1998 for measuring the instantaneous fuel consumption of an individual vehicle. The inputs of the VT-micro model are the instantaneous speed and acceleration of the vehicle. With these inputs, the instantaneous fuel consumption can be predicted by the following equation.

$$F(v_i, a_i) = \exp\left(\sum_{j_1=0}^{3} \sum_{j_2=0}^{3} K_{j_1j_2} (v_i)^{j_1} (a_i)^{j_2}\right),$$

where $v_i$ and $a_i$ are speed and acceleration of the vehicle at time $i$, respectively. $j_1$ and $j_2$ are the power indexes. $K_{j_1j_2}$ are constant coefficients (Zegeye et al., 2013) that can be found in Table 5.1.

<table>
<thead>
<tr>
<th>$K_{j_1j_2}$</th>
<th>$j_2 = 0$</th>
<th>$j_2 = 1$</th>
<th>$j_2 = 2$</th>
<th>$j_2 = 3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$j_1 = 0$</td>
<td>-7.537</td>
<td>0.4438</td>
<td>0.1716</td>
<td>-0.0420</td>
</tr>
<tr>
<td>$j_1 = 1$</td>
<td>0.0973</td>
<td>0.0518</td>
<td>0.0029</td>
<td>-0.0071</td>
</tr>
<tr>
<td>$j_1 = 2$</td>
<td>-0.003</td>
<td>-7.42E-04</td>
<td>1.09E-04</td>
<td>1.16E-04</td>
</tr>
<tr>
<td>$j_1 = 3$</td>
<td>5.3E-05</td>
<td>6E-06</td>
<td>-1E-05</td>
<td>-6E-06</td>
</tr>
</tbody>
</table>

5.1.2 MEF Model

By considering not only the impact of current acceleration on vehicle fuel consumption but also the history acceleration over a period prior to the current time, Lei et al. (2010) extended the VT-micro model to the MEF model in 2010, which replaces the instantaneous acceleration ($a_i$) with a composited acceleration ($\bar{a}_i$) and thus $F(v_i, a_i) = F(v_i, \bar{a}_i)$. The equation of $\bar{a}_i$ is as follows.
\[ \ddot{a}_i = \alpha \cdot a_i + (1 - \alpha) \sum_{t=1}^{T} a_{i-t} / T, \]

where \( \alpha \) is the acceleration impact factor, \( 0 < \alpha < 1 \).

5.1.3 VSP Model

VSP model was developed by Duarte et al. (2015) in 2015 based on a simplification of the forces applied to an individual vehicle. The model first estimates the power per mass unit (W/kg) consumed by the vehicle considering a combination of vehicle dynamics (speed, acceleration, rolling, and aerodynamic resistance) and road grade according to the following VSP equation.

\[ VSP_i = v_i(1.1a_i + 9.81g + 0.132) + 3.02 \cdot 10^{-4}v^3, \]

where the definitions of \( v_i \) and \( a_i \) are the same as previous. \( g \) denotes the road grade that is set to 0 in this chapter since the road grade of the experiment site can be neglected.

Then the instantaneous fuel consumption can be calculated by plugging the obtained \( VSP_i \) into the following equations.

\[
F(v_i, a_i) = F(VSP_i) = \begin{cases} 
  f, & \text{if } VSP_i < -10; \\
  aVSP_i^2 + bVSP_i + c, & \text{if } -10 \leq VSP_i \leq 10; \\
  mVSP_i + d, & \text{if } VSP_i \geq 10.
\end{cases}
\]

where \( a = 1.98E-03 \), \( b = 3.97E-02 \), \( c = 2.01E-01 \), \( d = 2.48E-03 \), \( f = 2.48E-03 \), and \( m = 7.93E-02 \) (Duarte et al., 2015).

5.1.4 ARRB Model

ARRB model (Akcelik, 1989), developed by Akcelik in 1989, is an elemental model based on the operation modes of the vehicle, such as cruise, deceleration, idling, and acceleration, which was adopted by Victor et al. (2019) that revealed interesting AV fuel consumption phenomena. To reproduce Victor et al.’s results and perform detailed analysis to the phenomena, this chapter also
calculates the fuel consumption with the ARRB model. The equation of the ARRB model is as follows.

\[ F(v_i, a_i) = \beta_1 + \beta_2 v_i + \beta_3 v_i^2 + \beta_4 v_i^3 + \gamma_1 v_i a_i + \gamma_2 v_i \max(0, a_i)^2, \]

where the definitions of \( v_i \) and \( a_i \) are the same as previous. \( \beta_1 = 0.666, \beta_2 = 0.019, \beta_3 = 0.001, \beta_4 = 0.0005, \gamma_1 = 0.122, \) and \( \gamma_2 = 0.793 \) (Akcelik, 1989).

