Mobility and Safety Implications of Automated Vehicles in Mixed Traffic by Recognizing Behavioral Variations of Drivers

by

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ABSTRACT

After the invention of first motor vehicle, Carl Benz took the vehicle for a public demonstration and collided with a wall. For more than a century, scientists and innovators are working around the least reliable part of vehicle, the human driver, by adding seatbelts, airbags, safety features and smarter cars. Introduction of Connected-Automated Vehicle (CAV) technology provided new opportunity to fix the bug in this system. Automated vehicles (AuV) would take the driving responsibility from human and drive the vehicles by analyzing and perceiving its' surrounding through a range of sensors. Connectivity feature of these vehicles would facilitate to sense the roadway and traffic conditions beyond the range of sensors and make informed and safer decision. While the vehicles equipped with these technologies becoming more common by the day, large scale market penetration will take a long time. Hence, our existing transportation infrastructure will pass through a transitional phase where both Human-driven vehicles (HuV) and AuVs share the roadway. Additionally, the prosperity and acceptance of these technologies depends on clear understanding of the implications on overcoming the limitations of traditional transportation system. In this regard, my research focused on developing a comprehensive modeling framework to establish numerical simulation of both types of vehicles (i.e., human driven, automated) while recognizing the variations of driving behaviors of human drivers. Modeling both vehicle types provided the opportunity to explore diverse mixed traffic scenarios to attain extensive insights of such traffic conditions.

Prior to developing the modeling framework, the variations of human driving pattern were identified through extensive analysis of real-world human driving data. Bi-directional (i.e., longitudinal, lateral) control features were analyzed to comprehend human instincts during driving which can be integrated in the human driver modeling. Further analysis was performed to classify driving behaviors based on these features for short and long-term. The upsides of studying human driving behavior rests not only on better understanding for modeling human driver but also on designing automated vehicles capable of addressing the variations of human driver behavior. Behavioral classification approach in this part of research used three vehicular features known as jerk, leading headway, and yaw rate to classify human drivers into two groups (Safe Driving and Hostile Driving) on short-term classification, and drivers'

habits are categorized into three classes (Calm Driver, Rational Driver, and Aggressive Driver). Through the proposed method, behavior classification has been successfully identified in 86.31 ± 9.84% of speeding and 87.92 ± 10.04% of acute acceleration instances.

In the next phase of this research, foundation of mixed traffic modelling was developed through car-following strategy formulation. This part of research proposes a naïve microscopic car-following strategy for a mixed traffic stream in CAV settings and measured shifts in traffic mobility and safety as a result. Additionally, this part of research explores the influences of platoon properties (i.e. Intra-platoon Headway, Inter-platoon Headway, Maximum Platoon Length) on traffic stream characteristics. Different combinations of HuVs and AuVs are simulated in order to understand the variations of improvements induced by AuVs in a traffic stream. Simulation results reveal that grouping AuVs at the front of traffic stream to apply Cooperative Adaptive Cruise Control (CACC) based car-following model will generate maximum mobility benefits for the traffic. Higher mobility improvements can be attained by forming long, closely spaced AuVs at the cost of reduced safety. To achieve balanced mobility and safety advantages from mixed traffic movements, dynamically optimized platoon configurations should be determined at varying traffic conditions and AuVs market penetrations.

Finally, grounded on prior research on human driving behavior and preliminary modeling framework of mixed traffic, this research objectively experimented with bi-directional (i.e. longitudinal, lateral) motion dynamics in a microscopic modeling framework to measure the mobility and safety implications for mixed traffic movement in a freeway weaving section. This part of research begins by establishing a multilane microscopic model for studied vehicle types (i.e. AuV, HuV) from model predictive control with the provision to form a CACC platoon of AuV vehicles. The proposed modeling framework was tested first with HuV only on a two-lane weaving section and validated using standardized macroscopic parameters from the Highway Capacity Manual. This model was then applied to incrementally expand the AuV share for varying inflow rates of traffic. Simulation results showed that maximum flow rate through the weaving section was attained at a 65% AuV share while steadiness in average speed of traffic was experienced with increasing AuV share. The results also revealed that a 95% AuV share could reduce potential conflicts by 94.28%. Finally, the results of simulated scenarios were consolidated and scaled to report expected mobility and safety outcomes from the prevailing traffic state as well as the optimal AuV share for current inflow rate in weaving sections

PREFACE

Works presented in this thesis are published or presented in peer-reviewed journals or conferences in the areas of transportation engineering. The list of published or presented articles are as follows:

1. **Seraj, M.,** and Qiu, T. Z. (2021). Multilane Microscopic Modeling to Measure Mobility and Safety Consequences of Mixed Traffic in Freeway Weaving Sections. Journal of Advanced Transportation, 2021. https://doi.org/10.1155/2021/6639649
2. **Seraj, M.,** J. Li, and T. Z. Qiu. (2020) Expansion of the Fundamental Diagram from a Microscopic Multilane Modeling Framework of Mixed Traffic. Journal of Advanced Transportation, Vol. 2020, pp. 1–15. https://doi.org/10.1155/2020/8878346
3. **Seraj, M.,** Li, J. and Qiu, T. Z., (2019). Real-Time Driving Behavior Recognition of Connected Vehicles for Advanced Driver Assistance System: A Data-Driven Approach on Safety Pilot Model Deployment Program. Proceedings of Transportation Research Board 98th Annual Meeting
4. **Seraj, M.,** J. Li, and T. Z. Qiu. (2018) Modeling Microscopic Car-Following Strategy of Mixed Traffic to Identify Optimal Platoon Configurations for Multiobjective Decision-Making. Journal of Advanced Transportaion, Vol. 2018. https://doi.org/10.1155/2018/7835010

Dedicated to my parents

Late Seraj Uddin Bhuiyan and Kamrun Nahar

My beloved wife, Aditi

and

The love of my life, my daughter, Rawyia

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CHAPTER 1 : INTRODUCTION

1.1 Background

The advances in automotive and infrastructure technology have shifted the focus from expanding the transportation system to efficient utilization of existing frameworks. Traffic collision and congestion problems continue to exist in our roadway and demand innovative approaches to diminish the adverse effects of these problems on road users. Furthermore, the high number of fatalities resulting from traffic collisions is a growing concern for road transportation authorities across the globe. According to the World Health Organization statistics, approximately 1.35 million people pass away every year due to traffic collisions (*Road Traffic Injuries: The Facts*, 2018). In Canada, the average collision-related fatality and serious injury rates are 2040 and 11130 per year, respectively, for the last 10 years (Canada, 2020) [Figure 1.1.(a)]. To put things into perspective, the number of people killed each year in traffic collisions are equivalent to four fully occupied Boeing 747 airplanes crashing every year without any survivors. While these statistics show the most devastating aspect of the existing transportation system, there are other adverse impacts too. According to the INRIX mobility research, each resident of six major cities in Canada (i.e. Toronto, Montreal, Vancouver, Winnipeg, Calgary and Edmonton) lost about 70 working hours in congestion in 2019 which is about 0.5% more than 2018 (*INRIX 2019 Global Traffic Scorecard*, 2020) [Figure 1.1(b)]. All these detrimental features of the existing transportation system have motivated the progress of innovative transportation technologies.

One of the pioneering transportation technologies in recent years involves connectivity and automation of vehicles and transportation infrastructure. The subsequent research on 'Connected vehicle technology', 'Automated Vehicle Technology', and 'Driver Behavior', amongst other related transportation topics, have variously contributed to some significant breakthroughs regarding traffic mobility and safety. Different features of connected–automated vehicle (CAV) technologies, including connected adaptive cruise control (CACC), assisted driving systems, connected intersections, among others, are capable of changing vehicle operation in transportation systems as well as influencing individuals' driving behavior and use of their vehicles. While much of the focus to date has been on the impact of these technologies in increasing traffic network efficiency, or enhancing safety, or both, identifying the secondary impact of these technologies due to presence of heterogeneous vehicle operations are equally important.

Diminishing trip delay, reduced emission and enhanced safety of road traffic are claimed to be achieved due to the presence of diverse levels of integrated connectivity and automated control systems for vehicles and transportation infrastructure. Although large-scale deployment of such technology could take decades to become a reality, simulating gradual increase of connected-automated driving system-based vehicles in traffic streams would enable us to presume the extent of potential positive contributions from these technologies. Numerous academic efforts have been made to understand the combinatorial effect of these advanced technologies in the shared presence of traditional human-oriented transportation systems. However, perceptual differences of mixed traffic stream and collaborative motion dynamics have impeded the progress of these technologies in expected nature. Furthermore, the ideal compositions of automaton-driven vehicles (AuV) in mixed traffic scenarios remain unfamiliar to most.

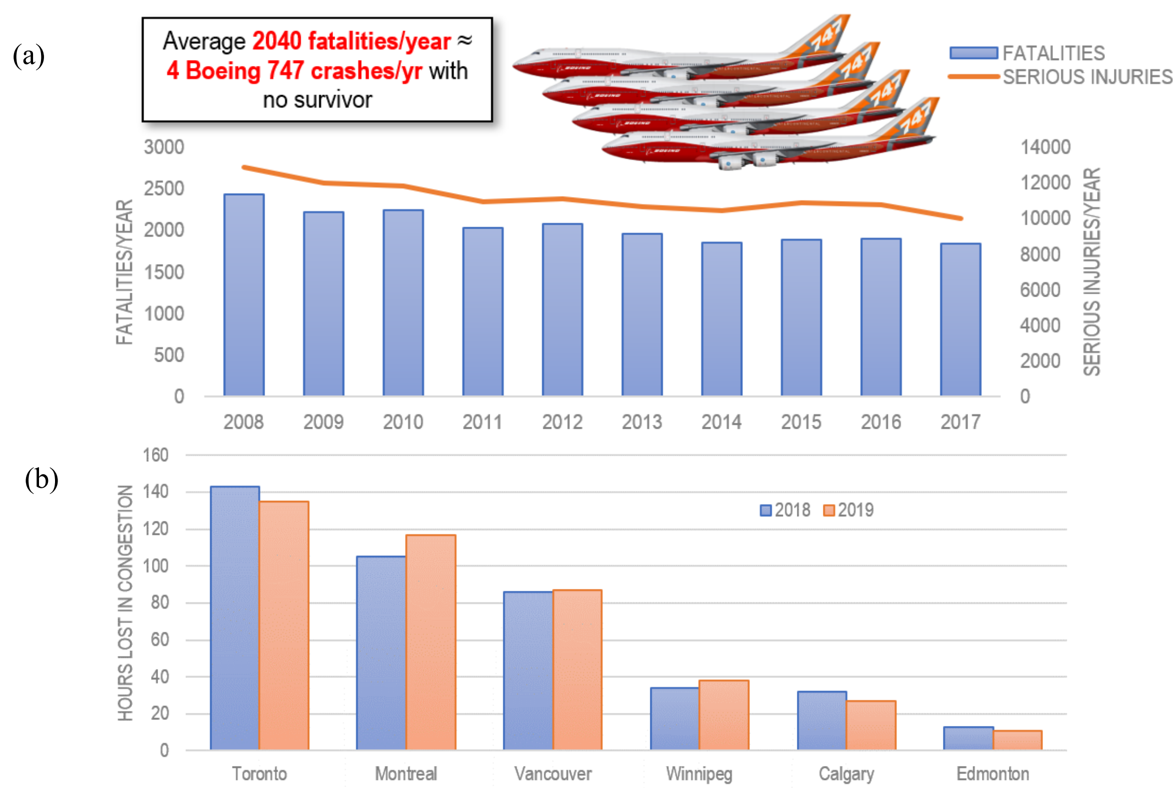

FIGURE 1.1 Road Traffic (a) Fatality facts of Canada from 2008-2017, (b) operational hindrance in major Canadian cities

Variations in traffic mobility and safety are regarded to be influenced by the heterogeneity of driving behavior of human drivers. Traffic streams including both AuV and Human-driven vehicle (HuV) are also susceptible to such diversified human driving behavior. Therefore, identifying the behavioral variations of human drivers is eminent in determining the degree of influence HuVs in mixed traffic mobility and safety.

1.2 Research Motivation

The comprehensive motivation of selecting this specific topic for research can be divided into four segments: preamble of CAV technology, inclusion of new technology with traditional transportation, key resulting features of traffic movement and intricate element of roadway network. The purpose of this research is selecting a delicate roadway component to determine the influences as fundamental resultants of traffic operation when both human and CAV equipped vehicles coexist.

The detrimental aspects of the existing transportation system have compelled a significant number of transportation agencies to shift their strategy towards adopting innovative technologies for the past few decades. CAV technology is one of such effort that showed propitious potential to reduce these inauspicious consequences without major restoration of existing framework. However, implementation complexity, legislative adjustments, high-speed wireless communication requirements could take decades to attain completely connected-automated traffic structure which opened up the possibility of an ecosystem including both HuV and AuV in shared roadways. The introduction and amalgamation of AuVs in existing transportation system would require careful considerations so that progress of CAV is not hindered by ineffective contributions.

One of the major complexities of the existing transportation system involves dissimilarity of human driving behavior. A single scenario could generate a wide range of human responses which make it difficult to predict an optimal automated strategy for such scenarios. For instance: a rear-end collision in the middle of the road would require the following vehicles to suddenly execute brakes to avoid colliding with the leading vehicle. However, reaction to such event and the extent of braking would vary between drivers depending on factors including perception-reaction time, age, sex, road surface conditions, weather etc. Now, introducing AuVs in this specific scenario could either be advantageous if they correctly apprehend the situation and diminish the instability caused by sudden braking. However, higher numbers of HuVs combined with behavioral variations among HuVs could diminish the positive impact brought by AuVs. Therefore, it is essential to comprehensively examine the heterogeneous effects of both HuV and AuV prior to launching.

Two major aspects of the transportation system include mobility and safety. Vehicles capable of transferring passengers and goods efficiently and safely bear the mark of an effective transportation system. The efficiency of the roadway networks is often measured by the highest number of vehicles that can traverse through the network with minimal delay or stoppings. On the other hand, the roadways with minimum number of collisions are regarded to be safe. Furthermore, mobility improvements often hinder the perception of safety for road users. Since both mobility and safety play vital roles in measuring the effectiveness of a transportation system, the mixed traffic scenarios generated from HuVs and AuVs should also be measured and compared with respect to changes in mobility and safety to identify the influence of introducing AuVs.

Finally, the motivation to choose the weaving section for this research rests on the fact that this component of freeway network plays critical roles on overall performance of the network. Weaving sections, where a merge and diverge in close proximity require vehicles either entering or exiting the freeway to execute one or more lane changes, are subjected to frequent lane-changing maneuvers due to inherent characteristics of traffic flow in this segment which leads to additional mobility and safety interests in comparison to other freeway segments. Despite the substantial importance of the weaving section in freeway operations, an insignificant amount of studies have been commenced to examine the potential consequences of AuVs on overall performance in varying mixed traffic scenarios. The lack of knowledge base in this direction has challenged and motivated the researcher to perform comprehensive research focusing the operation of weaving sections in mixed traffic conditions.

While new technologies can come with a lot of promise and potential, only perceptive integration of these technologies can ensure sustainable growth. Failure to apprehend the potential of CAV technologies can lead to unforeseen implications when introduced along with traditional HuVs and premature breakdown of this promising technology. In light of these key factors and their contributions in securing a superior transportation system, it is only natural to research on mixed traffic scenarios containing AuVs with traditional HuVs and quantify the degree of mobility as well as safety impact of CAV technology will have once introduced.

1.3 Definitions

The three key concepts pulled together for this research are Connected Vehicle technology, Automated Vehicle technology and Driving behavior. Outlined below are definitions of each that form the basis of understanding for the subsequent studies presented:

Connected Vehicle (CV) technology has been founded on concepts of connectivity and communication amongst vehicles, traffic infrastructures, and central traffic management center with the aim of safe, risk-free road travel characterized by high mobility rates and low rates of environmental impact (Transportation, 2015). With the advances in wireless communication technology, vehicles equipped with communication devices can connect and correspond with other vehicles (Vehicle to vehicle communication, V2V) and with road infrastructure (Vehicle to infrastructure communication, V2I) through dedicated short-range communication (DSRC) systems. Three major components of CV technology are Connection, Communication, and Cooperation (Figure 1.2). Connection ensures that vehicles, road-users, and infrastructure can communicate easily and steadily. Connectivity then facilitates the necessary and fundamental communication that ensures multilateral information from all sources (e.g. vehicle, road-users, infrastructure). In addition to the first two components of CV, cooperation ensures that all sources function together has harmoniously as possible.

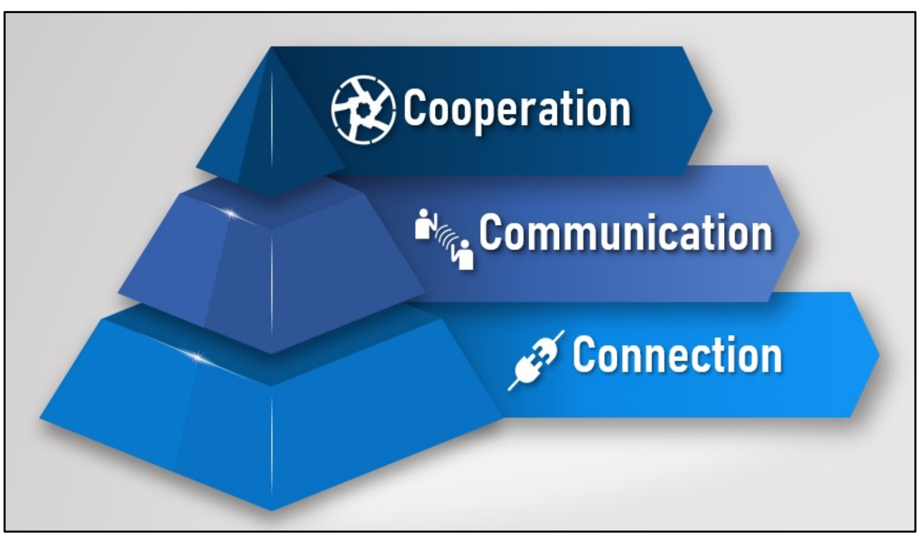

Figure 1.2 Three major components of Connected Vehicles

An Automated Vehicle (AV) incorporates technology that allows it to detect and evaluate its surroundings using a variety of technologies, including LiDAR, GPS, cameras, and computer vision (Ticoll, 2015). When defining Automated Vehicles (AV), they are divided based on a scale of automation – from partially to highly to fully automated. The Society of Automobile Engineers suggested 'Levels of Automation' are a worldwide standard used to indicate a vehicle's level of driving automation (Smith, 2014). There are a total of six levels of vehicle automation starting from Level 0: No Automation to Level 5: Full Automation. The higher the level, the more the vehicle is capable of monitoring and navigating the driving environment without human intervention (Figure 1.2). A vehicle with fully automated technology is an 'autonomous vehicle' that can detect its surrounding environment through numerous attached sensors and is capable of navigating traffic without human intervention. However, in this study I considered vehicles with *high* automation that still enables the vehicles to detect and evaluate nearby traffic status to make precise control decisions but differs from autonomous vehicles in the range of detection and influence in decision-making.

Both connected and automated vehicles have immense potential to transform traditional transportation systems through the creation of safe, interoperable communication among contributing parts of the system. Numerous studies have established notion that introducing these technologies will bring significant mobility and safety benefits (Paikari, Tahmasseby and Far, 2014; Minelli, Izadpanah and Razavi, 2015; Genders and Razavi, 2016; Olia *et al.*, 2016; Cronin, 2018; Rahman, 2019). Therefore, this study is built upon the perception that CV and AV technologies are capable of bringing positive changes in mobility and safety in comparison to traditional human driven transportation systems.

While the technological concept of the AV is a rapidly growing interest among researchers and practitioners, the vision of a fully automated vehicle-based traffic fleet will take decades to be realized. In the meantime, the notion of 'mixed traffic' should be accepted as a necessity and developed accordingly. Mixed traffic entails a vehicle fleet comprised of different vehicle types with varying automation levels. In the second study presented here, a mix of 'Level 0' automation with 'Level 3' automation is considered. Throughout this study, Level 0 of automation indicates driving by humans only and is therefore termed 'Human

Driving', and Level 3 of automation indicates minimal involvement from human drivers and is therefore termed 'Automated Driving'.

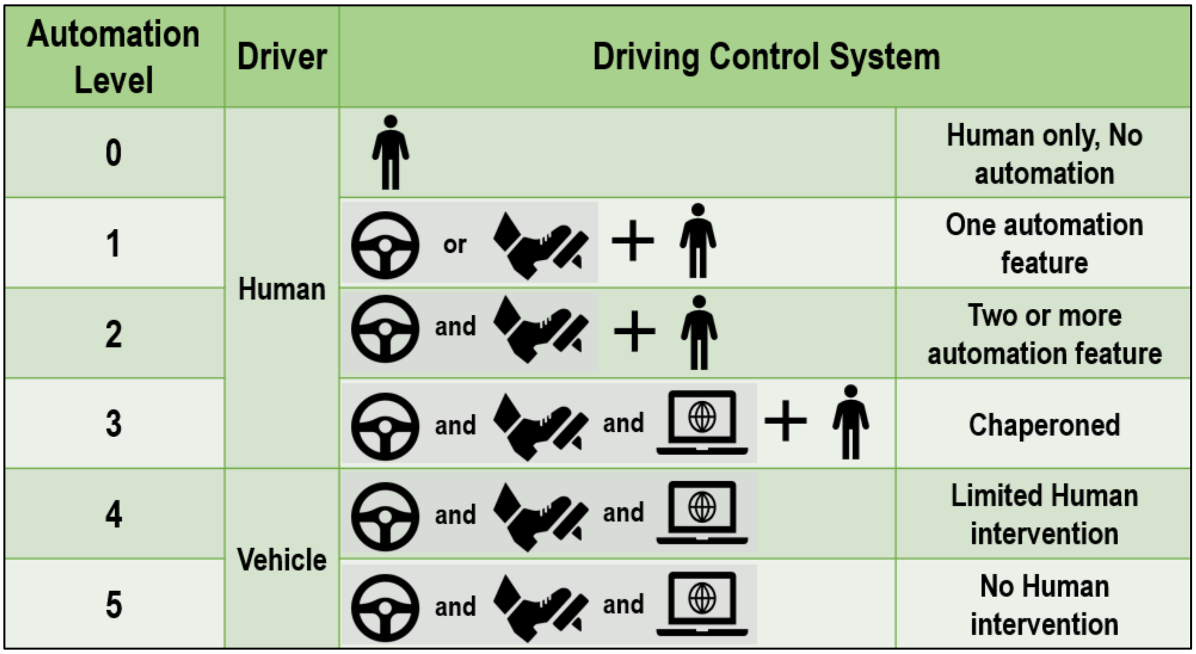

Figure 1.3 Different Levels of Automation (according to SAE)

The third concept, Driving Behavior, entails instantaneous control decisions by human drivers by detecting and evaluating the surrounding environment while driving. It is significant when considering Human Driving since the control of the vehicle depends on the individual driver. From a traffic safety perspective, almost 93% of all traffic collisions involve driver error to some extent, making driving behavior and behavioral heterogeneity highly significant. Additionally, a major component of CV technology is the 'Advanced Driver Assistance System' (ADAS), with potential applications in automated driving systems. Crucially, driving behavior recognition is the foundation of driver assistance systems, where driving behavior is categorized by driving maneuver types and other performance measures. As such, these systems can potentially act as an effective measure to enhance traffic safety, by identifying aggressive driving behavior and providing drivers with feedback to adjust their driving. With better grasp of these concepts, I will now focus on the research question of this study and determined objectives of this study to answer this research question.

Weaving sections can be referred to as freeway segments where two traffic streams weave as shown in Figure 1.4. In a freeway network, a weaving section is formed when a diverging area is positioned in close proximity to a merging area and both on, off-ramps are connected by auxiliary lanes. The length of weaving sections is usually measured from the point where the entrance gore is 2ft wide to where exit gore is 12 ft wide (Figure 1.4). Weaving sections experience intense lane changing maneuvers as drivers must access the suitable lanes for reaching their destination route. Hence, traffic in weaving sections can experience additional restrictions in maneuvering compared to other freeway sections. Weaving sections include main lanes, on-ramps, auxiliary lanes and off-ramps. Based on their configuration, a weaving section can be classified as Type A, Type B and Type C (Manual, 2000). In this research I will focus only on the Type A weaving section. In Type A weaving segments, all the weaving vehicles must make one lane-changing maneuver to reach their target lane.

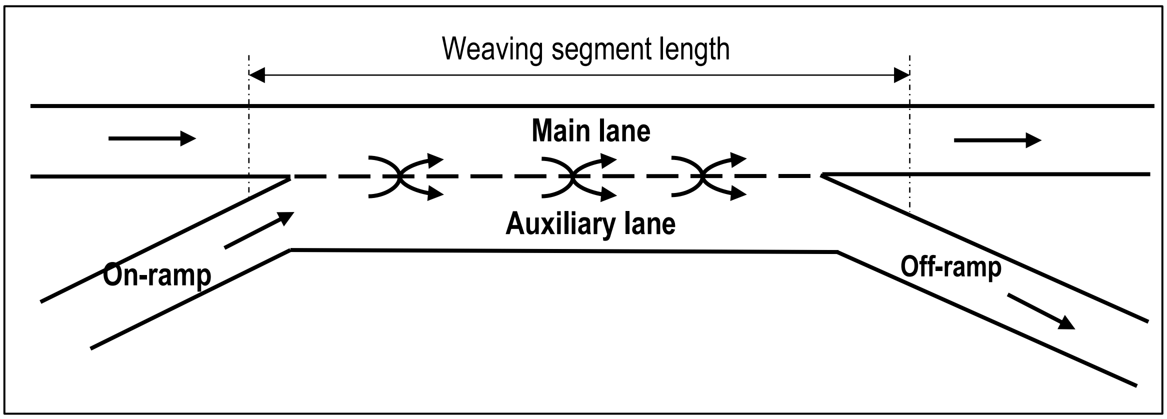

Figure 1.4 Anatomy of a Type-A weaving section

1.4 Research question and objectives

In the journey toward a completely automated transportation system, researchers and transportation planners need to address issues that will facilitate the integration of this new technology. A key research question in response to this need, then, is:

What are the mobility and safety implications of shared road-use by AuVs and HuVs, particularly considering the behavioral heterogeneity of human drivers in a freeway weaving section?

Specifically, the behavioral variations of human drivers need interpretation for AuVs so that they might be taught to respond accordingly. It is unrealistic to expect AuVs to resolve issues that may arise on shared roadways without this insight into human driver behavior. Furthermore, an assessment of potential benefits from AuVs presence in a traffic stream requires accurate measurement in order to address this research question. A quantitative analysis of potential benefits can lend weight to the argument for investment and development of CAV technology.

To attain the objective of answering the established research question, three key tasks have been determined, as listed below

1. **Task 1**: To identify and classify human driving behavior from naturalistic driving data
2. **Task 2**: To measure the impact of AuVs' car-following activity in mixed traffic with respect to mobility and safety
3. **Task 3**: To measure the impact of complete motions (i.e. car-following, lane-changing, gap acceptance) in mixed traffic with respect to mobility and safety when integrating recognized human driving behavior

Task 1 will provide the research foundations given that human drivers demonstrate heterogeneity in driving behavior and these diversifications bring more uncertainty in quantifying mobility and safety aspects of specific traffic states. The goal is to identify the pattern of the behavioral heterogeneity of human drivers by analyzing realistic driving data for different road types. This part of research focused on road class specific behavioral variation identification since the key research focus is specific roadway segment (i.e., freeway weaving section). As an extension to this process, driving behaviors are classified with regards to different timelines. Identifying the variations of key behavioral parameters are essential to estimate the scope of benefits from mixed traffic.

In order to estimate overall mobility and safety influences of AuVs on traffic streams we need to consider the fundamentals of traffic motion dynamics. Traffic streams are developed from aggregation of individual vehicles moving together in the same direction. Therefore, apprehending individual vehicle's movement maneuvers is imperative for exhaustive analysis. Vehicle's primarily have two-directional maneuvers: longitudinal maneuver which is essentially car-following and lateral maneuver that includes both lane changing and gap acceptance. Since car-following is the primary component and predominant driving maneuver of traffic motion dynamics, achieving task 2 will provide the substructure to measure the impact on mobility and safety. In this stage of the research, the assumption will be homogenous and standard human driving behavior in a mix with AuVs without any variations with regards to aggressive and defensive driving. Moreover, this stage will discard additional complexity from other components of motion dynamics such as lane changing decision, allowable gap acceptance etc. This stage of research will provide a simpler base to build on the rest of the study.

Finally, task 3 would include the full set of motions by mixed traffic to attain the range measurements of potential mobility and safety gains. While the motion dynamics will take all components (i.e., car-following, lane-changing, gap acceptance) into consideration, behavioral heterogeneity will also be integrated for human drivers in this phase of the research. To reduce complexity of interpreting the impact on mobility and safety, specific behavioral distribution of human diving behavior will be chosen based on results from Objective 1. Additionally, a specific roadway section (i.e., weaving section) with influential contribution to traffic network stability will be chosen for analysis instead of generalizing the results for all components of roadway network (e.g., merging section, diverging section, weaving section, mid-section etc.). Including bi-directional movement strategies for two types of vehicles along with behavioral heterogeneity of HuVs will bring a great deal of complexity and ambiguity in measured mobility and safety results. The study will therefore be limited to specific segment types of freeways with particular characteristics which will confine the outcomes to a considerably explainable level of detail.

1.5 Research scopes

Defining research scope provides more structured navigation through the research process. As stated in the research objective section, the research aims to explore the human driving characteristics and car-following implications of mixed traffic in the first two objectives. Both of these objectives cover relatively wider research scope which would be incomprehensible as a single research topic. Hence, the third objective streamlined the research scope to a manageable domain with specific roadway configurations, vehicle motion dynamics. With this in mind, it is of utmost importance to define the scope of the research in order to accomplish the defined objectives. The scopes of this research are listed below:

1. The research scopes for estimating mobility and safety implications are restricted to uninterrupted traffic flow sections of roadway network which are commonly

observable in freeways. Freeways and arterials with yield, stop or signal controls are beyond the scope of this research

2. Freeway network consists of four fundamental segments: basic segments, merging segments, diverging segments, and weaving segments. Among these four segments one specific segment is chosen for extensive analysis to deliver subjective evaluation on mobility and safety implications. Weaving section often produces recurrent congestion in freeway networks due to its' competing traffic movement patterns and, therefore, plays critical role in over traffic operation through freeways.
3. While the traffic movements through freeway segments are considered for implication estimations, driving behavioral classification considers different road types of traffic network to obtain a more comprehensive overview of behavioral variations depending on road types. Analysis of driving behavior in different road types also reinforce the assumption that the driving behavioral pattern of traffic in freeways are substantially different from other road types.
4. Some specific features are examined for behavioral classification of human drivers. The chosen features are capable of illustrating the bi-directional motion dynamics of vehicles resulting from drivers' control decisions. Number of features is limited to such a small number to extricate additional complexity in the classification process. Although additional features could result in more accurate classification, improvident addition of features could lead to interdependence among the features which could increase the complexity of the method and/or diminish classification accuracy.
5. In behavioral classification from naturalistic driving data, a fraction of available trip data is analyzed in this research. Firstly, the purpose was to select enough samples from a large dataset (of 13,792 trips) that is capable of portraying diverse real-world circumstances experienced by the drivers (e.g., driving through freeways, arterials and ramps within a same trip) while keeping the sample size within a manageable limit for analysis. Secondly, each selected trip should contain a fairly large number of data points to represent significant variations. The assumption behind this consideration was that a trip with 10000 data points (trip duration = 1000 sec or 16 min 40 sec) would be more capable of demonstrating drivers' behavioral variation than a trip with 1000 data points (100 sec or 3 min 10 sec). Excluding the remaining trips of the dataset

from analysis does not necessarily mean that the remaining trip data were wrong. It just assumes that adding data points from more trips would not add significant value to the considered sample trips.

6. Analyzing the broad spectrum of traffic flow scenarios from real-world traffic are inefficient and complicated. Consequently, the estimation of mobility and safety implications are contained within numeric simulation-based analysis of freeway traffic. Furthermore, it would be impossible to encounter diverse ranges of market share by automated vehicles due to unavailability of their large-scale presence in real-world traffic.

1.6 Organization of thesis

The remainder of this thesis is divided into five chapters including conclusion. The contents of three basic sections of this thesis are described below:

i. *Comprehensive Literature review (Chapter 2)* This chapter combines all relevant research efforts related to three key directions of this research: behavioral variations of human drivers and classification approach, car-following strategies and consequences for mixed traffic operation and complete motion of mixed traffic in freeway segments. A detailed literature review on these topics identified the state of the art in this topic as well as existing research gaps which can be addressed through this research.

ii. *Analyzing Naturalistic Driving Data (Chapter 3):* This chapter concentrates on analyzing real-world driving data of human drivers to recognize the variations in driving pattern. The primary output expected from the analysis are microscopic traffic dynamics modeling parameters for human-driven vehicles in freeway. The patterns of modeling parameters are studied to confirm the existence of variability in human driving behavior as well as substantial difference in driving pattern among distinct road types. Furthermore, the research makes headway towards developing a driving behavior classification method from analyzed driving features. The classification method aims at classifying individual trip behavior as well as long-term driving habits of individuals by accounting for bi-directional control decisions. Effects of exogeneous factors like geometric design of roadway, neighboring traffic, environmental factors are disregarded from this classification process due to unavailability of accurate information and influence of these factors.

iii. *Mobility and Safety Implications from Partial Motion Dynamics of Mixed Traffic (Chapter 4):* This chapter of thesis developed a mixed traffic car-following strategy with platoon formation policy among AuVs. Vehicle motion dynamics of mixed traffic containing both HuV and AuV are initiated from this chapter with acquired knowledge about human driving behavior from the previous chapter. Although the behavioral variations are excluded from this part of research to maintain the interpretability of the results, the key parameters of car-following models for HuVs are shaped by obtained information from Chapter 2. Furthermore, a wide range of platoon configuration for AuVs are examined here to identify the influence of platoon structure as well as AuVs position in traffic stream on overall mobility and safety of traffic. Since mobility and safety of traffic can be explained through various criteria, a set of parameters are chosen, considering the studied scenario (i.e., partial motion dynamic), to illustrate the resulting mobility and safety implications due to the presence of AuVs in the traffic stream. This chapter provides an overall direction to move forward with this research direction and to include additional complexity (e. g. complete motion dynamics, behavioral variations of HuVs) in subsequent research.

iv. *Implications of Complete Motion Dynamics of Mixed Traffic in Weaving Section (Chapter 5):* In light of obtained results from Chapter 3, this chapter expands to cover bi-directional motion dynamics of mixed traffic. Grounded on the foundation laid on previous chapters, variations of human driving behavior are also incorporated in HuVs' modeling. Since complete motion dynamics were enabled in identified behavioral variations, including such variation in partial motion dynamics (Chapter 3) would be impractical. Hence, obtained wisdom regarding behavioral variations of human drivers are incorporated at this stage of the research. Additionally, specific freeway segment is chosen to implement the vehicle motion modeling and implication measurements to produce more definite and precise estimations. Due to opposing flow patterns experienced in the weaving section, this element of freeway network is often subject to severe mobility and safety concern which makes this segment an ideal candidate to examine the extent of potential implications resulting from AuVs presence.

v. *Conclusion (Chapter 6)* combines the research objectives with obtained findings from entire research and their significance in advancing automated vehicle technology in the future. Key limitations of the research are also outlined in this chapter along with future research directions. This research aims to contribute to the existing body of knowledge regarding automated vehicle technology by delivering definite outcomes about resulting mobility and safety consequences. Since advancement of automated vehicle technology depends on successful adoption as well as appropriate interpretation of leading consequences of this technology, I think this research can assist in moving the needle towards the right direction.

It is critical for the coherence of the research that different components/tasks of research are associated with other components. In this regard, figure 1.5 illustrates the interconnectedness of three tasks of this research. In addition to the core research related outputs from task 1 and 2, supplementary outputs are also obtained from these components which have both scholarly and practical contributions.

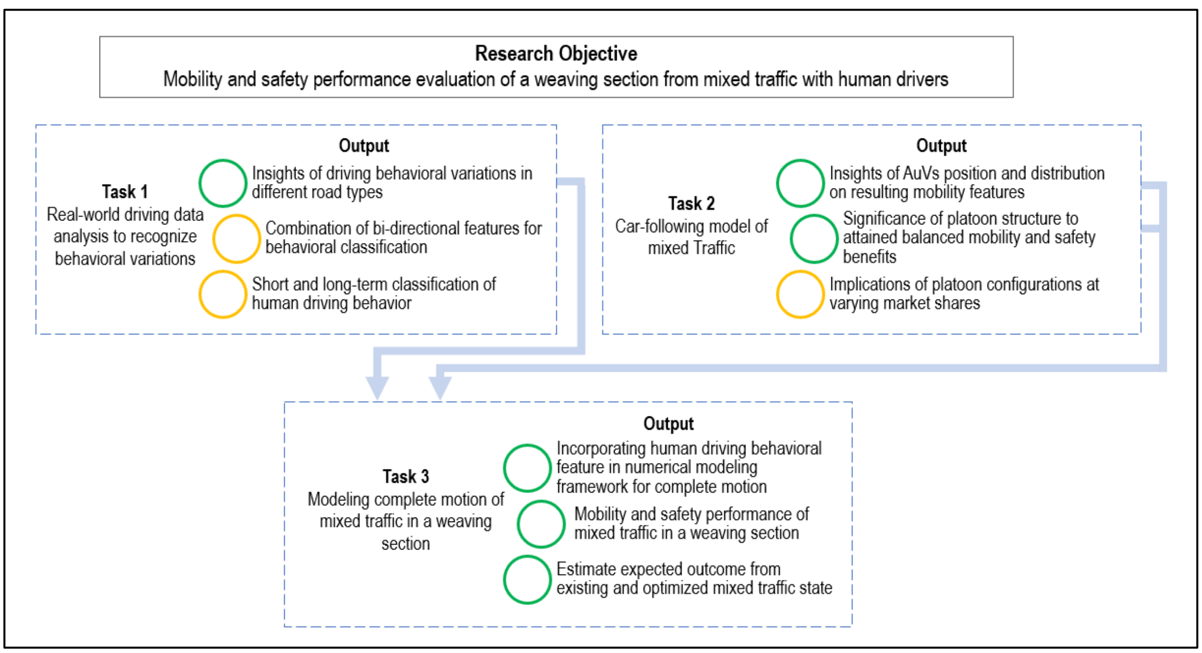

Figure 1.5 Interconnectedness of different tasks of the research

1.7 Conclusion

This chapter initiates the research operation by outlining the research objectives, scopes, and fundamental concepts to assist in traversing through this thesis. The foundation laid in this section of the thesis promotes informed decision making in subsequent parts of the research. The research idea conceived in this section follows the chronological order of research described in the 'organization of thesis' section and examines real-world human driving behavior to variations in driving patterns in the human counterpart of mixed traffic environments.

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CHAPTER 2 : LITERATURE REVIEW

2.1 Background

Literature review is an essential part of any research to provide a background of existing knowledge base. A comprehensive literature review on the research topic records the relevant research efforts in the similar direction to determine the scopes of contribution through new research. In compliance with the research objective, this literature review can be classified into three major categories. Since first objective deals with human driving behavior, the literature review starts with assessing relevant research articles in this topic to identify the state of the art in this direction while recognizing potential gaps in existing research. Similar to second objective, section 2.3 addresses the research efforts in mixed traffic movements without considering the implications of human components. Followed by section 2.4 which focuses on published literature in mixed traffic motions connecting freeway traffic movements. Finally, section 2.5 lists the identified gaps in these three directions from extensive literature review.

2.2 Behavioral Variations and Classifications of Human Driver

To recognize the behavioral variations of human drivers, identification of driving behavior and habit has long been of interest to researchers. Gibson and Crooks (Gibson and Crooks, 1938) conducted one of the earliest studies on driving psychology and concluded that driving pre-dominantly depends on drivers' perceptions of their surrounding environments. Safe driving, therefore, depends on his/her psychological safe spatial zone. In order to capture drivers' perception during driving, different physical measures have been identified and studied by a number of research teams (Wiesenthal, Hennessy and Gibson, 2000; Dula and Ballard, 2003; Dahlen and Ragan, 2004; Taubman-Ben-Ari, Mikulincer and Gillath, 2004; Sümer, Özkan and Lajunen, 2006; Richer and Bergeron, 2009; Joubert, Beer and Koker, 2016; Eboli, Mazzulla and Pungillo, 2017; Shinar, 2017; Eftekhari and Ghatee, 2018). Some specific driving measures studied include: speeding and/or hard braking (Johnson and Trivedi, 2011; Aljaafreh, Alshabatat and Najim Al-Din, 2012; Eren *et al.*, 2012; Paefgen *et al.*, 2012; Ellison, Greaves and Bliemer, 2015; Abuali and Abou-zeid, 2016; Lee and Jang, 2017), Jerky driving (Desai and Haque, 2006; Murphey, Milton and Kiliaris, 2009; Bagdadi and Várhelyi, 2011;

Huysduynen, Terken and Eggen, 2018), Tailgating (Xiong *et al.*, 2012; Underwood, 2013), Lane choice (Zhao *et al.*, 2012; Reimer *et al.*, 2013), Steering Angle (Ungoren and Peng, 2005; Zhao *et al.*, 2012; Underwood, 2013; Lee and Jang, 2017), Lateral Acceleration (Aljaafreh, Alshabatat and Najim Al-Din, 2012), passing gap during overtaking (Farah *et al.*, 2009) and included both longitudinal and lateral features as part of their categorization. While speed, accelerations are frequently used measures of driving behavior, jerk profile has been found to be more sensitive to safety-critical driving behavior (Murphey, Milton and Kiliaris, 2009). With regards to longitudinal control decision time and/or space headways are found to be more specific than speed, acceleration or jerk profiles in reflecting hostile driving (Underwood, 2013). Since consistent headways during driving is the socially accepted norm of safe driver, a driver's use of short and erratic headways could be partly explained by aggressive intentions. On the other hand, lateral control behavior is often associated with steering angle, lateral acceleration and lane choice. Increased variations in these features can differentiate between what is considered as safe and unsafe driving. While both longitudinal and lateral driving features take part in defining driving behavior, the collective impact both aspects remain uncharted.

A major motivation in driving behavior identification lies on developing techniques to modify that behavior (Inagaki, 2008; Staubach, 2009; Wang, 2010; Dong *et al.*, 2011; Li *et al.*, 2012; Son, Park and Park, 2015; Guo *et al.*, 2016). In recent times, personalized communication through connected vehicle-based ADAS system has become essential for the integration and development of driving behavior modification (Syed *et al.*, 2010; Diakaki *et al.*, 2015; Jiang *et al.*, 2017; Ryder *et al.*, 2017). In order to fit a driver's requirements, acceptability, and preferences, ADAS design should include a driver identification profile that considers both driving behavior and driving habit (Fugiglando *et al.*, 2017). However, techniques to label driving behavior from collected driving features varies widely in literature, some of which include rule-based (Taubman-Ben-Ari, Mikulincer and Gillath, 2004; Murphey, Milton and Kiliaris, 2009; Manzoni *et al.*, 2010; Lee and Son, 2011; Corti *et al.*, 2013), fuzzy logic based (Syed, Filev and Ying, 2007; Filev *et al.*, 2009; Kim, Sim and Oh, 2012; Dörr, Grabengiesser and Gauterin, 2014), and machine learning methods-based (Taubman-Ben-Ari, Mikulincer and Gillath, 2004; Ishibashi *et al.*, 2007; Constantinescu *et al.*, 2010; Johnson and Trivedi, 2011; Wang and Lukic, 2011; Karginova, Byttner and

Svensson, 2012). Due to its computational simplicity, robustness, and clear explanation, rule-based techniques of driving behavior identification are favored by numerous studies. However, larger set variables can create complex classification process in rule-based method but can be more readily resolved by fuzzy logic-based methods. Further, machine learning methods have become prevalent among practitioners in recent years due the availability of large, multivariate datasets. Yet, while machine learning methods can identify driving patterns from big data with larger sets of variables, these labelling techniques often contain complex and delicate structures and can result in inexplicable solutions. To avoid these pitfalls, we have used a small number of variables with relatively large datasets, and we have explored both rule-based and machine learning-based labelling techniques in order to choose an ideal technique for labelling unlabeled training data. Although the dataset chosen for this study may initially appear small, we feel that they are large enough to represent the behavioral variations of drivers as well as to demonstrate the proposed method of classification. Furthermore, the chosen dataset included the trips with higher number of records than remaining trips of the dataset which potentially accounts for most possible variations.

2.3 Car-following models for mixed traffic with impact evaluation

Aligned with the second objective of this research, the focus of this part of the literature review is on car-following strategies for mixed traffic environment. As such the literature explored here relate to car-following models for both forms of driving system. Numerous microscopic car following models have been proposed to imitate driving pattern of manual driving system (Chandler, Herman and Montroll, 1958; Helly, 1959; Evans and Rothery, 1973; Gipps, 1981; Bando *et al.*, 1995; Treiber, Hennecke and Helbing, 2000). Among the proposed stimulus-response-based car-following models, the intelligent driver model (IDM) is widely used in literature to depict manual driving dynamics. The ability of this model to define numerous microscopic (e.g., desired velocity, acceleration/deceleration limits etc.) and macroscopic (e.g., capacity, capacity drop, fundamental diagram etc.) phenomena made it the prevalent model. On the other hand, due to rapid growth of CAV technology, the longitudinal control models for automated vehicles were also examined by researchers (Li and Shrivastava, 2002; Orosz and Moehlis, 2011; Xiao and Gao, 2011; Davis, 2013; Hu *et al.*, 2017; Wang, Wu and Barth, 2017). These studies provide me with structures to work on car-following strategy in mixed traffic environment and identify the extents of potential paradigm shifts.

A clear distinction of the driving system is dictated by the operational authority. While the Human-driven Vehicle (HuV) represents driving-systems controlled by humans, the motion dynamics of vehicles with the Automaton-driven Vehicle (AuV)s are mandated by distinct levels of automation. AuVs' longitudinal movements are commonly portrayed with Adaptive Cruise Control (ACC) and Cooperative Adaptive Cruise Control (CACC). Many studies have analyzed the contributions of longitudinal control system of AUD vehicles on traffic mobility (Van Arem, Van Driel and Visser, 2006; Yi and Horowitz, 2006; Bifulco *et al.*, 2013; Delis, Nikolos and Papageorgiou, 2015; Ntousakis, Nikolos and Papageorgiou, 2015; Fountoulakis *et al.*, 2017; Sun, Zheng and Sun, 2018; Xin *et al.*, 2018; Ye and Yamamoto, 2018b; Zhu and Zhang, 2018). While mobility was the main focus of these studies, the impact of traffic movement from safety and environmental perspective were often ignored. Yeo et al. (Yeo *et al.*, 2008) proposed an integrated car-following and lane changing model to perform micro-simulation of oversaturated freeway traffic. The proposed algorithm considered complex dynamic interactions at a microscopic level to replicate vehicle movements. However, the aptitude of this model to capture possible consequences was not tested. Wang et al. (Chen *et al.*, 2018) proposed a car-following control for autonomous vehicle and identified the impact, focusing mainly on traffic flow characteristics. Liberis et al. (Bekiaris-liberis, Roncoli and Papageorgiou, 2016) took a macroscopic approach to identify traffic mobility parameters in a heterogeneous traffic environment. The authors used the market penetration rate of connected vehicles to estimate traffic states. Moreover, other researchers studied the impact of introducing AuV based vehicles with conventional vehicles (Chang and Lai, 1997; Vander Werf *et al.*, 2002; Ni *et al.*, 2010; Tientrakool, Y. C. Ho and Maxemchuk, 2011; van den Berg and Verhoef, 2016) on flow and mobility. Reviews of these studies provide me with the opportunity to constructively examine the contributions of earlier studies, identify the necessities to improve current knowledge and uncover the latent insights to progress promptly with CA technology.

While the mobility attributes of traffic flow were widely discussed in many studies, the safety aspects, which are equally if not more important, were relatively unexplored by a majority of the studies. The impact of automated vehicles on both safety and mobility were discussed by Fernandes and Nunes(Fernandes and Nunes, 2012). They studied platooning of AuVs with different communication schemes at various flow rates to improve roadway capacity. Several studies assessed the safety aspects of CAV based traffic. According to the National Highway Traffic Safety Administration (NHTSA), a complete adaptation of CAV based traffic movements would annually prevent 439,000–615,000 crashes (Administration, 2016). Li et al. (Li *et al.*, 2017) evaluated the impact of CACC control on reducing rear-end collisions on freeways. The study shows a reduction in safety improvements with increasing market share of AuVs. Rahman and Abdel-Aty (Rahman and Abdel-Aty, 2017) compared potential improvement in longitudinal safety due to varying market penetration of connected vehicles. According to the analysis presented, the managed-lane CAC control outperformed multi-lane control with regards to traffic safety. The report of Zabat et al. (Zabat *et al.*, 1995) stated that the presence of boundary layer along closely spaced vehicles would reduce aerodynamic drag, resulting in reduced fuel consumption and less emission. Platoon-wide environment-friendly CACC system was studied by Wang et al. (Wang *et al.*, 2017) and their objective assessment attained 2% fuel saving with 17% emission reductions. Mamouei et al (Mamouei, Kaparias and Halikias, 2018) argued that fuel-economy based ACC control model would not lead to highly conservative driving dynamics of traffic.