5.1.5 Overall Fuel Consumption

With the above equations for calculating vehicle instantaneous fuel consumption, the overall fuel consumption in a given period \([i^-, i^+]\) can be calculated by plugging the models into the following equation,

\[ F = \sum_{i=i^-}^{i^+} F(v_i, a_i) \Delta t, \]

where \( i^- \) and \( i^+ \) are the start and end time points, and \( \Delta t \) is the length of a time interval.

5.2 Result Analyses

5.2.1 Car-Following Experiment

Figure 5.1 plots the fuel consumption results of the car following experiment 1 obtained from different models with varying headway settings (headway setting 1 to 4). It is observed in both Figure 5.1 (a) and (b) that for the same tests, the fuel consumption calculated by the ARRB model is the highest, then is the VT-micro and MEF models, which have quite similar results. The results obtained from the MEF model are slightly less than the VT-micro model. One reason is that the composited acceleration plugged into the equation is equivalent to smooth the acceleration profile and thus the acceleration variation, as well as the calculated fuel consumption, decreases. The fuel consumption calculated by the VSP model is the minimum among the four models.

Although the values of the fuel consumption calculated by different models are slightly different, the variation trends of the fuel consumption with headway settings among different
models are consistent. That is, as found in both high-speed (Figure 5.1 (a)) and low-speed tests (Figure 5.1 (b)), fuel consumption decreases as the headway setting increases, indicating that AV energy efficiency could be enhanced with less pursuit of AV mobility. Based on the adopted fuel consumption models, a larger speed standard deviation will cause more fuel consumption. Thus, the results implicate that a longer headway setting may have less speed standard deviation and thus the following behavior of the AV becomes more stable, which will be further verified by the platooning experiment.

(a) High-speed tests
(b) Low-speed tests

Figure 5.1 Fuel consumption with varying headway settings for the car following experiment 1.

Further, Figure 5.2 plots the results of the fuel consumption obtained from different models with varying headway and speed variation settings for car-following experiment 1. Compared with Figure 5.2 (a) and (b), it is found that in the low-speed tests, either headway or speed variation settings have significant impacts on the fuel consumption, and the impacts of headway settings are more significant with a larger speed variation. However, in the high-speed tests, only the speed variation yields significant impacts while the impacts of headway settings on the fuel consumption are weak. It indicates that there is a great need to appropriately manage the AV headway settings
to mitigate the overall fuel consumption of pure AV traffic, especially when the traffic speed is relatively low, e.g., rural and urban areas.

Figure 5.2 Fuel consumption with varying headway and speed variance settings for the car following experiment 1.
Figure 5.3 plots the results of the fuel consumption obtained from different models with varying operating scenarios and speed ranges as described in the car following experiment 2. We find that the fuel consumption variation trends with speed ranges among different models and operating scenarios are consistent. That is, the fuel consumption increases as the speed ranges increase. Then, we fix the speed range and compare the fuel consumption of the AV regarding different operating scenarios. It is observed that whatever the mode of the leading vehicle (either AV or HV mode) is, the following vehicle with AV mode always requires less fuel consumption than the HV mode. This pattern is more obvious in the results of the VT-micro, MEF, and ARRB models. Moreover, we also observe that the AV-AV scenario yields the lowest fuel consumption while the HV-HV scenario yields the highest fuel consumption for the car following experiment 2. One explanation to the above findings is that the motions of the AVs are controlled by fast-responding on-board computers and sensors, which lead to a more stable driving behavior with less speed variation as well as less fuel consumption. However, the human drivers’ behaviors are characterized by dynamic and uncertainty, which may lead to relatively significant speed variations and thus cause higher fuel consumption, which could be verified by the speed profiles as shown in Figure 2.6.

5.2.2 Platooning Experiment

Figure 5.4 plots the fuel consumption results of the platooning experiment obtained from different models with varying headway settings. Similarly, although the detailed fuel consumption obtained from different models is different, the variation trends of fuel consumption with headway settings over the four models are almost consistent, which verifies the generality of the findings.

It is found in Figure 5.4 that for both AVs A and B, as the headway setting increases, the fuel consumption decreases, which is consistent with the findings we concluded from the car following experiment 1 (Figure 2.5). Compared the fuel consumption of AVs A and B, it is found
that for the same headway setting, the front vehicle (i.e., AV A) always consumes less fuel than the rear one (i.e., AV B). This result is consistent with Victor et al. (Knoop et al., 2019)’s observation, which indicates that AV string instability increases fuel consumption. In addition, Figure 5.4 reveals another interesting phenomenon. It is known that as the headway setting increases, the fuel consumption will appear a decreasing trend. However, as observed in Figure 5.4, the slopes of the fuel consumption curves of AVs A and B are different. The fuel consumption curve of AV B (i.e., blue dash line) has a larger slope than that of AV A (i.e., red solid line). It means that in the studied platooning system, as the headway setting increases, the energy consumption difference between AVs A and B decreases.