2.4 Complete motion dynamics of mixed traffic in freeway

Despite real-world pilots of AuVs and the significant advancement in knowledge on this technology, large-scale deployment of AuVs in contemporary traffic streams is not easily achievable, making the majority of existing literature studying the effects of mixed traffic reliant on traffic simulation. A number of simulation-based studies conducted mobility analysis for mixed traffic through capacity shifts (Shladover *et al.*, 2001; Vander Werf *et al.*, 2002; Van Arem, Van Driel and Visser, 2006; Kesting *et al.*, 2008; Kesting, Treiber and Helbing, 2010; Tientrakool, Y.-C. Ho and Maxemchuk, 2011; Shladover, Su and Lu, 2012; Lee, Bared and Park, 2014; Chen *et al.*, 2017; Ghiasi *et al.*, 2017; Liu *et al.*, 2018). These studies provided valuable insights about roadway capacity changes of mainstream traffic resulting from mixed traffic flow at varying market shares, although few explicitly explore the influence of integrating AuVs into freeway weaving sections. Furthermore, the few studies that included car-following (Seraj, Li and Qiu, 2018; Zhu and Zhang, 2018; Fu *et al.*, 2019) lack inclusion of weaving sections and their influence on lane-changing vehicles. In addition to capacity, the impact of AuVs on mobility has been evaluated through traffic speed (Khondaker and Kattan, 2015; Han, Chen and Ahn, 2017; Hong *et al.*, 2018). However, the aggregated impact on both of these parameters was underexplored by these studies. Malikopoulos et al. (Malikopoulos *et al.*, 2019) examined environmental implications, travel time, and traffic throughput in mixed traffic scenarios. Rios-Torres and Malikopoulos (Rios-Torres and Malikopoulos, 2018) examined both environmental and mobility aspects of mixed traffic flow for merging segments in a simulated environment. Despite the fact that weaving sections are critical components of freeway system, scarcely any study examined the possibility of mobility and safety paradigm shift in these sections due to introducing AuVs in traffic stream. Fazio, Holden and Rouphail (Fazio, Holden and Rouphail, 1993) used simulated conflict rates count to identify hazardous locations and compared with obtained crash rates. Uno et al. (Uno *et al.*, 2003) identified the potential conflicts in weaving sections by analyzing vehicle movements from recorded videos. Tilg, Yang and Menendez (Tilg, Yang and Menendez, 2018) proposed a mixed traffic model which was calibrated to replicate the traffic dynamics on a weaving section. Although findings from this study revealed the potential of AuVs to improve the capacity of the weaving section, other aspects of mobility and safety remain uncharted. Ye and Yamamoto (Ye and Yamamoto, 2018b, 2018a) conducted studies on heterogenous traffic flow and concluded that resulting the capacity improvements depends largely on AuV market penetration and car-following parameters. Both studies discussed the changes in macroscopic fundamental diagram to determine the changes in traffic flow parameters.

Several studies have been published in recent years that measure the safety impact of AuVs when mixed with HuVs. The study conducted by Hayes(Hayes, 2002) reported that fatality rates could eventually be reduced to 1% of current rates once a 100% market share of AVs was reached. Alternatively, Fagnant and Kockelman (Fagnant and Kockelman, 2015) predicted that the influence of AuVs could reduce the crash rate by 90% by the elimination of human error possibility. Multiple research papers explored the simulation approach to estimate the safety of traffic (Fan *et al.*, 2013; Huang *et al.*, 2013; Essa and Sayed, 2015; Shahdah, Saccomanno and Persaud, 2015). Fan et al. (Fan *et al.*, 2013) proposed a two-stage process to use the VISSIM simulation model outputs to calibrate for the surrogate safety assessment model at merging locations. A similar objective was followed by Huang et al.

(Huang *et al.*, 2013) for signalized intersections. Essa and Sayed (Essa and Sayed, 2015), on the other hand, studied the transferability of the calibrated parameters to different sites for simulation. From the perspective of the safety impact evaluation of mixed traffic, Ye and Yamamoto (Ye and Yamamoto, 2019) simulated mixed traffic to study traffic safety under various market shares of connected-automated vehicles (CAV) and argued that the cautious and accurate car-following strategy from CAVs would greatly contribute to traffic safety. Papadoulis et al. (Papadoulis, Quddus and Imprialou, 2019) developed a bi-directional decision-making control algorithm for AuVs to evaluate resulting safety implications at different market penetration rates. The results revealed that traffic conflicts could be reduced by up to 90-94% with a full AuD traffic stream. The safety implications of exclusive AuV lanes were identified by Zhang et al. (Zhang *et al.*, 2020) with different market shares and for multiple traffic demand scenarios. Results of this study indicated that a higher number of lanes would be required at high demand scenarios to attain significant safety improvements. In brief, the research efforts in measuring safety implications of AuVs in mixed traffic environment is summarized in Table 2.1

Table 2.1 Research summary of safety in mixed traffic environments

(Authors, Year)	**Safety Parameters**	**Findings**
(Moon, Moon and Yi, 2009)	(i) Time-to-collision (TTC); (ii) non-dimensional warning index	ACC strategy can prevent vehicle gaps from reducing to an unsafe level in different driving scenario
(Li *et al.*, 2017)	(i) Time Exposed Time-to-collision (TET); (ii) Time Integrated Time-to-collision (TIT)	90% reduction of rear-end collision risks due to CACC system
(Virdi *et al.*, 2019)	(i) TTC; (ii) Post Encroachment Time (PET)	Low CAV penetration showed increase in potential conflicts at lower headway and signalized intersections, higher CAV market share showed a global decrease
(Tu *et al.*, 2019)	(i) TET; (ii) TIT	Degradation from CACC to ACC had significant negative impact on longitudinal safety

(Papadoulis, Quddus and Imprialou, 2019)	(i) TTC; (ii) PET	Estimated conflict rates reduced with gradual increase in market share of CAV and finally reduced by 90-94% at 100% CAV penetration rate
(Shi *et al.*, 2020)	(i) TTC; (ii) TET; (iii) TIT	Mixed traffic flow can induce higher longitudinal collision risk at low market penetration of ACC driven vehicle due to individual heterogeneity
(Arvin *et al.*, 2020)	(i) Number of conflicts; (ii) Longitudinal volatility	Substantial safety improvement was observed at market penetration higher than 40%

Overall review of relevant literature solidified the common assumption that introducing AuVs in traditional transportation system would generate favorable mobility and safety implications. However, uncertainties regarding the magnitude of improvements as well as potential negative consequences remain equivocal. Furthermore, majority of the studies considered collective implications from dissimilar configurations of roadway segments which diluted the influence of natural impediment and variability resulting from individual segment structure. Hence, this research consciously identified a prevalent bottleneck segment of freeway and explored both mobility and safety implications from system level prospect.

2.5 Opportunities for scholarly contributions

When reviewing the literature related to driving behavior identification, recognition, and classification, three major research domains which can be addressed through this research are evident. They are: (i) the combination of both longitudinal and lateral driving features to detect adverse driving patterns, (ii) the implementation of techniques to determine both driving behavior (short time driving behavior) and driving habit (long-term driving behavior) of individual drivers, and (iii) the proposition of a simple yet informative ADAS interface to communicate detected behavioral information to drivers. While the as the part of broad research scope identification of behavioral heterogeneity in freeways would be sufficient, the research effort is further extended to make scholarly contributions in identified directions. The integration of bidirectional control decisions in classification improves the odds of precise categorization, since the combination of both features can capture a greater diversity of behavior that is potentially overlooked by one-dimensional feature-based classifications. A further contribution of this study will be to demonstrate the gradual development and changes in driving habits from driving behavior in both short-term and long-term driving behavior classifications. As a final contribution, this study proposes a user-friendly, real-time warning system for a driving behavior interface that includes the capability to provide long-term driving habit information. This final element also offers a future extension of the current study.

Although the reviewed studies in the second phase had remarkable contributions that helped to clarify the roles and influences of AuVs in traffic, the inadequacy of multi-objective decision-making approach to address AuVs' potential has influenced this research to further investigate the complex interdependencies of mixed traffic. This study segment seeks to contribute on three research gaps identified from the literature. These gaps are:

- The significance of AuVs' position and distributions along traffic stream,
- The variations of traffic flow attributes (i.e., mobility and safety) resulting from structural changes of CACC platoons,
- Adjusting platoon configurations dynamically to obtain balanced benefits from considered traffic attributes.

This part of the research can aim to employ the obtained insights about car-following of human drivers from previous phase of research in developing the microscopic modeling framework of mixed traffic. The key parameter values for car-following model of human driver can be chosen based on real-world human driving behavioral analysis. Utilizing these knowledges obtained from extensive analysis of human driving pattern will promote realistic representation of human car-following approach in microscopic model and generate rational simulation outputs. As a result, the measurements of mobility and safety implications resulting from car-following of mixed traffic will be more authentic and balanced.

Finally, the fundamental objective of this research is to measure and explain mobility and safety consequences of the gradual adoption of AuVs to freeway weaving sections by developing a microscopic multilane modeling framework. This part of research can decompose the mixed traffic environment into individual vehicle maneuvers to obtain the most precise estimations of AuVs' influence, regarded by the authors as a substantially original contribution. Many have estimated the implications of AuV by exploring mixed traffic from macroscopic and microscopic perspectives. Nevertheless, these studies were unable to capture the detailed dynamics (e.g., spatial and temporal perception of human driver, realistic lane-changing etc.) needed to properly measure and explain the resulting outcomes. The novelty is the integration of longitudinal and lateral motion dynamics into a single microscopic modeling framework. Furthermore, this study re-contextualizes the existing concepts of traditional traffic and control theory to establish a realistic multilane mixed traffic flow model that accounts for the anticipative nature of human drivers, incorporating this characteristic in AuVs through model predictive control. The holistic approach of this study, subjectively examining the causal effects of the presence of AuVs on mobility and safety in weaving sections sets itself apart from previous research attempts. Furthermore, the most significant feature of this research is to utilize the quantitative outcomes to provide qualitative explanations regarding AuV share and its corresponding impact. Key outcomes of this research include the relative scoring of the mobility and safety impact of different traffic scenarios as well as recommendations for the optimal AuV share for maximal expected benefits from traffic in weaving section. With the findings from this study, traffic management authorities can apply the recommended approach to improve the performance of a critical component of their freeway networks. At the same time, researchers can use these results to further illuminate the significant features of this technology, such as vehicle shares, inflow rate, and crash risk, and its influence in traffic operational processes.

2.6 Conclusion

This chapter performed a comprehensive literature review to establish a strong foundation and clear perception about existing knowledge base in this research topic. Founded on this base, following chapters of this research aims to make significant scholarly contributions to determine the potential consequences of mixed traffic motion on traffic mobility and safety on a freeway weaving segment.

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CHAPTER 3 : ANALYZING NATURALISTIC DRIVING DATA

3.1 Introduction

In the larger context of the research, this part of the dissertation plays a vital role. Since the objective of this research includes incorporating human drivers' behavior into the modeling framework of mixed traffic, it is imperative to recognize the behavioral variations in the first place. In this regard, this part of the dissertation analyzed real-world driving data from HuVs and distinguished among different driving patterns. The human drivers' behavioral findings from this chapter will be integrated in the final modeling framework in Chapter 5. Since the research is concentrated on the freeway weaving segment, the analyzing parameters will be categorized into road types which can also demonstrate the discrepancies in driver behavior depending on traversing the road. Final takeaway from this chapter will be parameter values of specific parameters to represent human driving behavior in freeways.

The recognition of individual driving behavior has played a vital role in identifying hazardous driving patterns, vehicle fuel consumption optimization, individualized vehicle control system design, and power management system design. Gradual expansion and integration of connected and autonomous vehicle (CAV)-based transportation systems have amplified the need to understand drivers' individual behaviors as well as the implications of behavioral variations of drivers on overall traffic. Recognition of driving behavior is now seen as intrinsic to the proper design and assessment of an Advanced Driver Assistance System (ADAS) as well as the enhancement of traffic safety through CAVs (Filev *et al.*, 2009; Murphey, Milton and Kiliaris, 2009; Doshi and Trivedi, 2010; Karginova, Byttner and Svensson, 2012; Bolovinou *et al.*, 2014; Wang, Xi and Chen, 2014). However, observations of real-world driving indicate that driving behavior is the result of instantaneous decisions made in response to the exogenous environment, including elements such as road type, surrounding traffic, and the physical and mental state of the driver. Assuming that these instantaneous driving decisions result from a complex fusion of different factors, this part of the research aims to recognize the behavioral variations of driving parameters of human drivers in different road types as well as dynamically identify distinct types of driving behavior by analyzing bidirectional control decisions.

3.2 Research Contributions

Driving behavior is a complex concept, and the common association of 'Driving behavior' with 'Driving Habit/Style' complicates its definition and identification further. The correlation between the terms, as understood within the related literature, offers clarification on the distinct levels of classification. Driving behavior, according to the literature, focuses exclusively on drivers' instantaneous decisions and correlates with the driving conditions experienced by drivers. Therefore, a precise understanding of the environment can provide better insight into driving behavior (Ericsson, 2001; Manzoni et al., 2010; Wang and Lukic, 2011). Furthermore, we can expect variations in decisions by the same driver at different times for the same driving conditions because of transformed habitual influence. On the other hand, research suggests that individual drivers' preferential driving behavior accumulates over time and develops into driving habit or driving style (Lajunen and Summala, 1995; Ishibashi et al., 2007; Murphey, Milton and Kiliaris, 2009; Kleisen, 2011; De Groot, Centeno Ricote and De Winter, 2012). While driving behavior varies in response, often erratically to external factors, driving habits change steadily in the longer term. The differentiated concepts of driving behavior and driving habit are necessary to distinguish between observed driving behavior on any given trip and developed driving habit from an accumulated driving history.

With this definition in mind, this chapter of the dissertation presents a simplified approach to dynamically identifying driving behavior by analyzing drivers' jerk, yaw rate, and leading headway profiles on different roadways. Jerk, yaw rate, and leading headway profiles are regarded as indicators of individual drivers' longitudinal and lateral control decisions. This research uses these indicators as a mean to decisively recognize the behavior of any given driver and thereby contributes to driving behavior research in two ways: 1), the results can generate more accurate representations that better identify hazardous driving behavior by analyzing bidirectional driving features for classification, and 2) this study can establish and distinguish between the two different behavioral classes for individual trip behavior and accumulated driving history. Additionally, this chapter presents the model for a convenient and cohesive ADAS interface that warns drivers in real time of unsafe driving behavior. This interface would also facilitate both drivers and regulatory organizations to review driving habits based on an accumulation of previous driving behavior.

The greater demand for understanding mixed traffic environments with AuVs and HuVs justifies the need for comprehensive research on human driving behavior observed from real-world driving experience in different road types. Traffic management authorities that apply the recommended approach derived from the results of this study could provide an efficient ADAS application of this promising technology to improve traffic mobility and safety. As such, the key contributions of this part of the research are listed below:

i. The first contribution of this research would be capturing the variations in human driving behavior in different road types through in-depth analysis of multiple parameters which can be adopted to human driver modeling.
ii. Another contribution of this research is capturing the behavioral evolution of a driver's instantaneous responses (i.e., short-term behavior) to driving habit (i.e., long-term behavior) by accounting for both longitudinal and lateral driving features.

In order to best present the findings, this chapter is organized as follows: Section 3.3 provides a detailed description of analyzed dataset; Section 3.4 presents the preliminary data analysis of selected dataset which reports the behavioral variations of human drivers through multiple parameters which will be used in later part of this research for modeling human drivers in mixed traffic; Section 3.5 describes the proposed classification method in detail; Section 3.6 evaluates the proposed method's performance when identifying behavioral pattern, followed by a description of the plans to extend the current research; Finally, a synopsis of the study findings concludes this chapter.

3.3 Data Description

As mentioned earlier, the scope of this part study includes analyzing naturalistic data for recognizing behavioral difference among drivers. In this regard, the data used is from Safety Pilot Model Deployment (SPMD) project led by the University of Michigan Transportation Research Institute (UMTRI). Figure 3.1 shows the collected data locations that contained different road types. In this project, different dimensions of driving data were collected from vehicle and vehicle users while they were driving along the real-world roads including freeways, arterials and ramps. More than 13,000 trip data were collected in this project which includes passenger cars, trucks and buses. The vehicles were equipped with few devices to enable Vehicle-to-vehicle communication, Vehicle-to-Infrastructure communication and recording precise GPS location to track vehicle motions. On the infrastructure side, there were 25 roadside unit (RSU) installed at different roads and intersections to obtain information from vehicles and roadway. In this project real-world driving data were collected from roadways of Ann Arbor, Michigan through integrated safety devices and the radar-based data acquisition system that were developed by the Virginia Tech Transportation Institute (VRI). These data were obtained via the Research Data Exchange website. There were four types of vehicle equipment configurations used, referred as Integrated Safety Device (ISD), Aftermarket Safety Device (ASD), Retrofit Safety Device (RSD) and Vehicle Awareness Device (VAD) based on their purpose and ability to collect, record, transmit and receive different sets of information to and from vehicles.

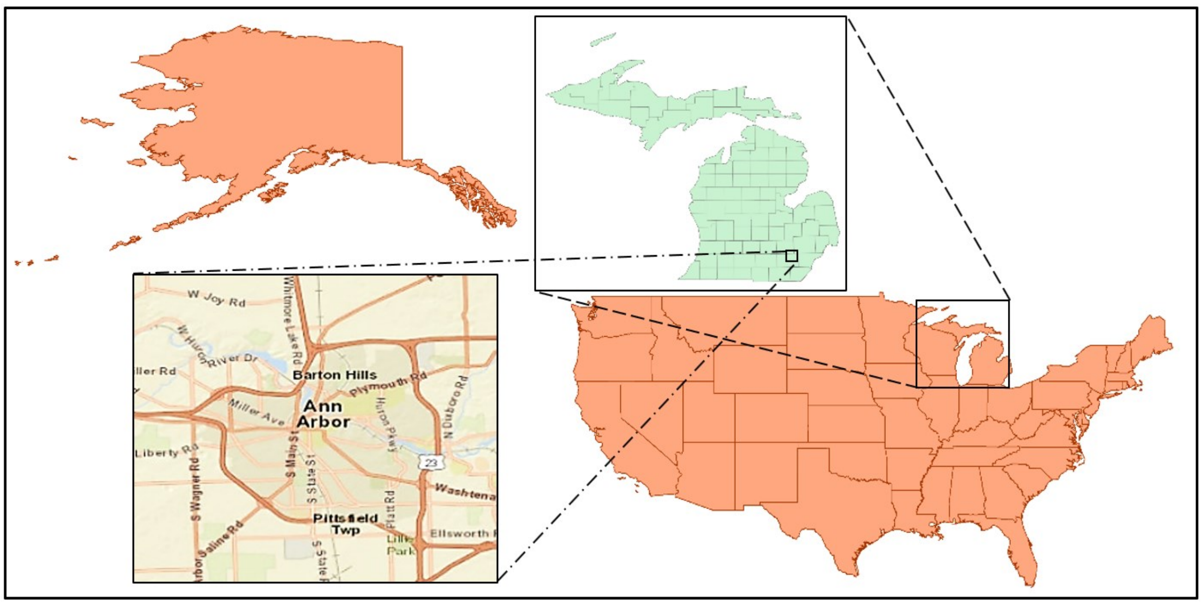

FIGURE 3.1 Safety Pilot Model Deployment Data Collection Location, Ann Arbor, Michigan, USA

Sensors attached to these CVs continuously collected information, including vehicle ID, trip ID, GPS longitude, GPS latitude, GPS UTC time, in-vehicle brake status, in-vehicle headlight status, in-vehicle speed, in-vehicle acceleration, in-vehicle steering position, in-vehicle throttle position, and in-vehicle yaw rate, amongst other types of information. From this large dataset, the top 550 trips (~4%), containing 7.94 million records in total (10.12%), were selected for this research by sorting the trips in descending order of available data records of each trip. Since bi-directional control decisions were taken to recognize the driving behaviors, the parameter representing both longitudinal and lateral driving features were analyzed here, which includes leading headway, longitudinal acceleration of leading subject vehicle and leading vehicle, lane position of the subject vehicle and leading vehicle, time-to-collision of subject vehicles, vehicle speed during lane-changing, yaw rate during lane changing, the duration of lane changing etc. Before going with recognizing driving behavior and classifying them for short-term and long-term, a preliminary analysis of obtained dataset was performed to apprehend the diversity as well as the significance of the data. This preliminary analysis not only helped to choose the predominant features for classification purpose but also assisted in later part of the research for setting simulation parameter values.

3.4 Preliminary data analysis

The preliminary analysis of sample dataset distributed the traffic dynamics into five major components which are: (i) Average speed, (ii) Extreme Acceleration-Deceleration, (iii) Lane-changing yaw rates, (iv) Average time headway and (v) Lane changing duration. The following sub sections provide more details of each analysis components.

3.4.1 Average speed

The selected trips were divided into three categories based traversed road type through map matching using high frequency GPS location data. These three categories of road types were: freeway, arterial and ramps. Average speed of these trip segments was measured to identify the speed characteristics of drivers at different road type and their response to different speed limits. Figure 3.2(a) showed the density distribution of average speed of vehicles at three different road types. The distribution showed significant difference in speed characteristics of drivers for each road type. While freeway average speed distribution found to be more concentrated towards higher speed values, arterial histogram was more distributed over the range. Ramp speed distribution showed much more similarity with arterial distribution than freeway distribution.

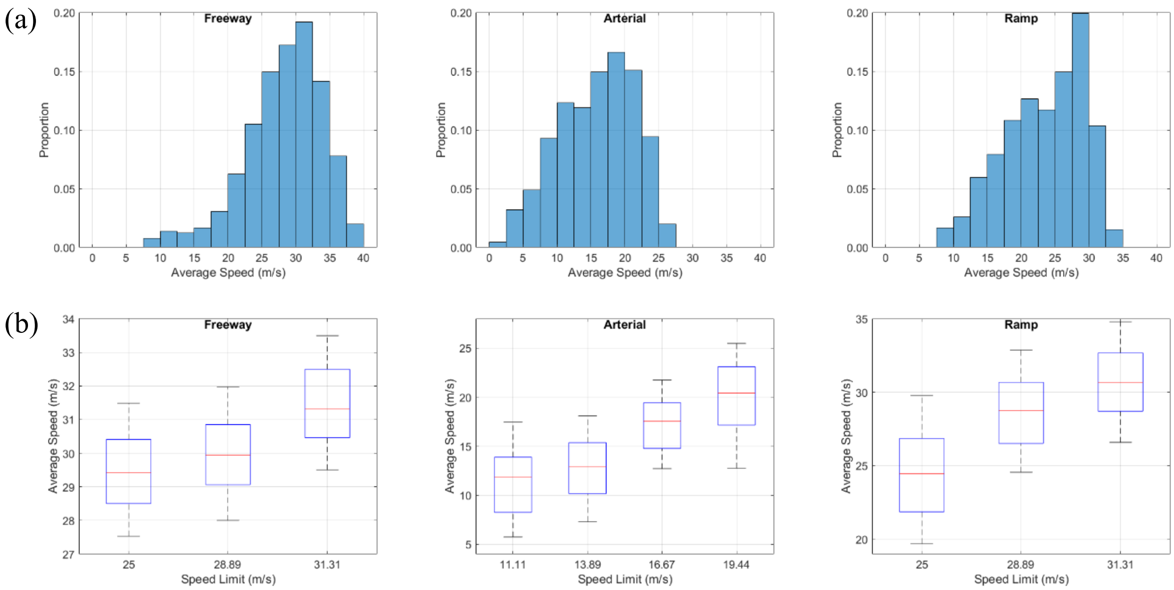

FIGURE 3.2 (a) Average speed distribution of studied road types, (b) Boxplots for different speed limit in studied road types

As evident from these figures, the speed distribution of each road type was significantly different. However, the difference came from varying speed limit in these roads. Also, the range of speed were found to be widely different from posted speed limit in same road type. In freeway, with lower posted speed limit (25m/s) experienced higher average free-flow speed than higher posted speed limit (28.89 m/s, 31.31 m/s) roadway segments (Figure 3.2(b)). According to the Highway Capacity Manual (HCM), the base free flow speed is estimated to be 2.2 m/s higher than posted speed limit. However, as observed from the obtained data, HCM suggested estimation did not held true for low-speed limit freeways. Findings from this analysis uncovered that, in mixed traffic scenarios, if the automated vehicles programmed to follow the speed limit, they will drive much slower than human driven vehicles, especially on freeways with slower speed limits. By driving slower than their counterpart, the automated vehicle may bring instability in traffic flow which can lead to mobility and safety issues. Analysis on arterial and ramp average speed showed relatively lower deflection from posted speed limits and followed HCM suggested estimation in most cases.

3.4.2 Extreme Acceleration-Deceleration

Decisiveness of a vehicle driver can be characterized by longitudinal acceleration and deceleration decisions. Longitudinal acceleration and deceleration profile also change for the same driver with the change of road type. In this analysis, the extreme acceleration and deceleration values were measured and compared for different road types. For each driver, the extreme deceleration was defined as the deceleration stronger than 5 percentile and acceleration stronger than 95 percentile was defined as extreme acceleration. The distribution of extreme acceleration and deceleration of all drivers are shown in Figure 3.3 for each road type. The distributions are fitted with Generalized Extreme Value (GEV) distribution model. The parameter of the GEV distribution model include shape parameter k, scale parameter σ and location parameter μ. The probability function is shown below

$$f(x|k,\sigma,\mu) = \begin{cases} \frac{1}{\sigma}\exp\left(-\left(1+\frac{k(x-\mu)}{\sigma}\right)^{-\frac{1}{k}}\right)\left(1+\frac{k(x-\mu)}{\sigma}\right)^{-1-\frac{1}{k}} & k \neq 0 \\ \frac{1}{\sigma}\exp\left(-\exp\left(-\frac{x-\mu}{\sigma}\right)-\frac{x-\mu}{\sigma}\right) & k = 0 \end{cases} \tag{3.1}$$

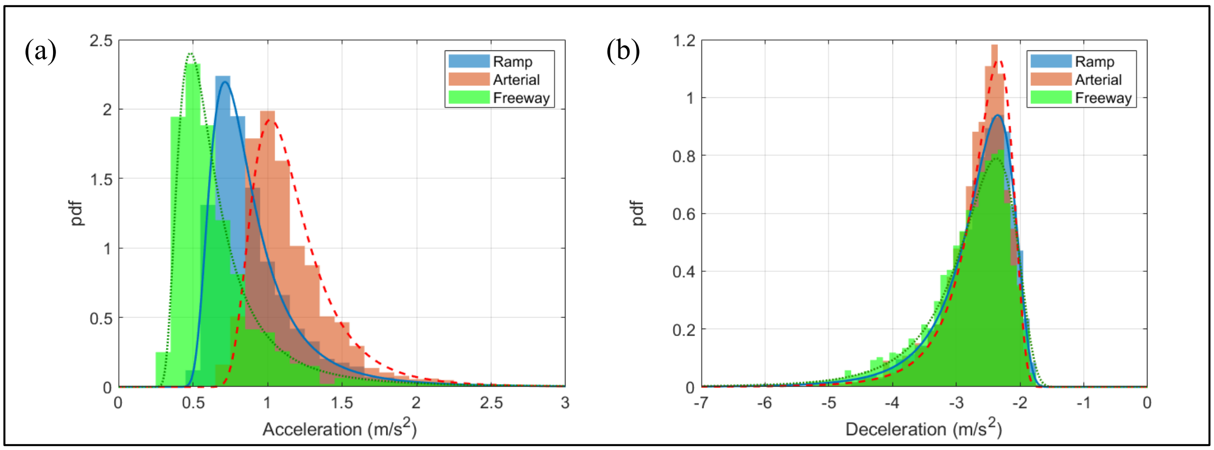

FIGURE 3.3 (a) Extreme acceleration and (b) extreme declaration distribution in studied road types

As portrayed in Figure 3.3(a), extreme acceleration distribution experienced more dissimilarity on different road types than extreme deceleration distribution. Additionally, human drivers have higher acceleration tendency in arterial (average = 1.17m/s^2) than freeways (average = 0.76 m/s^2). On the contrary, the extreme deceleration distribution was quite similar for all road types (average freeway = -2.83 m/s^2, ramp = -2.71 m/s^2, arterial = -2.66 m/s^2). Although, the range of extreme acceleration and deceleration on freeways were wider than other two road types. These information of human drivers' extreme acceleration and deceleration characteristics as well as variations depending on road types will assist in decision making process of automated vehicle with better insights about anticipative response in mixed traffic scenarios. The GEV distribution parameters for each road type are summarized at Table 3.1.

Table 3.1 GEV distribution parameters for extreme acceleration and deceleration at studied road types

Scenarios		κ	σ	μ
Freeway	Acceleration	0.3813	0.1608	0.5174
	Deceleration	0.1573	0.4412	2.4741
Arterial	Acceleration	0.1466	0.1878	1.1457
	Deceleration	0.1569	0.3309	2.5065
Ramp	Acceleration	0.2641	0.173	0.7541
	Deceleration	0.1658	0.3968	2.4102

3.4.3 Lane-changing yaw rate

To assist in lane-changing decision making of automated vehicles as well as perceive the human lane-changing characteristics, it is essential to learn human lane-changing maximum yaw rate at different road types. The sampled SPMD dataset was filtered for lane-changing events (total 1793 lane-changing events) and maximum lane-changing yaw rate was measured for those events during lane changing. Figure 3.4 illustrates the maximum lane-changing yaw rate distribution for freeway and arterial roads. Since the identified lane-changing maneuvers in ramps were negligible (total 19 lane-changing maneuver), the yaw rate distribution for this road type was not developed. Distribution of maximum lane-changing yaw rate provided insights about dissimilarities of human driving aggressiveness at different road types during lane changing and how these discrepancies should be addressed and adjusted for automated driving design.

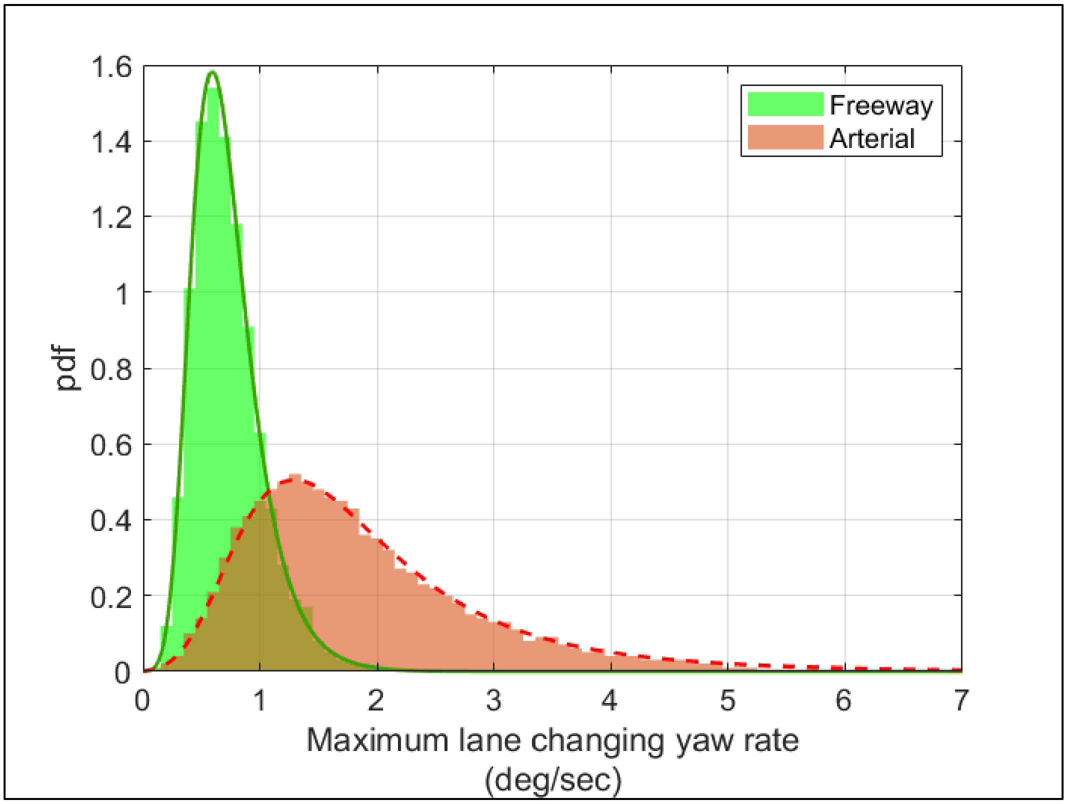

FIGURE 3.4 Maximum lane changing yaw rates distribution fore freeway and arterial roads

As observed from the figure, the yaw rate distribution for freeways were much more concentrated toward lower yaw rate values. Additionally, the spread of distribution was comparatively narrower than arterial roads which indicates more homogeneity in lane-changing behavior among drivers in freeways. On the other hand, the arterial road users were found to be more diverse with regards to lane changing. The distribution of maximum lane-changing yaw rate was covered a wider range than freeway. Furthermore, the peak of the distribution was reached at a higher yaw-rate (1.25 deg/sec) than freeway (0.58 deg/sec). The average maximum yaw rate of arterial lane-change (1.64 deg/sec) was much higher than the freeway lane change (0.61 deg/sec) which indicated that the drivers in arterial were more competitive than freeway for lane changing which could be explained by the fact that arterial roads usually have lower speed limits than freeways and enable drivers to execute fast lane changing without causing much safety concern.

3.4.4 Average time headway

The VAD installed in test vehicles recorded the relative distance of leading vehicle from subject vehicle at all time steps. These leading space headways was converted into time headway of the subject vehicle by dividing with the speed of subject vehicle. Since constant time headway is frequently used in adaptive cruise control design, this parameter can provide some significant insights about human driving characteristics. Previous studies disclosed that the lognormal distribution offers the best fit for time headway distribution of human drivers (Yang and Peng, 2010). To model the time headway of distribution of the sample dataset, the average time headway for each road type was calculated and plotted in Figure 3.5. The distribution is fitted using lognormal distribution function. The average time headway for freeway driving was 1.4 sec with 0.29 sec standard deviations. This result conforms with previous studies (Branston, 1976; Dey and Chandra, 2009) which concluded that average time headway for vehicles in highway during car-following ranges between 1.3 sec to 1.6 sec. In this segment of analysis different posted speed limits on highway was unrecognized as an influencing factor.

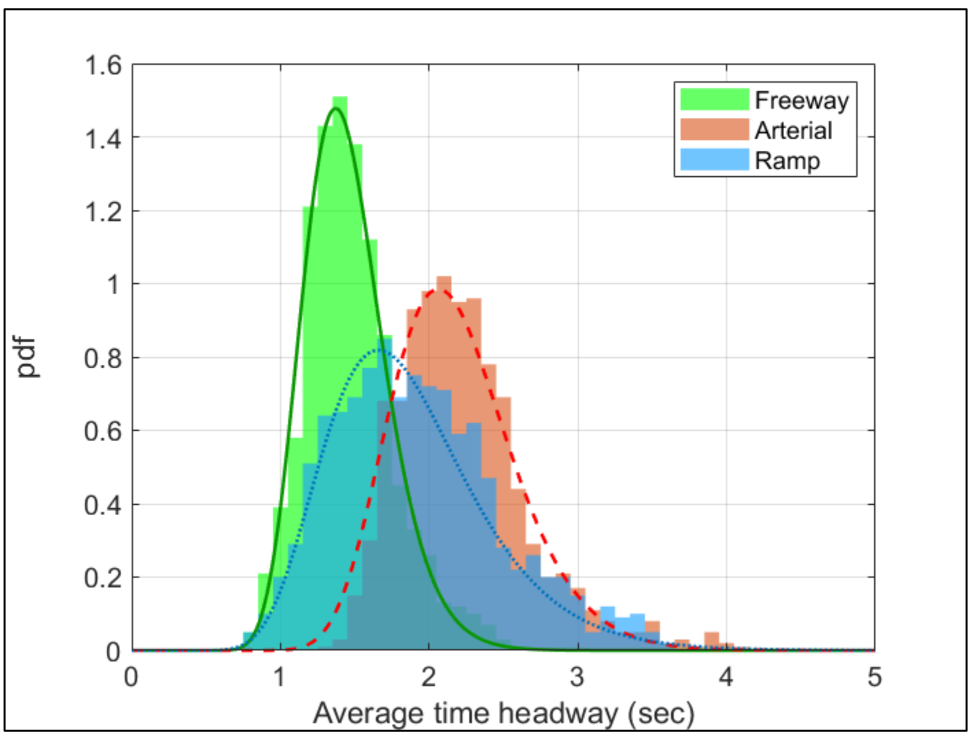

FIGURE 3.5 Average time headway distribution of studied road types

Similar distribution was plotted for arterial roads and ramps. The average time headway for arterial driving was 2.18 sec and standard deviation was 0.42 sec. Similarly, the average time headway for ramp was 1.87 sec with standard deviation of 0.54 sec. Since the analysis showed that human drivers' time headway changes with traversing road type, the automated vehicle design needs to account for this characteristic too. In arterial road, human drivers maintain higher time headway due to expected stop and go situation at intersections. Since freeways provide uninterrupted flow of traffic, the drivers were more confident in maintaining lower time headway. The ramps acted as transitional segments where drivers adjusted their time headway to prepare themselves for downstream roadway type. These insights of average time headway will be valuable for precise representation of human driver and their behavioral variations in forthcoming microscopic simulation model.

3.4.5 Lane changing duration

Similar to previous analysis, the lane changing duration was also measured from sampled dataset. This analysis will be helpful in developing multilane modeling framework of traffic as it will require prevailing duration as input in the model to execute lane changing maneuvers. While lane changing durations may depend on numerous factors, like vehicle type, surrounding traffic state, relative position, velocity of subject vehicle, lane changing direction (i.e. to left or to right) etc., the influences of these factors were disregarded in this analysis to reduce complexity in measurements for this analysis and modeling complexity in later part of the research. For a specific trip, the duration of a single lane change was measured by calculating the time span between which the yaw rate was higher than average lane changing yaw rate of traversing road type. Identified lane changing events were also filtered with other data sources (i.e. lane track, turn signal) to establish effective lane changing events. Total 1793 lane changing event was identified from sample dataset. Majority of the lane-changing maneuver was performed in arterial roads (1086-times, 60.57%) with only 19-times identified lane changing in ramps. Due to negligible number of lane-changing, the distribution for lane changing duration on ramps was not plotted. Figure 3.6 portrayed the lane changing duration distribution for both freeway and arterial roads from sample dataset.

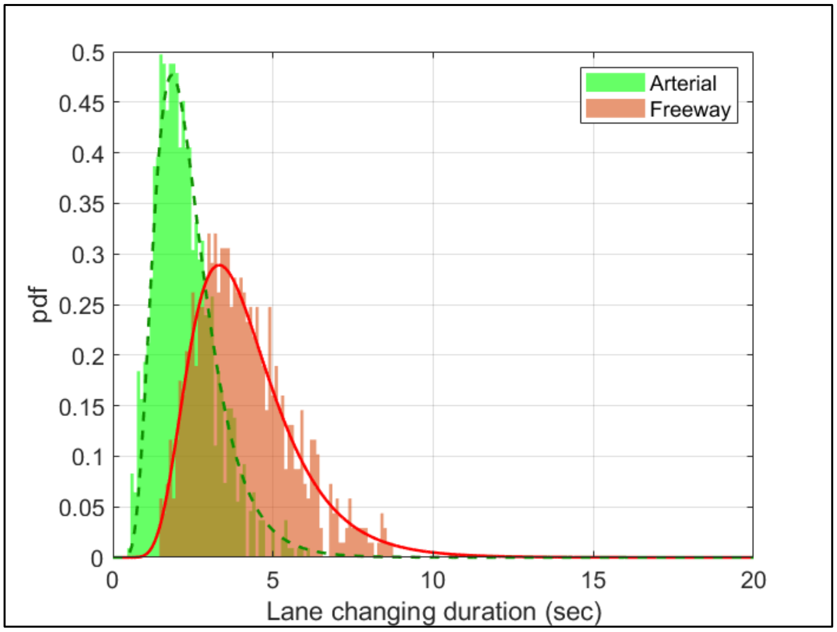

FIGURE 3.6 Lane changing duration distribution of studied roads

As observed in Figure 3.6, the lane changing duration of vehicles in arterial road was significantly lower from freeway. The average lane changing duration in arterial and freeway roads were 2.77 sec and 4.15 sec, respectively. The results from this analysis demonstrated that the human driver in arterial chose to execute change lane quickly and lower speed limits in arterial assist in some way to accomplish that goal. However, the speed limit in freeways were relatively higher which make the quick lane changing process a lot riskier than arterial. Additionally, as obtained from average time headway analysis, the vehicles at freeway are comfortable at driving a lower time headway then arterial which also restrict the opportunity to perform a quick lane change in between narrowly spaced vehicles. Finally, awareness obtained from this analysis will assist in developing microscopic modeling framework for lane changing vehicles.

3.5 Behavioral Classification Methodology

Grounded upon the preliminary analysis, the aim of this part of the research here is to categorize both short-term and long-term driving behavior. In this regard, I have chosen three recorded and derived driving features to represent bi-directional movement of vehicles and drivers' control decision. These features will also be used to categorize human driving behavior in two temporal scale, short-term and long-term. While short-term classification represents a driver's individual trip behavior, the long-term classification stands for an individual driver's driving habit, formulated from previous driving experiences. The classification of human driving behavior from sample dataset will be indirectly interpreted in microscopic modeling of human drivers in later part of the research.

The link between behavioral classification of human drivers in two-time scales are established by utilizing same features are for both classifications. Furthermore, both classifications of driving behavior are based on a fixed duration (5 sec) moving window along the classification period. Short-term driving behavior is classified into two distinct classes, Safe Driving and Hostile Driving, as defined below:

- Safe Driving: driving instances within a trip when the driver anticipates the surrounding roadway environment and subsequently executes composed control decisions.
- Hostile Driving: driving instances within a trip when the driver fails to assess the surrounding roadway environment and subsequently compensates by performing impulsive and hazardous control decisions.

The continuous accumulation of short-term classifications, gathered from trips in the driving history, facilitates long-term driver behavior classification. In this classification process, individual drivers are grouped into three categories, Calm Driver, Rational Driver, and Aggressive Driver, as defined below:

- Calm Driver: their share of cumulative hostile driving instances over the analysis period is below the specified lower threshold value
- Rational Driver: their share of cumulative hostile driving instances over the analysis period is within the lower and upper threshold value
- Aggressive Driver: their share of cumulative hostile driving instances over the analysis period is above the upper threshold value

3.5.1 Data preparation

As mentioned earlier, the data of this part of the research are borrowed from SPMD project. However instead of large disordered, incomplete trip records, a sample of 550 trips with organized and complete record was filter from dataset. The top 550 trips (~4%) were selected for this research by sorting the number of available data records of each trip in descending order, which contained 7.94 million data records (10.12%). Exploration of the subset of large SPMD dataset not only reduce computational complexity but also facilitate interpreting the obtained results. These sample trips traverse through all three types of road that has been considered in this study. Therefore, by all means this subset of large dataset represents the complete illustration of variation of driving behavior.

Among different operational data collected though data acquisition systems of equipped vehicles, three features (i.e., Jerk, Yaw Rate, Leading Headway) were chosen for driving behavior classification. These three features were expected to represent longitudinal and lateral control decisions undertaken by individual drivers. As the first derivative of acceleration/deceleration and second derivation of velocity, jerk is a more effective feature than velocity and acceleration in driving behavior classification. Also, longitudinal and lateral decisions of individual driver are incorporated within this single feature. Yaw rate measures a vehicle's lateral movement rate and characterizes driver's lateral behavior. Measurements of leading headway stand for driver's longitudinal control decision since the gap between vehicles is often dictated by car-following behavior. Therefore, the combination of these three mutually inclusive features can capture instantaneous variations of drivers' longitudinal and lateral control decisions and, hence, assist in classifying drivers' behavior in real-time.

3.5.2 Driving Behavior Classification Algorithm

The selected three features outlined above for classification were extracted from the chosen 550 trips. In addition to those three features, vehicle ID, trip ID, latitude, longitude, and time stamps were also included in the dataset, which were used to geographically locate the trip route and split the route based on road type. Figure 3.7(a) presents the segmentation of a sample trip from the dataset. Data points were placed on the map based on the longitude and latitude information of this trip. The same information was used to classify the sample trip in different segments based on the road types (i.e., arterial, ramp, freeway) traversed during the trip. Figure 3.7(a) utilizes three shades of blue to represent the three different classes of road considered in this study, as well as details of the different segments. Two pie charts within the figure illustrate the proportions of trip duration and trip length for each class of road gathered from the whole trip. The assumption that one can observe substantial diversity in the driving environment between freeway and arterial roads motivated this road type-based splitting of trips. Based on the understanding that driving behavior is directly influenced and impacted by the surrounding environment, classifying all driving behavior using the same standards, even when the trip traverse's different road types, would lead to erroneous categorization since it would ignore key factors that can change driving behavior.

Additionally, visual observations of classifying features showed significant disparity in behavior depending on road class. Figure 3.7(b) highlights the distinctions between the different road type features for the sample trip that was plotted on Figure 3.7(a). Plotted feature profiles on arterial roads showed greater fluctuations of feature values in comparison to feature profiles on the freeway. All three features showed higher ranges of variability when the trip was along arterials as compared to freeways. To emphasize the driving behavioral contrasts, each trip in the larger study was divided based on GPS location (i.e. longitude, latitude) into three road types: Freeway, Arterial, and Ramp. Features of the same road types were grouped together to classify short-term and long-term driving behavior. Altogether, 66.20% (5.26 million data points), 31.76% (2.52 million data points) and 2.04% (0.16 million data points) data were labeled as freeway, arterial, and ramp, respectively from training dataset (550 trips).

Once the features (i.e., jerk, yaw rate, leading headway) were sorted based on road types using the geolocation of each time stamp, the distribution of the features were plotted (Figure 3.8). The dataset of each road type was compared with the others by using an unpaired two sample t-test to justify the assumption of substantial disparity of features between road types. Comparison results of each pair (i.e., Freeway vs Arterial, Arterial vs Ramp, Freeway vs Ramp) presented significant difference (i.e., $p\text{-value} < 0.0001$) in the mean of each feature at 99% confidence level while assuming unequal variance of tested samples.