![Figure 5.3 Fuel consumption with varying operating scenarios and speed ranges for the car following experiment 2.](image)
Figure 5.4 Fuel consumption with varying headway settings for the platooning experiment.

To help readers observe the variations of the fuel consumption difference, Table 5.2 shows the fuel consumption difference between AVs A and B with varying headway settings and models. The fuel consumption difference is calculated by \((F_B - F_A)/F_A\), where \(F_A\) and \(F_B\) are the fuel consumption of AVs A and B, respectively.

Table 5.2 Fuel consumption difference of different models with varying headway settings.

<table>
<thead>
<tr>
<th>Headway</th>
<th>VT-micro</th>
<th>MEF</th>
<th>VSP</th>
<th>ARRB</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>13.85%</td>
<td>10.17%</td>
<td>7.16%</td>
<td>19.44%</td>
</tr>
<tr>
<td>2</td>
<td>11.33%</td>
<td>8.31%</td>
<td>5.29%</td>
<td>14.81%</td>
</tr>
<tr>
<td>3</td>
<td>6.85%</td>
<td>4.88%</td>
<td>3.30%</td>
<td>8.52%</td>
</tr>
<tr>
<td>4</td>
<td>3.73%</td>
<td>2.52%</td>
<td>1.58%</td>
<td>5.00%</td>
</tr>
</tbody>
</table>

It is observed in Table 5.2 clearly that as the headway setting increases, the energy consumption difference between AVs A and B decreases. This phenomenon is consistent over all models, which not only provides insights into the fuel consumption management of future AV traffic but also reveals an important characteristic of the current AV car following design. That is, to reduce the overall fuel consumption of future AV traffic, policies could be made to encourage...
the use of longer headway settings. Also, Victor et al. (Knoop et al., 2019) argued that AV string instability increases fuel consumption. With the results shown in Figure 5.4 and Table 5.2, we can draw the following conclusion of the current AV following design, i.e., as the AV headway setting increases, the stability of the formed AV string increases, which indicates that the string unstable issue of the current AV car following design can be mitigated using longer headway settings. Moreover, with longer headway settings, the overall fuel consumption of the AV platoon (string) can be reduced as well.

5.3 Chapter Summary

This section investigated the fuel consumption of commercial AVs with different operating scenarios, speed ranges, and headway settings. Based on the field experiment data of commercial AVs, several classical or state-of-the-art fuel consumption models were employed to measure the instantaneous fuel consumption of the AVs. The empirical analyses found that there is a tradeoff between AV mobility and fuel consumption regarding different AV headway settings. As the AV headway increases, the corresponding fuel consumption decreases. Also, we found that in the low-speed tests, either headway or speed variation settings have significant impacts on fuel consumption. However, in the high-speed tests, only the speed variation settings yield significant impacts, while the impacts of headway settings on the fuel consumption are weak. Additionally, the car following experiment 2 indicates that the AV technology could help to yield less fuel consumption, especially when AVs serve as following vehicles. Moreover, we found that as the AV headway setting increases, the AV string stability increases and thus the overall fuel consumption of the AV string decreases. Following these findings, to reduce the overall fuel consumption of pure AV traffic, policies could be made to encourage the use of longer headway settings.
Chapter 6: The Road Ahead

This dissertation systematically studied the potential impacts of commercial AVs on future traffic from the AV FD, AV car-following characteristics, and AV energy consumption aspects. We now close this dissertation with a summary of the main findings and a discussion of the possible avenues to extend this work.