(a)

(b)

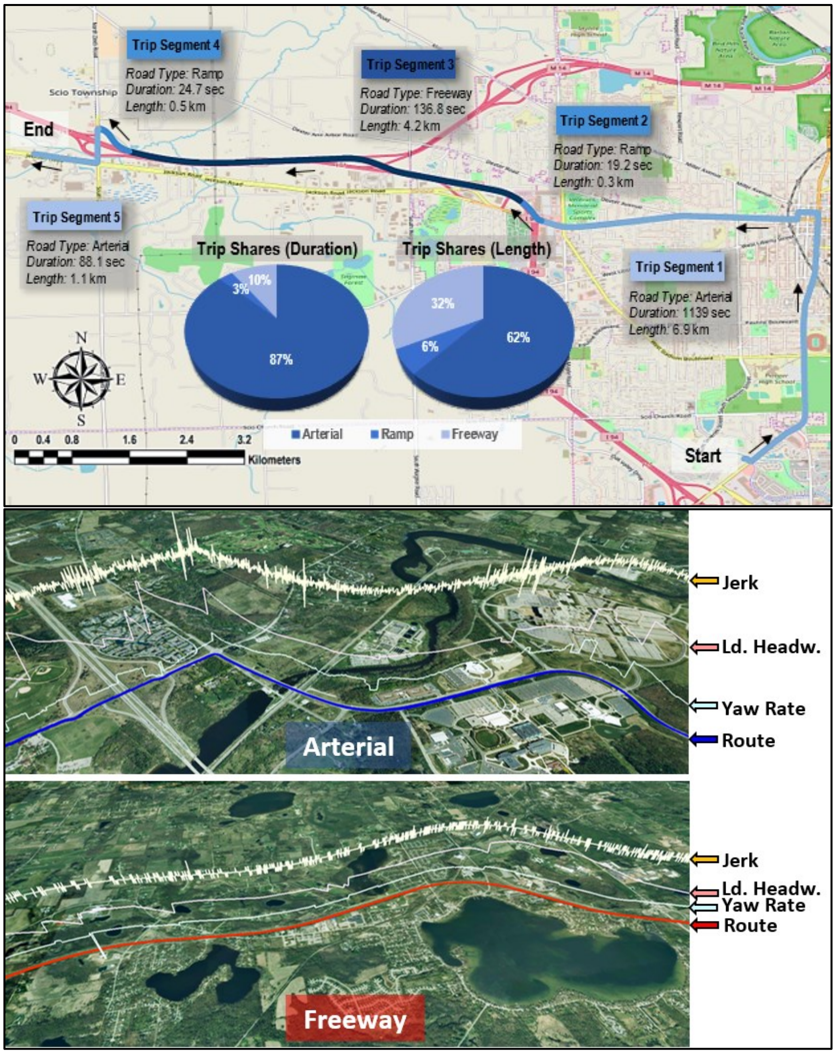

FIGURE 3.7 (a) Road type classification of a sample trip, (b) Contrast of driving features on different road type

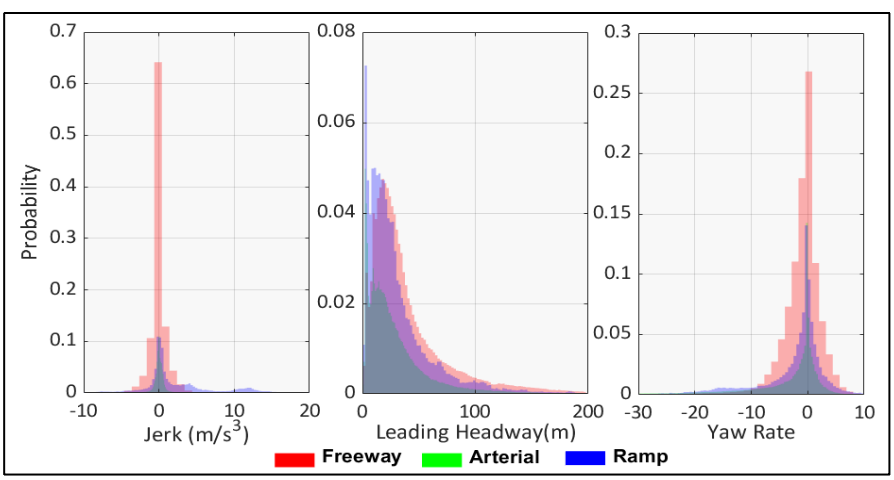

FIGURE 3.8 Distribution of chosen features for studied road types

Upon confirmation of attributional difference among road types, the absolute mean of each feature for the three road types was calculated and stored in a database. Next, the standard deviations of each feature for all trips with a moving window of $t_c = 5$ sec (50 data points) were calculated. The coefficient of variation (CoV) was then calculated by dividing the measured standard deviations with the absolute mean of current road type within the time window (Equation 3.2). Since the CoV is the measure of relative variability, this statistical attribute of each driving feature was exerted when identifying hostile driving behavior for classification. As noticed from the distribution of jerk and yaw rate was similar to normal distribution. Hence, using standard equation for calculating CoV for these two features would be acceptable. On the other hand, since the distribution of leading headway did not follow normal distribution, using the same equation to calculate CoV for this feature would be flawed. It is perceivable from observation of the skewness that, the leading headway distribution could be fitted with log-normal distribution. Hence, instead of standard CoV calculation, geometric CoV was measured for leading headway feature. Although geometric CoV has no theoretical background as an estimate of standard CoV, the term was used in literature to be analogous to CoV.

Finally, the CoV datasets of each feature were scaled within [0 1] range for each of the road types (Equation 3.3). Since the absolute values of studied features were significantly different, the classification was conducted using scaled (i.e. standardized) coefficient of variations instead.

$$CoV_f(t) = \begin{cases} \dfrac{SD_f(t-t_c,\ t)}{\bar{f}_R} & f = jerk, yaw\ rate \\ \sqrt{e^{SD_f^2(t-t_c,\ t)} - 1} & f = leading\ headway \end{cases} \tag{3.2}$$

$$CoV_f'(t) = \frac{CoV_f(t) - CoV_{f,R}^{min}}{CoV_{f,R}^{max} - CoV_{f,R}^{min}} \tag{3.3}$$

Here, $CoV_f(t)$ = coefficent of variation of feature *f* (i.e. jerk, yaw rate) at time *t*; $SD_f(t - t_c,\ t)$ = standard deviation of feature f within time $t - t_c$ and *t* ($t_c = 5sec$); $\bar{f}_R$= mean of absolute values of feature *f* at roadtype *R*; $CoV_f'(t)$= scaled coefficient of variation of feature f at time t; $CoV_{f,R}^{min}$ = minimum coefficient of variation for feature f on current roadtype R; $CoV_{f,R}^{max}$ = maximum coefficient of variation for feature f at current roadtype R.

Once scaled, and the unlabeled CoVs of features were available, labeling methods of short-term driving behavior were explored using K-nearest neighbor (KNN), hierarchical clustering, and neural networks-self organizing maps as viable, partitioned clustering options for classifying behavioral features under the unsupervised machine learning method. Among other researchers, KNN was used to classify driving behavior (Johnson and Trivedi, 2011; Karginova, Byttner and Svensson, 2012). The efficiency of KNN in dealing with large datasets makes this method a perfect candidate for labeling unlabeled feature data. However, the output of KNN clustering failed to provide reasonable classification [Figure 3.9(a)]. The clusters that resulted from KNN were unable to represent explicit differences between two clusters. Increasing cluster size led to increased complexity in classification without proper explanation of individual cluster characteristics. Additionally, the clusters, specifically for freeway and arterials, were incapable of addressing the impacts of all three features in classification process. As a result of the irrational division of traffic features resulting from KNN, a much simpler rule-based classification approach was then examined.

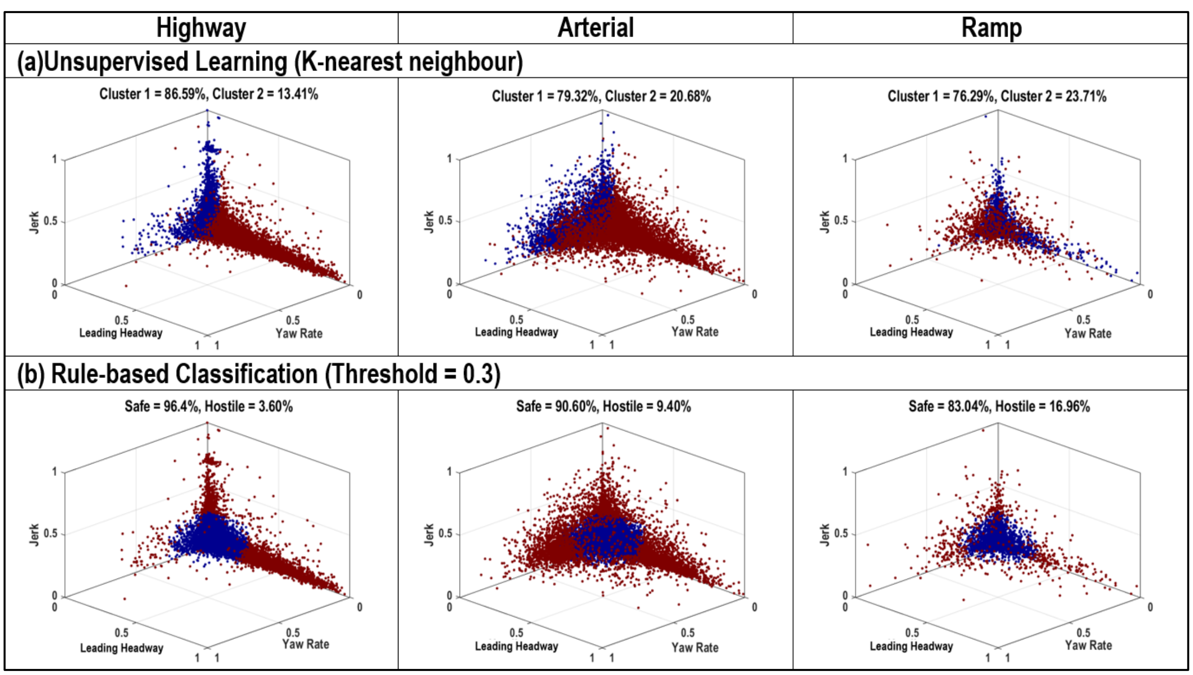

FIGURE 3.9 Labeling distinct features using (a) unsupervised learning and (b) rule-based classification methods

Using the rule-based classification process, a threshold value of scaled CoV was chosen to label driving decisions. If the scaled CoV value of any of these three features was higher than the threshold value, the driving behavior for that time window was labeled as 'Hostile Driving'. In the process of labelling traffic behavior, different threshold values of CoV were explored to identify the sensitivity of the threshold value. The results indicated that reducing threshold value of scaled CoV would lead to a higher share of 'Hostile Driving'. Therefore, staying within a conservative spectrum of behavior identification, a small threshold value of scaled CoV (0.3) was chosen [Figure 3.9(b)]. Followed by the labeling process, several supervised classification learner methods (i.e. logistic regression, discriminant analysis, support vector machine, decision tree) were employed with respect to the labeled training data to identify the best classifying model. Among the explored models with 10-fold cross validation, the decision tree model provided the highest accuracy ($\sim 100\%$) in correctly classifying training data for all road types. Hence, the trained decision tree model was used as the short-term classifier.

The following summarizes the steps involved in labelling the training dataset to enable subsequent classification. While the selected threshold for classifying behavior was the same for all types of roads (i.e. freeway, arterial, ramp), the threshold value was applied on scaled CoV values of studied features, derived by balancing different ranges of feature values into a common unit. As illustrated earlier in Figure 3.9, the ranges of these features were significantly different with respect to different road classes. Hence, the same threshold value on scaled parameters resulted in different CoV values for different road classes. In the end, the behavior-classifying limit remained the same for a specific feature on a specific road class and demonstrated a dynamic quality with changing road types as well as features.

Algorithm 3.1: Algorithm for Short-term Classification Learner

1. Identified road type and CoV for corresponding road type within the time window $[(\mathrm{t}-\mathrm{t_c}),\ \mathrm{t}]$
2. An unlabeled training set, $\mathrm{S_u^t} = \{(\mathrm{CoV'_{f=\{jerk,ld.\ headw.,yaw\ rate\}}}(\mathrm{t})\}_{\mathrm{t}=1}^{\mathrm{T}}$
   Here, T = number of training instances.
3. If $\mathrm{CoV'_{jerk}}(\mathrm{t})\ |\ \mathrm{CoV'_{ld.\ headw.}}(\mathrm{t})\ |\ \mathrm{CoV'_{yaw\ rate}}(\mathrm{t}) > \mathrm{threshold}$ then
   $\mathrm{Driving\ Behavior_{short-term}}[(\mathrm{t}-\mathrm{t_c}),\mathrm{t}] = \mathrm{Hostile\ Driving}$
   Else $\mathrm{CoV'_{jerk}}(\mathrm{t})\ |\ \mathrm{CoV'_{ld.\ headw.}}(\mathrm{t})\ |\ \mathrm{CoV'_{yaw\ rate}}(\mathrm{t}) \le \mathrm{threshold}$ then
   $\mathrm{Driving\ Behavior_{short-term}}[(\mathrm{t}-\mathrm{t_c}),\mathrm{t}] = \mathrm{Safe\ Driving}$

Following from this, measured values of road type specific shares of 'Hostile Driving' on total driving instances were used to categorize long-term driving behavior. For instance, 9.40% samples out of total training data demonstrated 'Hostile Driving' behavior while driving through arterial roads. To recognize long-term driving behavior on arterials for a specific driver, accumulated classified (i.e. safe, hostile) driving history was considered, and the share of cumulative hostile driving along arterial roads are compared with training 'Hostile Driving' shares. This analysis considered 0.5 as lower threshold and 1.0 as upper threshold to classify long-term driving behavior into Calm, Rational, and Aggressive driving behavior. As a result, if the cumulative 'Hostile Driving' share of a driver, along arterials, is less than 4.7% (=0.5×9.4%), then that driver would be classified as a 'Calm Driver' on that road type. On the other hand, if the same share increased above 9.4% on the same road type, then that driver would shift to an 'Aggressive Driver' on arterials. A similar process was followed to classify long-term behavior of drivers on other road types and total travel history.

To provide further clarification of the long-term behavior classification process, a hypothetical scenario is presented here as an illustration, in the context of the algorithm that describes the process of long-term behavioral classification based on road types and overall driving history. Suppose a specific driver had made 30 trips, and the three feature values (i.e. jerk, yaw rate, leading headway) were collected, scaled, and stored according to the short-term behavior classification process. Then, the average hostile driving proportion of these 30 trips was measured for long-term behavior classification, using the three specified road types (i.e. freeway, arterial, ramp) as well as overall trips. By analyzing this road user's driving history of 30 trips, let us imagine that they showed average hostile driving behavior on freeway, arterial, and ramps for 5.17%, 4.27% and 11.84% of the total driving time, respectively. I would find that the average hostile driving share for total trips to be 2.95% when the total number of trips was evaluated for driving behavior. Once these values were obtained from the driver's history, it would be compared with the stored road-specific and overall-average hostile driving shares of the training dataset. The average hostile driving shares of the training dataset would be 3.60%, 9.40%, 16.96%, and 5.79% for freeway, arterial, ramp, and total trip, respectively. Once calculated, these values would form the basis of road-type specific classification by comparing the driver's hostile share with the training datasets hostile share. In this example, this driver's hostile share on freeway (5.14%) was found to more than "1.0 ×hostile share of training data on freeway (3.60%)" , therefore, the driver's long-term behavior, based on their driving history of 30 trips, had classified them as an 'Aggressive Driver' on freeways. Similarly, road-type specific, long-term classification would label this driver's behavior on arterial, ramp, and total trips as a 'Calm driver' [4.27% < 0.5×9.40%], 'Rational driver'[0.5×16.96%<11.84%<1.0×16.96] and 'Rational driver' [0.5×5.79%<2.95%<1.0×5.79%], respectively. Figure 3.10 presents the implemented classification algorithm in a flow chart to capture the progression of behavioral classification process.

Algorithm 3.2: Algorithm for Long-term Classification

1. Hostile driving shares from training dataset for each road type
2. Accumulated road type specific hostility driving percentages and overall hostility driving percentages
3. (a) Road-type Specific Classification

   If $\%_{\text{Hostile Driving}_\text{R}} < \text{threshold}_{\text{lower}} \times \%^{\text{training}}_{\text{Hostile driving}_\text{R}}$

   then $\text{Driving Behavior}_{\text{long-term}}(\text{R}) = \text{Clam Driver on road type }'\text{R}'$

   Else if $\text{threshold}_{\text{lower}} \times \%^{\text{training}}_{\text{Hostile driving}_\text{R}} \leq \%_{\text{Hostile Driving}_\text{R}} \leq$
   $\text{threshold}_{\text{upper}} \times \%^{\text{training}}_{\text{Hostile driving}_\text{R}}$

   then $\text{Driving Behavior}_{\text{long-term}}(\text{R}) = \text{Rational Driver on road type }'\text{R}'$

   Else if $\%^{\text{training}}_{\text{Hostile driving}_\text{R}} > \text{threshold}_{\text{upper}} \times \%^{\text{training}}_{\text{Hostile driving}_\text{R}}$

   then $\text{Driving Behavior}_{\text{long-term}}(\text{R}) = \text{Aggressive Driver on road type }'\text{R}'$

Here, R = road type (i.e. freeway, arterial, ramp).

3. (b) Overall Classification

If $\sum_{R=\{\text{freeway,arterial,ramp}\}} \%\text{Driving}_R \times \%\text{Hostile Driving}_R) < \text{threshold}_{\text{lower}} \times \sum_{R=\{\text{freeway,arterial,ramp}\}} \%\text{Driving}_R^{\text{training}} \times \%\text{Hostile driving}_R^{\text{training}}$

then $\text{Driving Behavior}_{\text{long-term}} = \text{Clam Driver}$

Else if $\text{threshold}_{\text{lower}} \times \sum_{R=\{\text{freeway,arterial,ramp}\}} \%\text{Driving}_R^{\text{training}} \times \%\text{Hostile driving}_R^{\text{training}} \leq \sum_{R=\{\text{freeway,arterial,ramp}\}} \%\text{Driving}_R \times \%\text{Hostile Driving}_R) \leq \text{threshold}_{\text{upper}} \times \sum_{R=\{\text{freeway,arterial,ramp}\}} \%\text{Driving}_R^{\text{training}} \times \%\text{Hostile driving}_R^{\text{training}}$

then $\text{Driving Behavior}_{\text{long-term}} = \text{Rational Driver}$

Else if $\sum_{R=\{\text{freeway,arterial,ramp}\}} \%\text{Driving}_R \times \%\text{Hostile Driving}_R) > \text{threshold}_{\text{upper}} \times \sum_{R=\{\text{freeway,arterial,ramp}\}} \%\text{Driving}_R^{\text{training}} \times \%\text{Hostile driving}_R^{\text{training}}$

then $\text{Driving Behavior}_{\text{long-term}} = \text{Aggressive Driver}$

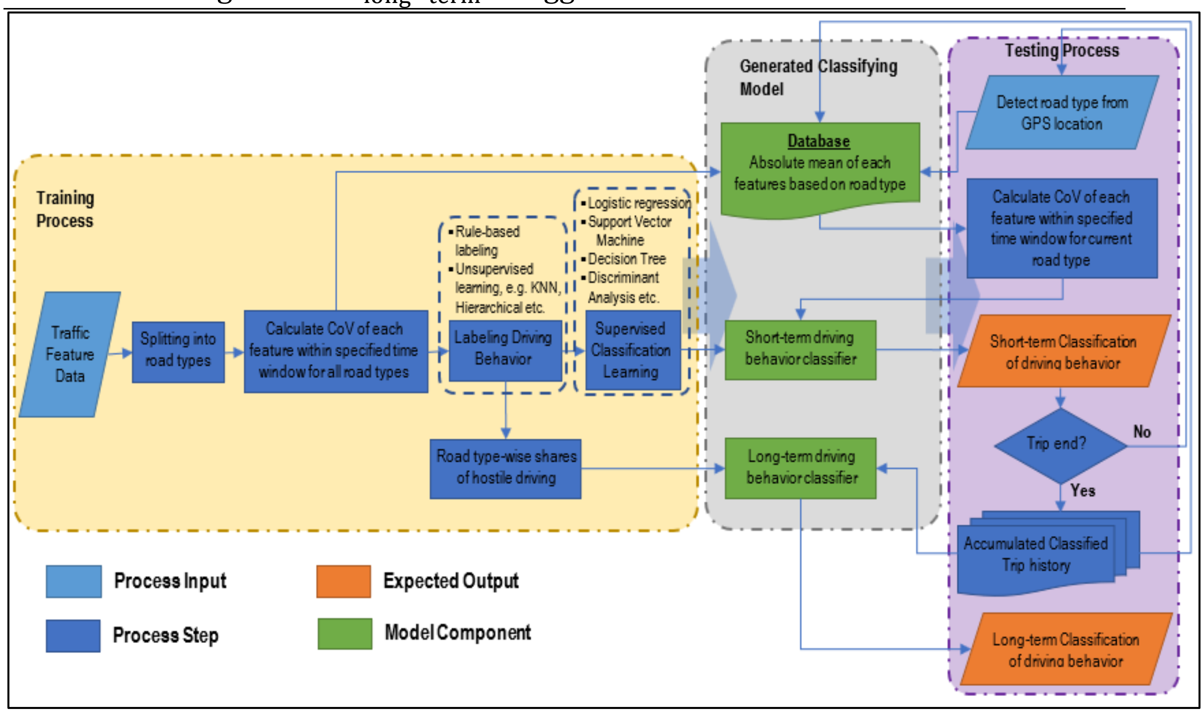

FIGURE 3.10 Flow chart of the driving behavior classification algorithm

3.6 Model Variability

Variability is an operative dimension of behavior which are often controlled by reinforcers like surrounding responses, environment, topography, frequency etc. One of the key constraints of the developed model is disregarding the inputs of reinforcers in behavioral variability of human drivers. As a result, the developed model might generate dissimilar identification and classification of driving behavior once these inputs from exogenous factors are considered. These exogenous factors could vary widely in nature and so would the behavior classify model's outputs. Since the objective of this part of the research was developing a simple model for classifying driving behavior considering bi-directional features, the complexity induced from exogenous factor variability were disregarded at this stage of development. However, the proposed model can be extended in the future by incorporating these reinforcers as inputs in the models to attain more reliable behavioral classification.

Another critical assumption made in the development of this behavioral classification model was regarding driving feature outputs (i.e., jerk, leading headways, yaw rates) as direct representation of drivers' behavior. While these outputs were generated from control decisions taken by drivers, they were translated and adjusted through multitudes of mechanical transformation prior to yield these driving features. Hence, these features were not necessarily a direct portrayal of individuals diving behavior rather adjusted responses from observed driving environment and to achieve idiosyncratic aspiration.

3.7 Performance Evaluation

The generated classification models from the training data were executed on 'test trips' to classify driving behavior. To qualify as a 'test trip', those with the highest number of datapoints (20% of training trips) were selected among the remaining 110 trips on the database (except trips used for training purposes), which suggested that they were long and thus expected to contain the most diverse behavioral variations. The same time window of 5 sec (50 data points) was maintained to reshape classification features data. The proposed classifying model categorized the selected test trips for both short- and long-term. The obtained hostility instances for the total number of test trips varied between 1.45% to 18.53% with a mean of 5.67%. The short-term classification of all the trip segments for a sample test trip is shown in Figure 3.11 which displays driving road types, the classification features' CoV profiles, and hostile driving instances during a 28min 23.7 sec long trip (341-time stamps). All 110 trips were categorized, with the short-term driving behavior classifier following the same process for specific road types and total trips.

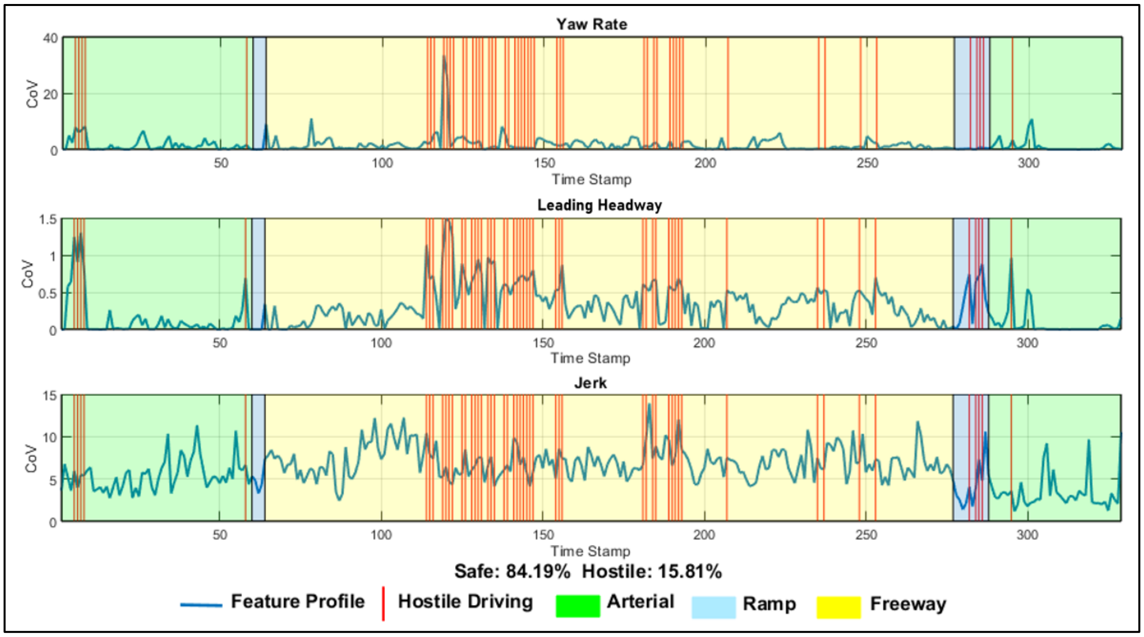

FIGURE 3.11 Short-term driving behavior classification of a test trip.

Although the classifying model identified hostile driving behavior through longitudinal and lateral feature recognition, the precision of identified behavior had yet to be tested. To do so, the velocity and acceleration profiles of each trip as were taken explicit identifiers of hostile behavior. Then, mean velocities within a predetermined time window were measured and compared with the corresponding road type's speed limit. Subsequently, the time stamps with mean velocities higher than 10 miles above speed limits were labeled as 'Hostile Driving' instances. As a result, this classification method only used the speeding behavior of the driver. A second process measured the acceleration range of each time window determined from the classification by acute acceleration change. Time stamps with an acceleration range higher than 2.5 m/s^2 were labeled as 'Hostile Driving' behavior. Both explicit classification measures (i.e. classification by speeding, classification by acute acceleration change) were compared with the model classification output (i.e. short-term driving behavior classification) to evaluate the behavioral disparity identification capability of the proposed method. Figure 3.12 presents a sample trip behavior classification using the aforementioned methods.

For the sample trip, comparison of short-term behavior classifications from the generated classifying model using speeding-based classification provided 87% accuracy. Similar comparisons with acute acceleration-based classifications presented 84% precise behavioral identification. Another analysis of speeding instances identification revealed that the proposed short-term classifying model accurately identified 19 out of 23 speeding instances as hostile driving behavior for the sample trip. Similarly, 17 out 25 instances are identified though short-term classification while comparing with acute acceleration change-based classification. The identification accuracy for all 110-test trips in comparison to the speeding-based classification was, on average, 86.31%, with a standard deviation of 9.84%. Likewise, the comparison with the acute acceleration change-based classification presented an 87.92% average accuracy with 10.04% standard deviation.

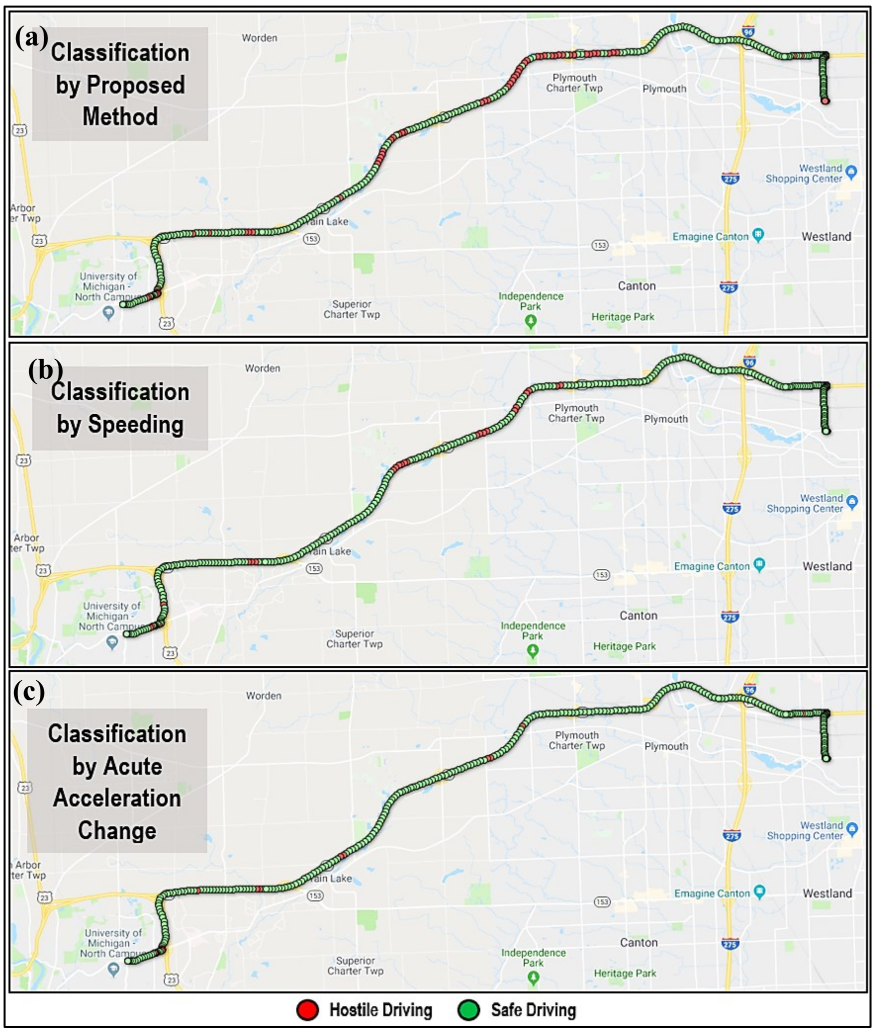

FIGURE 3.12 Evaluation of (a) proposed classification method in comparison to (b) speeding-based classification, (c) acute acceleration change-based classification.

The short-term classification based on multiple driving features was further compared with the classification process proposed by Murphey et al. (Murphey, Milton and Kiliaris,

2009) to demonstrate the aptitude of the proposed methods in identifying behavioral extremity. Murphey et al. (Murphey, Milton and Kiliaris, 2009) proposed a single feature-based (i.e. jerk) classification of driving behavior into three groups (i.e. calm, normal, aggressive). The division of the groups were founded on threshold values of jerk profiles CoV (e.g. CoV of a time window < 0.5 then driving behavior = calm, 0.5< CoV of a time window< 1.0 then driving behavior = normal, 1.0 < CoV of a time window then driving behavior = aggressive).

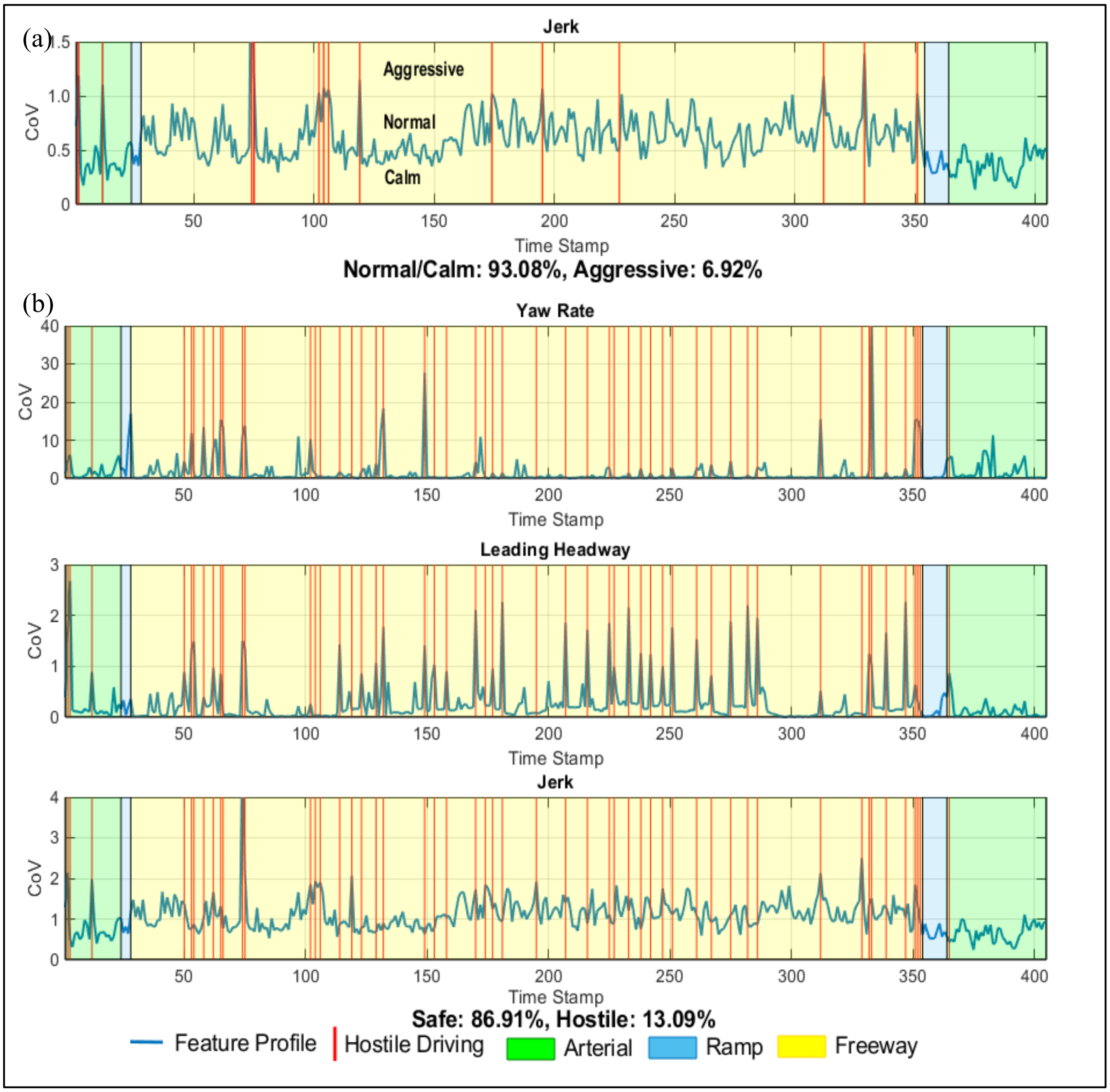

FIGURE 3.13 Behavioral classification of a sample trip by (a) analyzing jerk feature and (b) analyzing multiple driving features

To measure the CoV, the average jerk value was measured on different road types and at different levels of service from 11 standard drive cycles. **Figure 3.13(a)** shows the classification of the sample trip by method in (Murphey, Milton and Kiliaris, 2009), and **Figure 3.13(b)** shows the classification of the same trip by method proposed in this paper. The average jerk for level of service C on a freeway, CD on arterial and ramps values were chosen to follow the jerk-based classification as these levels of services are usually expected in these road classes. Classification of the sample trip by the proposed method identified 13.09% of driving as hostile driving instances during the trips by analyzing three features, whereas classification by the method of Murphey et al. (Murphey, Milton and Kiliaris, 2009), identified 6.92% of driving as aggressive driving instances. Therefore, the additional features were capable of increasing the identification of hostile driving instances by just under 47%. Notably, the average jerk value used for calculating CoV was different for both methods, resulting in different jerk profile scales. Additionally, in contrast to the method in (Murphey, Milton and Kiliaris, 2009), the proposed method had a different threshold for different road types, generated by analyzing the training dataset.

To illustrate the long-term, behavior classification functionality of the proposed classifying process, the previously classified 110 test trips were presumed to be driven by the same driver at separate times. This assumption was necessary since the demographic information about the drivers making the trips in this dataset was inaccessible. As such, it was impossible to link the data with a specific driver. Taking this assumption into consideration, hostility shares on both specific road types and total trips were measured on the short-term classification. The hostility proportions of each trip were also compared with the training data's hostility proportions and classified into Calm, Rational, and Aggressive driving behavior by scaling training hostility shares with the lower threshold (0.5) and upper threshold (1.0). Long-term categorization was performed by measuring the moving averages of hostility shares (including all previous trips) and by matching that measurement with the hostility limits $(< 0.5\text{: Calm}, 0.5 - 1.0\text{: Rational}, > 1.0\text{: Aggressive})$ of three groups (i.e. calm, rational, aggressive). Figure 3.14 illustrates both types of test trip classification for specific road types as well as for the total trip. Each blue dot on the plots of **Figure 3.14** represent the hostility proportion of each trip that could be utilized to perform short-term classification. The red curve on the plots portrays the progression of driver behavior by taking all previous trips into account (moving averages of blue dots). Different color patches (i.e. yellow, green, red) on the plots illustrate the boundary regions of specific behavioral classes (i.e. calm driver, rational driver, aggressive driver). While individual trip hostility fluctuated frequently, the behavioral progression in long-term was relatively stable and only changed gradually over time.

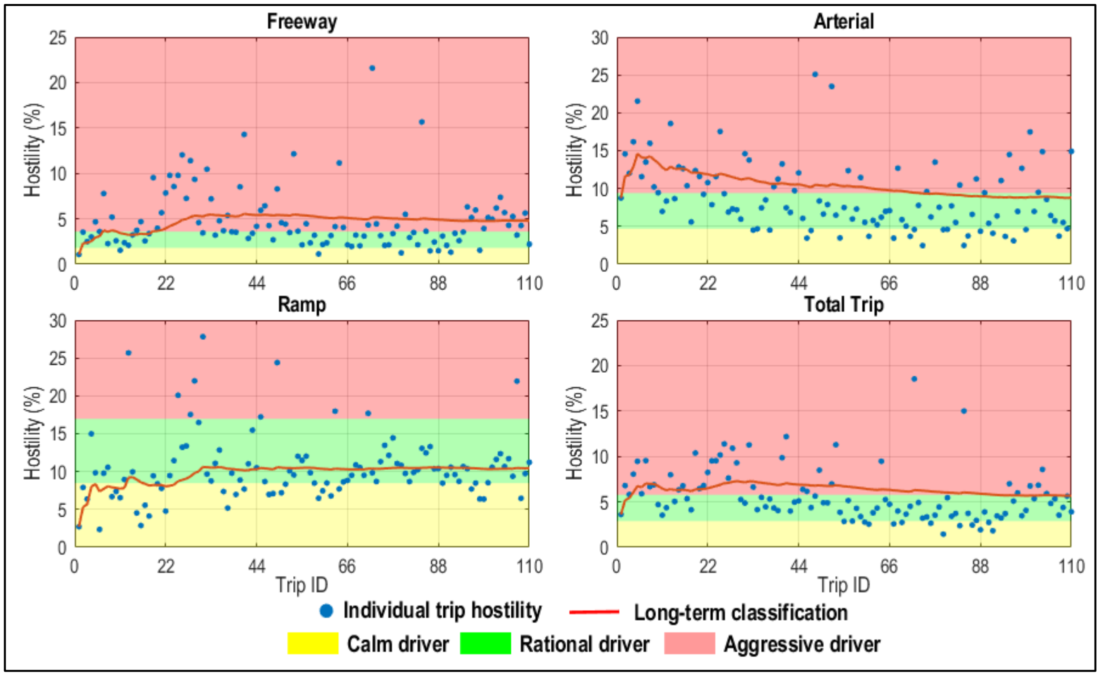

FIGURE 3.14 Illustration of long-term classification for individual trips and resulting accumulated trips.

The proposed method of long-term classification was capable of identifying the changing patterns of driving habits for the number of total trips and road type specific habits. In Figure 3.14, the total trip hostilities of the accumulated trips were highly weighted towards to freeway hostility, which suggests that the largest portion was traversed though freeways. Moreover, the comparison between freeway and arterial hostility shares demonstrated higher long-term behavioral variability on arterial roads (standard deviation = 1.48%) than on freeways (standard deviation = 0.84%). The paired sample t-test on long-term freeway and arterial hostility showed significantly lower hostility on freeways at a 95% confidence interval (t-score = 29.557, p-value < 0.001). The obtained comparison result did not necessarily mean that the driver was more aggressive on arterials than freeways, since the classifying threshold for freeways was different. As a result, the long-term behavior on arterials graduated from 'aggressive' to 'rational', even with higher hostility than on freeways. Since ramp road-types had a relatively low share (2.5% in average) on total test trips, the influence of long-term ramp hostility on total trip hostility was discarded for comparison.

The identified hostility categorization of the 110 test trips was further analyzed to reveal short-term behavioral distribution on different road types. As shown in Figure 3.15, the hostility behavior was different from one road type to another. For instance, freeway hostility was skewed towards the origin, with the highest proportion lying between 2.5-5.0%. This skewness towards lower hostility could be explained by the fact that drivers, in general, tend to operate with less variations in control while driving on freeways. Whereas, the probability distribution of arterial hostility was relatively balanced over a larger range of hostility (0-27.5%). The driver had to experience more frequent disruptions, due to geometry, traffic control measures etc., while driving through arterials that could result in such diverse hostility patterns on arterials. Similarly, ramp hostility showed a central tendency towards the median. Since ramps are connecting links between freeways and arterials, the hostility pattern in this transitional phase is expected to be influenced by both road types' distribution. A paired, two-sample t-test between the measured hostility ranges was carried out in order to identify significant dissimilarity in behavior on distinct road types. The results of the t-test showed that the hostility behavior on a specific road type was significantly different from other road-types with a 99% confidence level.

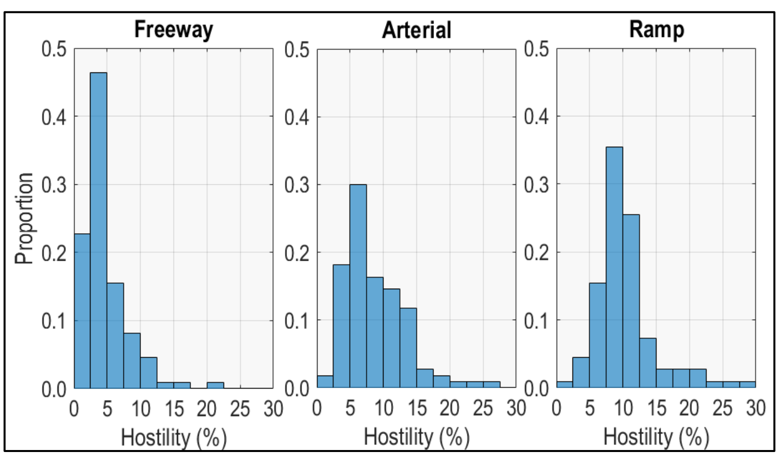

FIGURE 3.15 Hostility distribution for test trips on different road types

3.8 Correlation between behavioral classification and parameters of motion dynamics

Following the evaluation of proposed classification method, I attempted to correlate the identified short-term driver behavior with aforementioned parameters of motion dynamics. In this regard, random sampling from 550-trips were made to generate 10 subsets with 110 trips in each subset. For each subset, the average hostility percent was measured after all the trips were classified through short-term classification. Additionally, average speed, extreme acceleration, extreme deceleration, lane changing yaw rates, average time headway and lane changing duration was calculated and mean value measured for both freeway and arterial road types. The purpose of this analysis was to demonstrate that these parameters could be connected with average hostility of traffic. Obtained parameter values and % hostility values are presented in Table 3.2 for freeway and Table 3.3 for Arterial.

Table 3.2 Average Hostility and traffic flow parameters of freeways for analyzed sample subsets

Subset	% Hostility	Average speed (m/s)	Extreme acceleration (m/s^2)	Extreme deceleration (m/s^2)	Lane changing yaw rates (° /s)	Average time headway (s)	Lane changing duration (s)
1	4.53	30.53	0.341	-3.576	0.473	1.44	4.29
2	4.88	28.59	0.470	-2.345	0.402	1.54	4.29
3	5.34	30.92	0.383	-2.511	0.413	1.34	4.22
4	5.67	29.65	0.396	-3.072	0.416	1.47	4.27
5	5.94	32.23	0.542	-2.594	0.332	1.42	4.30
6	6.47	31.06	0.509	-2.078	0.348	1.32	4.29
7	7.81	30.62	0.424	-2.589	0.352	1.33	4.22
8	8.18	28.90	0.269	-3.134	0.356	1.29	4.16
9	8.26	28.07	0.408	-2.535	0.284	1.28	4.17
10	8.52	27.62	0.246	-2.831	0.294	1.35	4.22

Table 3.3 Average Hostility and traffic flow parameters of arterials for analyzed sample subsets

Subset	% Hostility	Average speed (m/s)	Extreme acceleration (m/s^2)	Extreme deceleration (m/s^2)	Lane changing yaw rates (° /s)	Average time headway (s)	Lane changing duration (s)
1	5.34	14.01	1.301	-2.476	1.592	2.18	2.87
2	5.89	14.24	1.220	-2.442	1.741	2.12	2.76
3	6.17	14.93	1.258	-2.384	1.517	2.27	2.82
4	6.54	16.35	1.174	-2.510	1.498	2.21	2.74
5	6.73	15.21	1.085	-2.397	1.636	2.03	2.63
6	7.19	16.44	1.209	-2.296	1.291	2.10	2.65
7	7.25	15.94	1.131	-2.549	1.441	2.09	2.68
8	7.80	15.43	1.138	-2.330	1.302	1.97	2.69
9	8.29	16.55	1.117	-2.500	1.426	2.048	2.647
10	9.13	14.04	1.255	-2.628	1.450	2.301	2.704

Different machine learning models were passed through these parameters as input and % hostility as response to develop a regression model which can be used to estimate expected % hostility from measured parameter values. For freeway, quadratic support vector machine was found to be best fit of the data (RMSE= 0.672, R^2= 0.83, MSE= 0.451). Cubic support vector machine provided the best fit for arterial data (RMSE = 0.053, R^2 = 0.63, MSE = 0.003). With these models, we could measure the traffic flow parameter values (i.e. average speed, extreme acceleration, extreme deceleration, lane changing yaw rates, average time headway and lane changing duration) for specific road types to estimate the hostility of traffic. However, prediction traffic hostility was not the goal of this analysis. The whole idea was to not develop a prediction model for estimating traffic hostility from traffic flow parameters but to confirm the presumption that traffic flow parameter could be influenced by the driving behavior. Low RMSE and MSE value with high R^2 values of the developed models for both road types proved that postulation with high level certainty.

3.9 Future Extensions

Since the major motivation of behavioral classification lies in pursuing drivers to maintain safe driving patterns, providing real-time feedback on driving style is imperative to harness the benefits from driving behavior classification. With the assistance of connected vehicle technology and smartphones, identified instantaneous hostile driving behavior information can be conveyed to drivers through a user friendly ADAS interface, designed to easily communicate both short-term and long-term behavioral classification information **(Figure 3.16)**. Detected hostile behavior through short-term classification can be announced by a verbal and visual warning. **Figure 3.16(a)** provides an interface design for this purpose. The yellow circle in the middle would start blinking once hostile driving behavior is detected, thereby providing the driver with a visual warning. Additionally, a verbal warning can be issued (alarm sign on the picture). Other information can also be provided through same interface. This real-time warning system is assumed to induce cautiousness in drivers and, hence, promote safe driving behavior. In addition to the real-time response, the driving habits of individual drivers can be tracked through long-term classification. At the end of each trip, classified trip characteristics could be stored in a database to facilitate long-term behavioral classification. Previous classified trip history can be analyzed through the long-term classifier and conveniently displayed on the interface to identify both road type-specific and overall driving habits **(Figure 3.16(b))**. The left most dial in Figure 3.16(b), shows the overall long-term behavioral classification from the trips within the time range where the Yellow region indicates 'Calm', Green region indicates 'Rational', and the Red region represents 'Aggressive' driving behavior. The indicator arm of the dial gauge in this diagram lies within yellow and green regions suggesting that this driver's behavior falls within 'Calm' and 'Rational' driving behavior. Other three gauges in Figure 3.16(b) shows road type-specific long-term driving behavior and trip shares on each road type [value at the bottom right corner of each gauge].

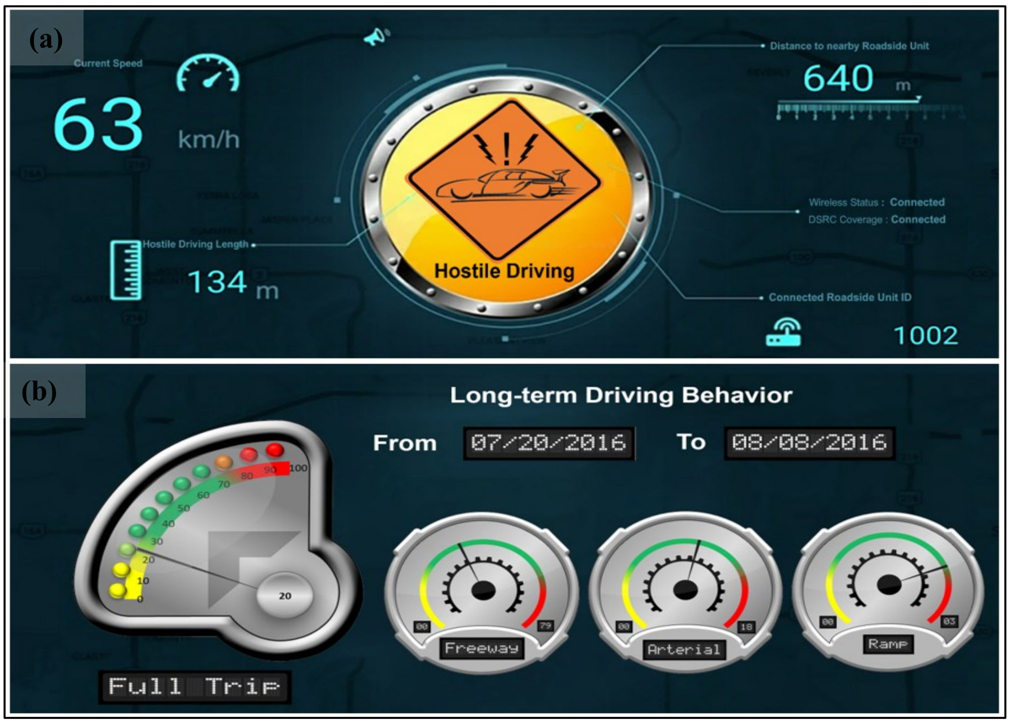

FIGURE 3.16 Abstract ADAS interface for communicating (a) real-time warning, (b) long-term behavioral information to drivers.