6.1 AV Fundamental Diagram

To help understand the impacts of commercial AVs on traffic flow, we proposed a general method that combines both empirical experiments and theoretical models to construct an FD for AV traffic. High-resolution trajectory data with multiple commercial AVs following one another in a platoon with different headway settings were collected to study the AV traffic flow characteristics. Data analysis results revealed that the traditional triangular FD structure remains applicable to describe the traffic flow characteristics of AV traffic. The comparisons and discussions among the FD results of AVs and human-driven vehicles indicated that though the shortest AV headway setting can significantly improve the road capacity, other headway settings may decrease the road capacity compared with existing human-driven-vehicle traffic. Further, this dissertation empirically verified that AV headway settings may affect the stability of the traffic flow. A mixed traffic FD construction approach was proposed to provide the basis for analysis, modeling, and simulation of future mixed traffic and draw managerial insights. The proposed general FD modeling approaches, which may be easily calibrated despite uncertainties and evolutions of the AV technologies, can serve as a methodological foundation for future mixed traffic flow studies.
This study can also be extended in the following directions. It would be interesting to verify the mixed traffic FD formula proposed in this dissertation by field experiment data with mixed-brands AVs and mixed headway settings. Moreover, the generated triangular FD alluded to issues such as the balance between traffic throughput and stability, which also raise the need to further investigate these issues from the perspective of management and policymaking. Also, it will be interesting to study the impacts of the connected vehicle technology and corresponding cooperative behaviors in conjunction with AVs on future mixed traffic performance.

6.2 AV Car-Following Characteristics

To verify theoretical findings in Li (2020) and study the vehicle following behaviors of commercial AV control design, this study collected field experiment data for AVs. Parameters of the parsimonious linear AV-following model proposed in Li (2020) were estimated with linear regression using the collected trajectory data. Based on the relationship analysis among the estimated parameters (i.e., \(k, \Delta, \tau\)) and the stability analysis, the following theoretical findings were verified:

1) There exists a tradeoff between the time lag gap and the safety buffer.

2) There exists a relation between the time lag gap and AV string stability.

3) A possible explanation to the observed string instability of the AV following design is that a relatively short headway (and thus better user experience on vehicle mobility) is set by automakers at a cost of compromising string stability.

4) The tradeoff between the mobility and stability can be observed that as the time lag increases, the oscillation period gets longer, and the oscillation amplification gets smaller.

Moreover, the estimated parameters with the field experiment data reveal the following findings beyond that reported in Li (2020):
1) The estimated vehicle control sensitivity factors vary across different speed and headway settings.

2) The estimated results for key parameters of the AV following design are not consistent over different speed conditions.

One possible reason to this inconsistency is that the following behaviors of the design cannot be fully interpreted by the proposed simple linear model due to the intrinsic limitations of the linear model. Thus, there is a need to investigate nonlinearity and stochasticity in AV following modeling. This inconsistency also reveals that the commercial AV-following design puts much of the safety into the nonlinear control side while the linear control only dominates in a very small speed variation range.

Overall, these findings provide managerial insights into future AV traffic management, and it will be helpful for transportation stakeholders to realize the tradeoffs to better understand the limits and challenges faced in using AV technology to improve traffic performance. Nonetheless, it should be pointed out that this study has several limitations and can be further improved in the following directions. First, this study uses a linear AV following model, though parsimonious, does not consider the speed difference term used in many vehicle following models. Incorporating this term will represent general linearized second-order vehicle controls and further enhance the generality of the analysis. Second, the inconsistent model estimations under different speed conditions reveal the need for investigating nonlinearity and stochasticity in AV following modeling. This also raises cautions of using linear models to describe ACC behavior in simulation, which most traffic simulation does. Moreover, this study looked at the AV-following designs produced by several vehicle makers. More AV longitudinal control designs could be used to validate the proposed findings in future research. Also, it will be interesting to study vehicle-
following behavior with incorporating the communication ability of the vehicle and thus the vehicle becomes a connected and automated vehicle, the upgraded version of AV.

6.3 AV Energy Consumption

We investigated the fuel consumption of commercial AVs with different operating scenarios, speed ranges, and headway settings. Based on the field experiment data of commercial AVs, several classical or state-of-the-art fuel consumption models were employed to measure the instantaneous fuel consumption of the AVs. The empirical analyses found that there is a tradeoff between AV mobility and fuel consumption regarding different AV headway settings. As the AV headway increases, the corresponding fuel consumption decreases. Also, we found that in the low-speed tests, either headway or speed variation settings have significant impacts on fuel consumption. However, in the high-speed tests, only the speed variation settings yield significant impacts, while the impacts of headway settings on the fuel consumption are weak. Additionally, the car following experiment 2 indicates that the AV technology could help to yield less fuel consumption, especially when AVs serve as following vehicles. Moreover, we found that as the AV headway setting increases, the AV string stability increases and thus the overall fuel consumption of the AV string decreases. Following these findings, to reduce the overall fuel consumption of pure AV traffic, policies could be made to encourage the use of longer headway settings. However, an over-long following headway may degrade the driving experience and drop the road capacity. Thus, this opens up future research needs for investigating an equilibrium between AV mobility and fuel consumption. Also, since the mixed traffic of AVs and human-driven vehicles will share the road for a long time, it is interesting to study the impacts of commercial AVs with different headway settings on the overall fuel consumption of mixed traffic.
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