Detected long-term driving behavior can assist road traffic operation and safety authorities, insurance companies, and other associated organizations to offer incentives for 'Rational driving' as well as to penalize 'Aggressive Driving' as an approach to promote safe driving on roadways. An extension of this research is to develop a smartphone application to detect and broadcast driving behavioral information to drivers in real time. Furthermore, the application could store both short-term and long-term driving history and analyze the effects of ADAS on driver's behavior and habit. The goal of the analysis would be to determine the ADAS' effectiveness in stimulating shifts in driving behavior.

3.10 Concluding remarks

This study presents a simple, efficient, and adaptable driving behavior classification technique developed by analyzing both longitudinal and lateral driving features collected though connected-vehicle technology from real-world trips. The thresholds of the proposed classification method can be modified to accommodate driver type classification for authorities' purposes and requirements. With the consideration of both longitudinal and lateral features of driving, the proposed method has greater capacity to sense unsafe driving behavior as compared to singular feature-based classification methods. This study took a unique approach by distinguishing between driving behavior and driving habit as well as classifying drivers' behavior from both behavioral and habitual contexts. As such, this study worked around the concept of instantaneous behavioral classification and used that information to categorize drivers' driving habits. Authorities considering behavioral classification are not only interested in immediate contextual driver responses but also in a driver's driving style that may reveal safety hazards that they may cause, and the extent of safety risk taken by allowing them to continue driving. This study covers both aspects of required classification to facilitate authorities' decision-making processes regarding the reward or penalty to drivers for their driving behavior.

Although this research brought a different perspective in driving behavior classification research, the research attempt was constrained by some imperative limitations. To begin with, the demographic information was unavailable in the dataset which restricted to connect driving features with individual driver. A principal assumption of this study was considering selected driving features to represent driving behavior which might not always be true, but practical to perform such comprehensive studies. The mechanical components of vehicle refined the behavioral action (i.e., braking, accelerating, following) by driver when those were translated into driving features (i.e., jerk, leading headway, yaw rate). Furthermore, the influence of exogenous factors other than different road types were disregarded in the classification model development. Hence, some hostile driving events could account for exogenous factors like weather conditions, surrounding traffic, roadway geometry etc. and not represent driving behavior of an individual. Testing the applicability of developed model on a sample dataset (e.g., from SPMD data, from field-test data etc.) with clearly defined hostile events and contributing factors could further refine the model. Lack of testing data restricts the applicability and transferability of developed model.

While this research was limited to three distinct features in the form of continuous variables to illustrate longitudinal and lateral decisions, other features could also be studied to identify more significant markers of characterization. Furthermore, partial datasets of the large SPMD database were analyzed in this study to demonstrate the classification technique. Since the primary aim of the study was to propose and present a simplified classification technique, potential bias of analyzed datasets has been ignored. In brief, this study is an attempt to gain insight into driving behavior and habit though a simple categorization process that considers both longitudinal and lateral control decisions. Furthermore, this study is extension-ready with respect to ADAS design and its impact on driving behavior and habit modification.

This segment of research acknowledged and identified the behavioral diversity of human drivers based upon naturalistic driving data. Comprehending behavioral heterogeneity provided the foundation upon which to build this research and to address the established research question. The following research on mixed traffic dynamics then drew upon the required parameter values of human driving gained from this study to establish realistic scenarios for simulation. Since attaining such diversified experimental cases of mixed traffic would be unfeasible from real-world traffic, the insights obtained from this study would be instrumental in developing simulated platform to recreate naturalistic traffic conditions.

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CHAPTER 4 : PARTIAL MOTION DYNAMICS OF MIXED TRAFFIC AND RESULTING MOBILITY AND SAFETY IMPLICATIONS

4.1 Introduction

After the analysis of driving behavioral variations in previous chapter, this chapter of dissertation shifts the focus of the research in developing the foundation for mixed traffic modeling. This chapter engages in measuring the resulting mobility and safety influences through interpretable parameters while establishing the car-following component of vehicle motions for both vehicle types in a modeling structure. Although both HuVs and AuVs car-following models are utilized in the modeling framework, the parameters for both vehicle types are kept constants for all simulated scenarios to eliminate interpretational complexity from mobility and safety characteristics.

The integration of connectivity and automated control systems into vehicles is at the technological forefront when addressing key transportation concerns such as diminished trip delay, fuel efficiency, reduced emission, and enhanced safety of road traffic. Although a fully automated vehicle-based traffic stream could take decades to become a reality, a gradual increase of automated driving system-based vehicles, in both market share and traffic stream composition, would facilitate gradual and nuanced insight into the potential gains from these technologies. Thus far, however, varied perceptions of mixed traffic streams and their collaborative motion dynamics have hindered both researchers and practitioners from progressing with these technologies. Furthermore, the ideal composition of automated vehicles and conventional traffic remains elusive. In response to these problems, this study proposes a simple yet effective car-following strategy for mixed traffic stream and measures its impact on mobility and safety. Additionally, the car-following strategy involves platoon development in a Connected-Automated Vehicle (CAV) environment, and the study explores various platoon configurations to determine platoon parameters at different traffic states to obtain maximal benefits.

Numerous and important studies have been conducted to interpret the complex dynamics of combined traffic movements (Bekiaris-Liberis et al., 2017; Chen et al., 2017; Fakharian, 2016; Ghiasi et al., 2017; Liu et al., 2017; Talebpour & Mahmassani, 2016). While these studies have addressed the degree of impact made by automated driving technologies through simplified to complex macroscopic and mesoscopic modeling, the present study addresses the need for the modeling of microscopic car-following behavior in heterogeneous traffic, necessary for the study macroscopic consequences on mobility and safety. With that intention, the objective of this part of the research is to provide insights into distinct forms of impact whilst simulating automated-control-enabled vehicles in homogenous roadway segment and distributions along traffic stream. These insights into mixed traffic movements and platoon characteristics should facilitate future considerations of otherwise under-studied aspects of mixed traffic dynamics (e.g., lane-changing, gap acceptance, merging etc.) in order to properly assess the benefits of automated-vehicle integration. Furthermore, traffic operational authorities can take the findings presented here into account to impose different control strategies (e.g., dynamic aggregated controls for manually driven vehicles, dynamic personalized controls on connected vehicles etc.) on traffic to attain maximum improvements with regards to reduced travel time, collision rates, greenhouse gas emissions etc. The rationale behind exploring the car-following strategy of mixed traffic separately supported by the fact that car-following is the principal state of driving irrespective of vehicle types, driver and traffic state. Majority of the travel time is spent on following other vehicles on the road while driving. Due to their absolute domination in comparison to other vehicle maneuvers (i.e. lane-changing, gap acceptance), car-following models are often expanded to develop macroscopic traffic flow model which are supposed to precisely resonate the traffic states of roadways. Although in later part of this research I will address this contentious assumption about car-following, for now, this study will particularly emphasis on microscopic car-following approach in mixed traffic scenarios and interpreting the resultant mobility as well as safety repercussions in macroscopic range.

This chapter of research is organized as follows: a car-following strategy for mixed traffic is proposed and described in the following section. The description of simulation procedures, as well as the discussion on obtained results, are covered respectively in the two subsequent sections. The analysis of simulation results include recognizing the impact of AuVs location and distribution on traffic operation as well as impact on selected mobility and safety parameters. Following on, the subsequent section proposes an approach to obtain dynamic optimal platoon configuration for specific traffic state. The final section provides the synopsis of findings of the study as well as recommendations for future research.

4.2 Partial Motion Dynamics Model for Individual Vehicle

Interactions and behaviors of vehicles at microscopic levels have macroscopic implications. Parameters like maximum accelerations, comfortable decelerations, desired headways etc. are directly linked to traffic mobility and safety aspects because they factored in large scale estimation and can have both positive and/or negative effect. Car-following models provide individual vehicles' acceleration from dynamic interactions with adjacent vehicles, control constraints to generate velocity and position to determine vehicle trajectory. The car-following models of vehicles in mixed traffic was schemed here to simulate real-traffic movements. As mentioned earlier, the existence of two types of vehicles driving system was considered for combined traffic. The proposed driving strategy identified all potential combinations of leading vehicle and subject vehicle based on driving systems to determine suitable car-following models.

The proposed car-following mechanism presumed that HuVs would maintain conventional car-following behavior irrespective of the leading vehicle's driving system [Figure 4.1]. In this regard, intelligent driver model (IDM) (Treiber et al., 2000) was chosen to represent human drivers' car-following behavior. Extensive applications of this model across different studies developed this model as a perfect example to simulate HuVs' car-following behavior. An enhanced version of traditional IDM was used to determine a realistic longitudinal control decision of HuVs (Equation 4.1). Discretized kinematic equations were used for all vehicles irrespective of the driving system to determine vehicle's velocity and position (Equation 4.2 & 4.3).

$$\dot{v}(t+\Delta t) = a\left[1-\left(\frac{v(t)}{v_0}\right)^4-\left(\frac{s_0+\max\left[0, v(t)\times T+\frac{v(t)\times \Delta v(t)}{2\sqrt{ab}}\right]}{s}\right)^2\right] \tag{4.1}$$

$$v(t+\Delta t) = v(t)+a(t)\times \Delta t \tag{4.2}$$

$$p(t+\Delta t) = p(t)+v(t)\times \Delta t+\frac{1}{2}a(t)\times \Delta t^2 \tag{4.3}$$

Where, $\dot{v}$ = acceleration of vehicle (m/s^2) , v=velocity (m/s), p= vehicle position (m), a= maximum acceleration , v_0=desired velocity, s_0=leading gap at jam density (5m), b=desirable deceleration, Δv=velocity difference with leading vehicle, T=desired headway. Chapter 2 provided a detailed prospects of human driving behavior which assisted in determining the parameter values of car-following model. For instance, the desired velocity was taken as a random normal variable which ranges between speed limit and 5 m/s above speed limit for a specific driver. Desirable deceleration was taken as -3m/s^2 which was similar to the average extreme deceleration value for freeways (-2.83 m/s^2). To maintain the common practice, same value of maximum acceleration value was adopted (3 m/s^2). Finally, the desired headway was taken as a log normally distributed variable with average of 1.4 sec and standard deviation of 0.3 sec which was similar to acquired intelligence from Chapter 2.

To demonstrate the car-following mechanism of AuVs, both ACC and CACC based car-following were implemented. A human-driven leading vehicle would prompt the AuV to follow ACC with relatively high desired headway. Provided that the leading vehicle was an AuV, the subject vehicle would choose CACC based car-following with relatively lower headway between vehicles which would lead to form a platoon of AuVs. Whether the subject vehicle would join the CACC platoon depends on the leading vehicle's platoon ID. Platoon ID is an identification number assigned to an AuV that represents its order of position in the platoon. If an AuV is a part of a platoon, it will have a fixed platoon ID, otherwise it's platoon ID will contain a platoon ID = 0 (zero). While travelling through roads, the built-in communication technology of AuVs would enable them to identify the leading vehicles driving system as well as platoon ID. If the platoon ID of the leading vehicle was equal to the Maximum Platoon Length, then the subject vehicle would form a new platoon by maintaining Inter-platoon Headway and as a leader of the new platoon. In addition, if the leading vehicle's platoon ID was lower than Maximum Platoon Length, the subject vehicle would join the platoon by maintaining Intra-platoon Headway. I adopted the ACC and CACC car-following models developed in (Hu et al., 2017). The accelerations of the subject vehicle were determined with respect to relative position and velocity. The following equation was used to determine the acceleration of the subject vehicle:

$$\dot{v}(t + \Delta t) = k_1(\Delta p(t) - v(t) \times T - s_0) + k_2 \Delta v(t) \tag{4.4}$$

Where, k_1, k_2 = control constants for relative distance and speed respectively ($k_1, k_2 > 0$), $\Delta p(t)$= position difference with leading vehicle. The stability of the proposed ACC system was proved in (Hu et al., 2017). Suitable k_1, k_2 values were chosen according to (Hu et al., 2017) to implement realistic simulation accounting for the sensitivity of these factors. Similar approach of dual consensus was taken by Wang et al. (Wang et al., 2017) where both position and velocity consensus were considered to determine acceleration/deceleration decision. While both ACC and CACC car-following model used Equation (4.4) to determine acceleration values for AuVs, higher desired headways (T=1.25 sec) distinguish ACC mode with CACC mode ($T \leq 1.0$ sec).

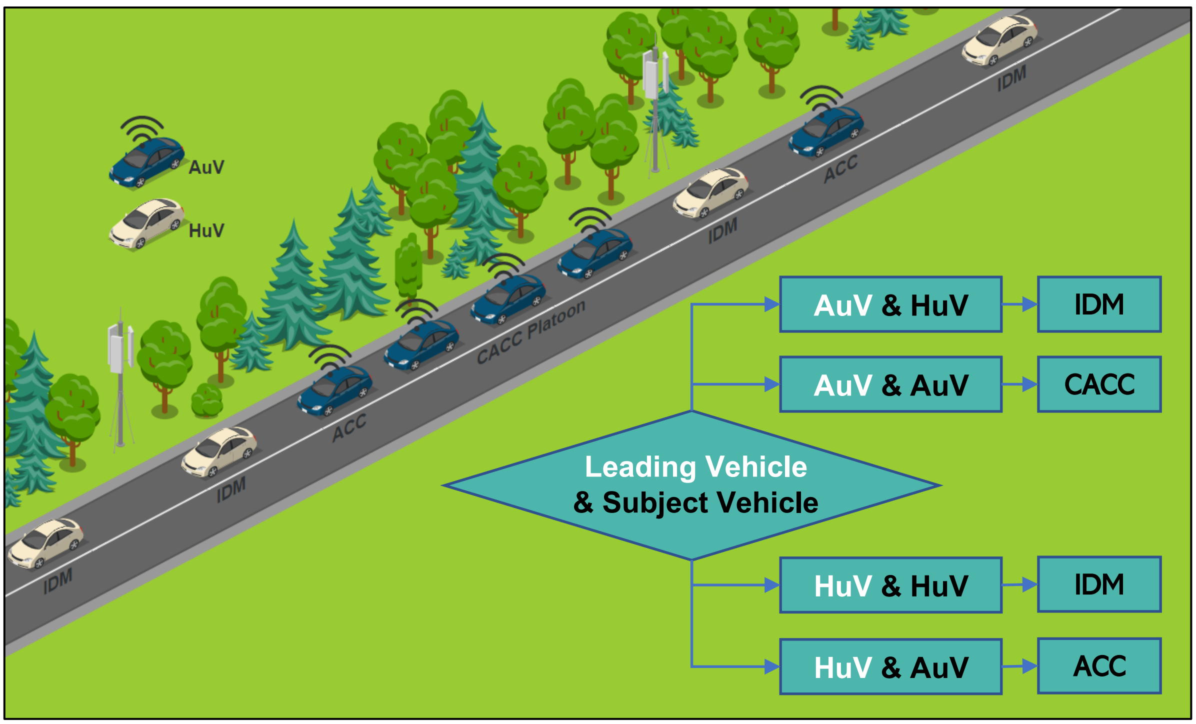


FIGURE 4.1 Proposed car-following strategy for mixed traffic

4.3 Simulation Process

A microscopic simulation structure was built on MATLAB to replicate vehicles' motion on a two-lane directional highway. Simulating only car-following strategy without involving lane-changing and/or gap acceptance maneuver allowed me to establish a single lane traffic stream without interruptions of any form. The simulation environment was grounded on numerical analysis-based car-following behavior. All previously mentioned motion dynamic equations were coded to follow proposed car-following strategy. A stream of 20 vehicles following a controlled leading vehicle was simulated for numerous scenarios. The time headways between the vehicles in traffic stream were manipulated to simulate distinct traffic flow rates. In the simulation environment, the acceleration of the first vehicle was controlled consciously to generate multiple shockwaves and to observe the reaction of the vehicles behind it. Each simulation ran for 1000-timesteps and 20 times for each scenario. The desired headway (T) for HuVs was considered as a log normally distributed random variable with mean value of 1.4 sec and standard deviation of 0.30 sec. The value of this distribution of desired headway was similar to obtained mean time headway and standard deviation for freeway driving by human drivers from previous chapter. Multiple runs for each scenario were executed to ensure that the obtained outcome was free from anomaly. The average value of 20 runs were listed for analysis.

In the beginning of the simulation, the first vehicle was travelling at 25 m/s for 210-time steps, then accelerated at 1.67 m/s^3 rate for 60-time steps followed by steady state (acceleration/deceleration rate = 0 m/s^3, velocity = 35 m/s) for 120-time steps. Finally, the controlled vehicle at front decelerated again at 1.67m/s^3 rate for 60-time step to regain 25m/s velocity and moved with constant velocity for the remaining time steps. Since the simulation setup did not allow any vehicle to perform lane-changing maneuver, all the vehicles in traffic stream had to follow the first vehicle and its trajectory based on characteristics of their own. The combinations generated from the following variables sets were simulated to represent various traffic states encountered in roadways as well as to identify the variations on improvements obtained by introducing the AuVs in the connected automated vehicle (CAV) environment:

A. Initial Flow rate (veh/hr): (i) 1400, (ii) 1800, (iii) 2400
B. AuV Market Share (%): (i) 25, (ii) 50, (iii) 75
C. Maximum Platoon Length (vehicle): (i) 3, (ii) 4, (iii)5, (iv) 6
D. Inter-platoon Headway (sec): (i) 2, (ii) 4, (iii) 6, (iv) 8
E. Intra-platoon Headway (sec): (i) 0.5, (ii) 0.75, (iii) 1.0, (iv) 1.25

The variables set were restricted by the above values to limit the analysis complexity and discussions within manageable ranges while covering a wide range of variations in traffic conditions. Platoon parameters (i.e. Maximum Platoon Length, Inter-platoon Headway, Intra-platoon Headway) were varied within reasonable ranges to identify observable trends. Two distinct driving systems were simulated by assigning specific values of driving system [0 for HuV, 1 for AuV]. The driving system values assigned for vehicles were used to implement the proposed car-following strategy on the CAV environment. Assigned driving system values were also useful to adopt proper sets of motion dynamic equations.

4.4 Analysis, Results and Findings

4.4.1 Impact of AuV location and distribution

Before analyzing the mobility and safety aspects of AuVs on traffic, the influences of AuVs location and distribution in traffic stream was explored. It was hypothesized that the positions of AuVs in traffic stream dictated their impacts on remaining vehicles. To prove this hypothesis, the proposed car-following strategy was simulated by allotting AuVs at diverse combinations of positions with gradually increasing the initial flow rate and AuV market share. To clearly comprehend the significance of vehicle position more clearly and to reduce the intricacy of comprehension, only two features were analyzed: acceleration fluctuation of HuV in the vehicle group and variations of maximum traffic flow at varying traffic state. Since numerous combinations of AuVs' distribution are viable at different penetration rates of AuVs, only a handful of combinations were selected to cover most possible variations.

Initially, these distributions were generated by placing AuVs as far apart as possible (--% Comb-1) in the vehicle stream while maintaining target AuV market share. Gradually, AuVs were grouped together in different combinations. The purpose of placing AuVs in such an order was to visualize and measure the impact of AuVs location and distribution along the vehicle stream. The combinations are listed in Table 4.1. The first column of the table showed percentages of AuVs in the traffic stream. The numbers on second column of the Table 4.1 identify the position ID of AuVs in the traffic stream. Other vehicles, except the positions mentioned in table, were HuVs. The last column of the table provides distinct combination name of each distribution of AuVs. These combinations were simulated on developed simulation environment by virtually placing AuVs in the mentioned position IDs of the vehicle stream and by following proposed car-following strategy for mixed traffic. The listed combinations on Table 4.1 were assumed to represent varying ranges of AuVs distribution on vehicle group. Analyzing these sets of vehicle location and distribution provided the opportunity to shed light on resulting impacts due to AuVs' position on traffic stream.

TABLE 4.4 List of AuV combinations simulated for different market penetrations

AuV Market Share	Distribution of AuVs (position)	Combination Name
25%	4, 8, 12, 16, 20	25% Comb-1
	4, 5, 10,11, 16	25% Comb-2
	5, 6, 7, 13, 14	25% Comb-3
	9, 10, 11,12 17	25% Comb-4
	2, 3, 4, 5, 6	25% Comb-5
	16, 17, 18, 19, 20	25% Comb-6
50%	2, 4, 6, 8, 10, 12, 14, 16, 18, 20	50% Comb -1
	2, 3, 6, 7, 10, 11, 14, 15, 18, 19	50% Comb -2
	2, 3, 4, 8, 9, 10, 14, 15, 16, 20	50% Comb -3
	2, 3, 4, 5, 10, 11, 12, 13, 18, 19	50% Comb -4
	2, 3, 4, 5, 6, 7, 8, 9, 10 ,11	50% Comb -5
75%	2, 3, 4, 6, 7, 8, 10, 11, 12, 14, 15, 16, 18, 19, 20	75% Comb-1
	2, 3, 4, 5, 6, 9,10, 11, 12, 13, 16, 17, 18, 19, 20	75% Comb-2
	2, 3, 4, 5, 6, 9, 10, 11, 12, 13, 16, 17, 18, 19, 20	75% Comb-3

From the analysis, the simulation outcomes of the initial flow rate of 1800 veh/hr with different AuV market proportion is provided in Figure 4.2 to demonstrate the influences of AuVs position and distribution along the stream from both microscopic and macroscopic perspective. Figure 4.2(a) represents the variations of maximum flow rates resulting from the proposed car-following strategy at listed combinations. Figure 4.2(b) shows the average coefficient of variations (CoV) of acceleration of HuVs in the simulated vehicle stream. Boxplots for a specific combination were plotted from the maximum flow rate and average CoV of acceleration data of simulated scenarios with varying platoon parameters, as listed before. Macroscopic analysis on maximum flow rates at different AuV shares (Figure 4.2(a)) identified the pattern of gradual increment with increasing AuV shares in the traffic. However, the increase in maximum flow rate was relatively low at lower AuV market share (25%) than higher market share (75%) which was expected due to higher CACC platoon forming opportunity among AuV vehicles at higher market penetration rate. Observations of different combinations revealed that combinations with scattered AuVs lead to lower maximum flow rates in comparison to combinations with grouped AuVs which was perceptive due to higher possibility of forming platoons at combinations with grouped AuVs in vehicle fleet. Additionally, grouping AuVs at the front of the vehicle stream (i.e. 25% Comb-6, 50% Comb-5, 75% Comb-3) resulted in 6.7- 11.5% higher maximum flow rates in comparison to the scattered distribution of AuVs (i.e. 25% Comb-1, 50% Comb-1, 75% Comb-1).

Analysis on microscopic characteristics of HuVs were undertaken by measuring the average CoV of acceleration at different market shares and combinations of AuVs. The resulting analysis showed a gradual decreasing CoV of acceleration with increasing shares of AuVs. Similar to macroscopic analysis, the maximum amount of decrease in CoV (1.69 – 6.63%) was observed from combinations with AuVs at the front of the traffic stream grouped together. Specific analysis on Maximum Platoon Length's influence on acceleration fluctuations of HuVs revealed that increasing Maximum Platoon Length reduced the average coefficient of variation of acceleration for AuVs. Similar analysis on the other two platoon parameters (i.e. Inter-platoon Headway, Intra-platoon Headway) demonstrated a reciprocal relation with acceleration fluctuations (increasing Inter and Intra-platoon Headway increased the average CoV of acceleration).

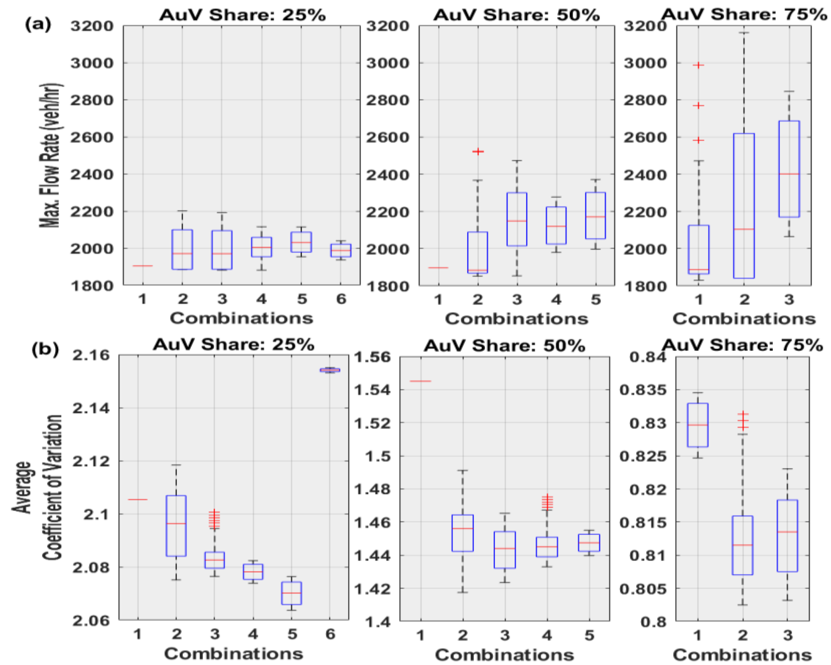


FIGURE 4.2 Influences of AuVs' position on (a) Maximum Flow Rate, (b) Average Coefficient of Variation of Accelerations.

The analysis of the remaining initial flow rates and AuV market share revealed that creating platoons of AuVs by positioning them at the front of traffic stream would be beneficial to the rest of vehicles in the traffic stream. The AuV vehicles positioned at the stream front would be able to ingest a significant extent of abrupt change due to sudden acceleration/deceleration and transmit diminished impact to following vehicles in the fleet. Furthermore, increasing market shares of AuVs could gradually reduce the acceleration fluctuation of HuVs. Finally, increasing the flow rates could inversely influence traffic flow improvements with a specific AuV location and distribution combination. The notion of traffic flow improvements guided the authors in this study to explore mobility improvement potentials of the proposed car-following strategy by placing AuVs at ideal positions along the traffic stream.

4.4.2 Impact on Mobility

Since creating platoons of AuVs was found to be the most effective way of acquiring associated benefits, influences of AuVs on traffic mobility were examined with respect to three key variables of platooning: Intra-platoon Headway, Inter-platoon Headway and Maximum Platoon Length. Combinations of these three variables within listed sets were utilized to generate various platoon scenarios for simulation and analysis. The impact of these platoon structures on mobility was measured and compared with the help of two parameters: Average Travel Time (ATT) [Equation 4.5] and Average Travel Distance (ATD) [Equation 4.6]. Later, case scores were computed by providing equal weights to ATT, ATD [Equation 4.7]. Different cases of platoon configurations were simulated and evaluated through case scores. Higher dispersion from base-case (0% AuV share) scores indicated higher mobility improvements. The objective of this analysis was to identify the optimal platoon configuration to improve mobility by increasing ATD and reducing ATT. The following equations were used to identify the mobility gains.

$$ATT = \frac{\sum_{j=1}^{J} ATT_j}{J} = \sum_{i=1}^{I} \frac{\left(p_{i,j} - p_{i,j-1}\right)}{v_{i,j}} \tag{4.5}$$

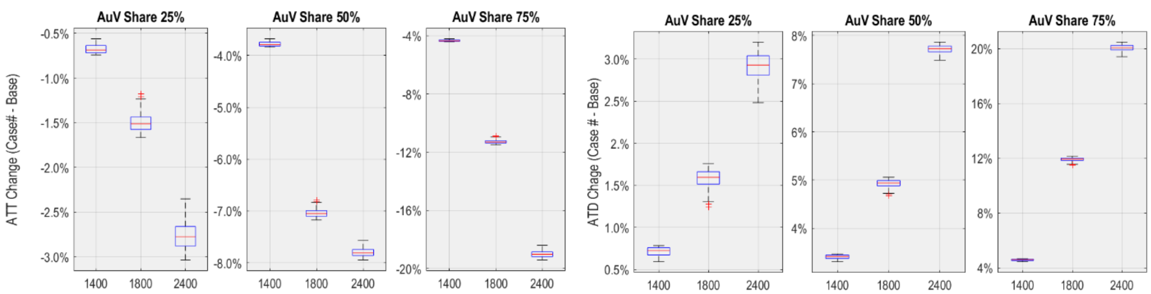
$$ATD = \frac{\sum_{J=1}^{J} ATD_j}{J}, \;\; ATD_j = \frac{(p_{I,j} - p_{1,j)}}{I} \tag{4.6}$$

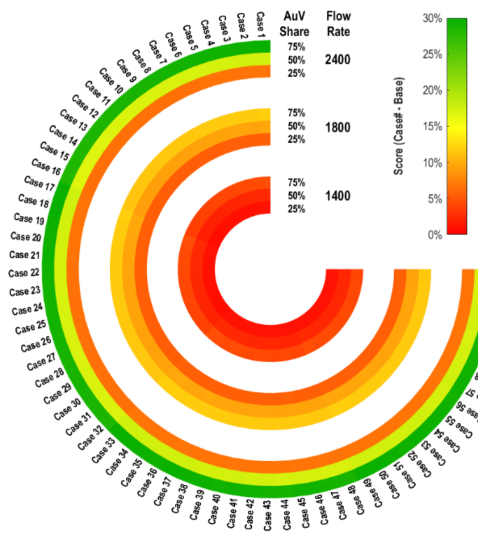
$$Score_{Case\ k} = \frac{\sum_{J=1}^{J} v_{1,j}\left(ATD_{j,Case\ k}\right)}{J} - (ATT_{Case\ k}) \tag{4.7}$$

Here, i =vehicle index ($I=21$); j = time index (J=1000); $v_{i,j}$ = velocity of vehicle i at time step j; $p_{i,j}$ = position of vehicle i at time step j, $Score_{SCase\ k}$= score of case k. Aforementioned [Section 4.4] platoon variables (i.e. Maximum Platoon Length, Inter-platoon Headway and Intra-platoon Headway) were explored to generate distinct platoon scenarios. The combinations of these parameter set produced 64 distinct platoon configurations that were simulated for chosen traffic flows and AuV market shares to detect the capability of mobility improvements. Moreover, the limits of mobility improvements due to variation of platoon configurations were also reveled in this analysis. Figure 4.3 (a, b) portrayed the changes in ATT and ATD for studied cases in comparison to base case (0% AuV). Obtained mobility score improvements from base-cases at different traffic states are presented in Figure 4.3(c). The three-quarter circles showed comparative mobility progresses at different flow rates and AuV market shares simulated for the analysis. The color bar on Figure 4.3(c) indicated the extent of generated mobility score improvements. Figure 4.3(d) revealed detail analysis for a specific flow rate and AuV share.

Figure 4.3 (a) depicted the variations of ATT at varying inflow rate and AuV marker shares for simulated 64 platoon structures. The boxplots showed the distribution of these ATT changes for specific traffic state (i.e., flow rates, AuV share). As evident from the boxplots, at any AuV share, increasing flow rates eventually increased the mobility benefits by reducing ATT from base case. On the other hand, increasing AuV shares for specific flow rate reduced the ATT of the simulated traffic stream. Furthermore, the implications of diverse platoon structures resulted into broader ATT variations in lower market share (25% AuV) than higher market share (75% AuV). Additionally, these ATT variations due to platoon structures were acute at lower flow rate (1400vph) than higher flow rate (2400 vph). Figure 4.3 (b) compared the changes in ATD resulting from simulated traffic flow rates and AuV shares. Analysis results indicated that with increasing flow rates the ATD benefits increased. However, the influence of simulated platoon structures was increased at higher flow rates. Furthermore, the increase in ATD value were consistent with increasing AuV share in traffic stream.

For clear understanding of the impact of platoon configurations at a specific traffic state, mobility improvements at initial flow rate of 1800 veh/hr and 75% AuV share is provided in figure 4.3(d) as an example. As observed in Figure 4.3(d), sixty-four (64) separate platoon configurations were generated from listed parameter set [Section 4.4]. Parameters for each case were listed in the table on Figure 4.3(d). The mobility improvement column was calculated by comparing the base-case (flow rate=1800 veh/hr, AuV share =0%) with the corresponding cases and transforming the value into a percentage. Negative percentages indicate impaired mobility and positive percentages denote improved mobility resulting from a specific platoon configuration. When inspecting Figure 4.3(d), it was found that maximum mobility benefits [11.91% improvement on case score] could be obtained from Case 33 [Platoon Configuration: Intra-platoon Headway = 0.50 sec, Inter-platoon Headway = 2 sec and Max. Platoon Length = 5] and Case 49 [Platoon Configuration: Intra-platoon Headway = 0.50 sec, Inter-platoon Headway = 2 sec and Max. Platoon Length = 6] for that specific traffic state. A declining trend of mobility gains were captured with increasing Inter and Intra-platoon Headway. Additionally, increasing Maximum Platoon Length parameter showed expansion with regards to mobility which came to a halt at Maximum Platoon Length =5.





Case	Intra-platoon headway	Inter-platoon headway	Max. platoon length	Mobility improvement %	Case	Intra-platoon headway	Inter-platoon headway	Max. platoon length	Mobility improvement %
1	0.50	2	3	11.86%	33	0.50	2	5	11.91%
2	0.75	2	3	11.82%	34	0.75	2	5	11.86%
3	1.00	2	3	11.78%	35	1.00	2	5	11.81%
4	1.25	2	3	11.74%	36	1.25	2	5	11.77%
5	0.50	4	3	11.72%	37	0.50	4	5	11.84%
6	0.75	4	3	11.68%	38	0.75	4	5	11.79%
7	1.00	4	3	11.65%	39	1.00	4	5	11.75%
8	1.25	4	3	11.61%	40	1.25	4	5	11.70%
9	0.50	6	3	11.59%	41	0.50	6	5	11.77%
10	0.75	6	3	11.55%	42	0.75	6	5	11.73%
11	1.00	6	3	11.51%	43	1.00	6	5	11.68%
12	1.25	6	3	11.47%	44	1.25	6	5	11.63%
13	0.50	8	3	11.45%	45	0.50	8	5	11.70%
14	0.75	8	3	11.42%	46	0.75	8	5	11.66%
15	1.00	8	3	11.38%	47	1.00	8	5	11.61%
16	1.25	8	3	11.34%	48	1.25	8	5	11.57%
17	0.50	2	4	11.88%	49	0.50	2	6	11.91%
18	0.75	2	4	11.84%	50	0.75	2	6	11.86%
19	1.00	2	4	11.80%	51	1.00	2	6	11.81%
20	1.25	2	4	11.76%	52	1.25	2	6	11.77%
21	0.50	4	4	11.78%	53	0.50	4	6	11.84%
22	0.75	4	4	11.74%	54	0.75	4	6	11.79%
23	1.00	4	4	11.70%	55	1.00	4	6	11.75%
24	1.25	4	4	11.65%	56	1.25	4	6	11.70%
25	0.50	6	4	11.68%	57	0.50	6	6	11.77%
26	0.75	6	4	11.64%	58	0.75	6	6	11.73%
27	1.00	6	4	11.60%	59	1.00	6	6	11.68%
28	1.25	6	4	11.55%	60	1.25	6	6	11.63%
29	0.50	8	4	11.58%	61	0.50	8	6	11.71%
30	0.75	8	4	11.54%	62	0.75	8	6	11.66%
31	1.00	8	4	11.50%	63	1.00	8	6	11.61%
32	1.25	8	4	11.45%	64	1.25	8	6	11.57%

FIGURE 4.3 Variations on (a) ATT, (b) ATD , (c) mobility scores due to varying platoon configurations at different flow rates and AuV Shares (d) specific flow rate (1800 veh/hr) and AuV share (75%).

Further exploration of Figure 4.3(c) revealed that increasing AuV market could bring broader mobility enhancement at higher flow rates [yellow to green bands on 2400 veh/hr flow rate]. Increased AuV share at low flow rates had a diminishing effect on mobility [light red to deep red bands on 1400 veh/hr flow rate]. Another finding of this analysis was that the closely spaced AuVs with long platoons would generate more mobility improvements. Hence, the maximum mobility benefit was experienced on Case 33 and Case 49. Although the analysis concluded that closely spaced, long AuV platoons could attain higher mobility benefits, close proximity of AuV platoons and long chain of AuVs in these platoon configurations would severely restrict merging vehicles from neighboring lanes, on-ramps, side roads etc.

Analysis on platoon parameters at different traffic state revealed that, with other parameters being constant, increasing platoon length resulted into improved mobility gains. Similar investigation on inter-platoon headway presented that increase in inter-platoon headway would reduce traffic mobility if other two parameter remain constant at a specific traffic state. Analysis of intra-platoon headways coincides with the insights of inter-platoon headway analysis. Therefore, compactness of AuVs would bring more mobility benefits in roadway sections with minimal conflict points (e.g. spans between on/off-ramps on freeways, sections between intersections in arterial etc.). The notion of conflict points led to the next section of this study, examining the impact of AuVs on traffic safety.

4.4.3 Impact on Safety

Although Case 33 and 49 were found to be an obvious choice among 64 tested platoon configuration cases with respect to mobility enhancements, all aforementioned cases were examined again to identify the potential impact on traffic safety. Findings from AuVs location and distribution influenced the simulation of safety improvements by placing a series of AuVs at the front of traffic stream to obtain optimal benefits. Since no merging traffic was considered, the safety enhancements were examined as a measure of potentials to reduce rear-end collision risks. Three safety surrogate measures were considered in this regard: Time-to-collision (TTC), Time Exposed Time -to-collision (TET) and Time Integrated Time-to-collision (TIT).

TTC, TET and TIT, introduced by Hayward, Minderhoud and Bovy (Hayward, 1971; Minderhoud & Bovy, 2001), were widely used by traffic safety researchers to evaluate perceived safety at a traffic state. The time required for two successive vehicles in the same lane to hit if they maintain their current velocity is represented by TTC. Higher TTC would indicate safer traffic condition and vice versa. TTC can be used to evaluate safety of a traffic environment, since lower TTC is indicative to potential dangerous situation (Vogel, 2003). Both TET and TIT are derived from TTC to measure safety improvements from macroscopic standpoint. Since TET is the summation of instances when TTC are lower than threshold value, the lower TET value is expected at safer traffic conditions. TET value was measured by Equation (4.9) where TTC values for each vehicle at each time stamp ($TTC_{i,j}$) were compared with the threshold TTC (TTC^*)value to calculate TET value for each scenario. TIT measures the value of TTC lower than the threshold TTC. Similar to TET, a higher TIT value indicates higher safety concerns. The values of these parameters were measured using the following equations:

$$TTC_{i,j} = \begin{cases} \frac{p_{i-1,j} - p_{i,j} - L}{v_{i,j} - v_{i-1,j}} & if\ v_{i,j} > v_{i-1,j} \\ Inf & if\ v_{i,j} \le v_{i-1,j} \end{cases} \tag{4.8}$$

$$TET = \sum_{j=1}^{J} TET_j, \quad TET_j = \sum_{i=1}^{I} \delta_j \Delta j, \quad \delta_j = \begin{cases} 1 & \forall\ 0 < TTC_{i,j} < TTC^* \\ 0 & else \end{cases} \tag{4.9}$$

$$TIT = \sum_{j=1}^{J} TIT_j, \quad TIT_j = \sum_{i=1}^{I} [\frac{1}{TTC_{i,j}} - \frac{1}{TTC^*}] . \Delta j \qquad \forall\ 0 < TTC_{i,j} < TTC^* \tag{4.10}$$

The threshold TTC values to measure TET and TIT was set as 1.5 sec, similar to standard threshold TTC value suggested in Surrogate Safety Assessment Model (Gettman et al., 2008). Resulting changes with regards to safety are displayed on Figure 4.4. Figure 4.4(a) presented total TET and average TIT values over the simulation period on base-cases which were utilized to measure safety improvements gained with the introduction of AuVs. Figure 4.4(b) displays the range of changes on total TET values at different traffic states with varying platoon structures. Increasing AuV shares showed a gradual decline of total TET values. The extent of declination was much higher in higher flow rates. However, an exception was observed at high flow rates and lower AuV shares (Flow rate =2400 veh/hr, AuV share =25%) where total TET value increased from base traffic states. Therefore, it can be stated that higher AuV share is required to bring noticeable safety improvements with increasing flow rates. Figure 4.4(c, d) shows analysis results of average TIT changes. As showed in earlier figure [Figure 4.3(a)], both factional circles revealed resulting improvements on average TIT parameters. Figure 4.4(c) showed resulting safety improvements of the vehicle stream for different platoon configurations, AuV shares and flow rates by comparing with base average TIT-values. This analysis considered average TIT values of HuVs only in the traffic stream. Average TIT values of HuVs in the CAV environment were compared with corresponding vehicles on base case for this analysis. The average TIT reduction of HuVs was found to be within the range of [-20.76% 8.55%]. Additionally, higher safety gains were achieved with shorter platoons including AuVs sparsely spaced.

On the other hand, Figure 4.4(d) shows the analysis by comparing average TIT values of all vehicles with base case. For this analysis, it was assumed that there was no collision risk for AuVs [average TIT values = 0 for AuVs], irrespective of platoon configurations. Comparison between Figure 4.4(c) and Figure 4.4(d) shows significantly higher improvements on average TIT values for all vehicles over HuVs. The range of average reduction is much higher on Figure 4.4(d). Detailed analysis of safety enhancement for a specific traffic state provided further insights on the impact of platoon configurations. For instance, simulation results of 1800 veh/hr flow rate with 75% AuV share traffic state revealed that increasing AuVs' stretch over the traffic stream resulted in greater safety benefits for remaining vehicles. Hence, the maximum safety gain was attained from Case 16 (-10.23% reduction on average TIT of HuVs) for this specific traffic state. Although a similar pattern was observed for other traffic states, unexpectedly high safety concerns were experienced for some cases [dark red strip on Figure 4.4(c) for 2400 veh/hr with 25% AuV share]. Moreover, maximum safety gains on HuVs were obtained on 50% AuV share at 1800 veh/hr flow. The findings from safety impact analysis has led me to conclude that increasing AuVs with increasing flow rates would improve safety of all vehicles if AuVs form short, sparse platoon in start of traffic stream. Although, rear-end collision risk for HuVs would proportionately reduce with increasing AuV share at comparatively high and low flow rate, this correlation between safety gain and AuV share did not hold true for flow rates near capacity level.

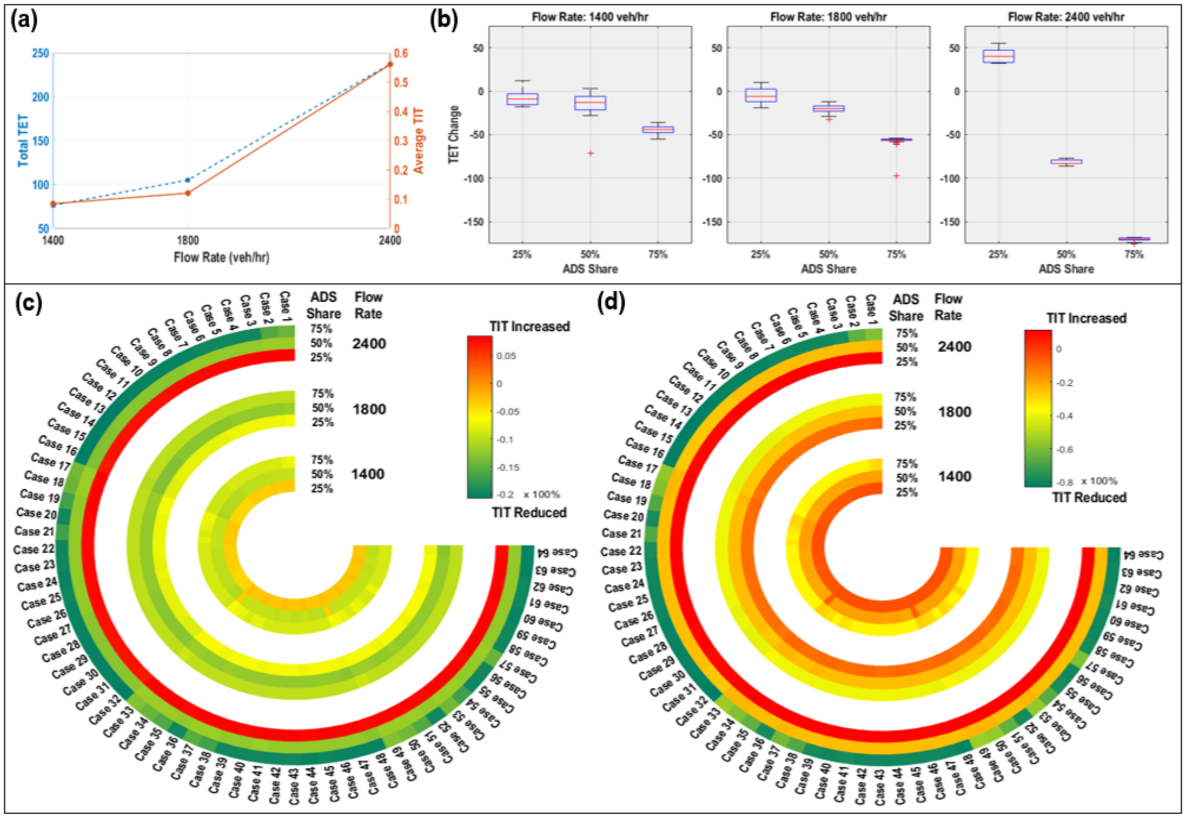


FIGURE 4.4 (a) Base-case safety parameter values at varying flow rates. (b) Changes in total TET, (c) Variations of Average TIT values considering HuVs only, (d) Variations of Average TIT values considering all vehicles, due to varying platoon configurations at different flow rates and AuV shares.

Exploring the evolution pattern of platoon parameters provided important insights on safety feature. While other parameters (i.e. inter-platoon headway, Max. platoon length) remain same, continuous increment of intra-platoon headway showed reduction on rear-end collision expectation. Inter-platoon headway followed similar pattern as intra-platoon headway. However, range of safety improvement in both parameters depend on maximum platoon length. Magnitude of safety gains were much higher at small platoons (i.e. Max. Platoon length =3) than big platoons (i.e. Max. Platoon Length).

4.5 Identification of Optimal Platoon Parameter Set

An analysis of proposed car-following strategy delivered insights regarding mobility and safety improvement potentials due to presence of AuVs at mixed traffic conditions. One key finding of the analysis was that the expectation to obtain multi-objective improvements (i.e. mobility and safety) from single platoon configuration was impractical. Since mobility gains maintained a reciprocal relationship with safety enhancements, a sub-optimal platoon configuration could be determined to procure maximum gains from these two features. Another compelling outcome of prior analysis involved recognizing the fact that both traffic flow rates and AuV market shares had influence on obtained benefits. Hence, achieving maximum mobility and safety advantages from fixed sub-optimal platoon configuration at different flow rates was unrealistic. To this end, it was necessary to present an approach that identified dynamic sub-optimal platoon configurations for multi-objective decision-making purposes.

Influenced by Khondaker and Kattan (Khondaker & Kattan, 2015), an analysis was performed to identify the sub-optimal platoon configurations to maximize mobility, and safety enhancements generated by AuVs. Collective influences from these two features were measured by placing different weights on them to get resulting variations on improvements [Figure 4.5(b)]. Three sets of multi-objectives functions were investigated to obtain suitable platoon structure. Sets for platoon variables were chosen from earlier analyses to identify sub-optimal configurations. This analysis is termed as meta-modeling in the literature to determine the sub-optimal configuration from studied parameter by considering the impact of both contributing factors in decision making. In this case, the platoon structure parameters were switched to measure the resulting mobility and safety implications at different traffic states (i.e., flow rates, AuV shares) with the aim to maximize the benefits from both mobility and safety perspective by assigning different weights on these factors.

FIGURE 4.5 Observed variations of (a) individual features due to diverse platoon variables listed and (b) listed multi-objective function sets resulting from changing platoon variables

The optimization of platoon variables for different multi-objective function identified each feature's (i.e., mobility, safety) individual and collective inclinations. To obtain clear and precise insights of these trends, the vehicle fleet with 1800 veh/hr flow rate and 75% AuV market share is demonstrated in Figure 4.5. The improvements obtained due to AuVs were scaled within range [0 1] using extreme values from prior analysis of all the features [Figure 4.5(a)]. For mobility improvements, the scenario scores were scaled within the above-mentioned range. Extreme average TIT values measured in safety impact analysis were applied to measure safety scores of different platoon configurations. This action was performed due to variations of units in measures of effectiveness and to bring them in the same scale for optimization. Reviews of individual features identified a gradual reduction of mobility improvements with an increase of Intra and Inter-platoon Headway. However, safety improvements showed opposite pattern. Figure 4.5(b) showed the results of a set of objective function with predefined weight put on mobility and aspects. The goal of this analysis to obtain sub-optimal platoon configurations for predefined objective sets. Also, to identify the objective function with maximum benefits from the assorted weight sets. Analysis of combined impacts identified that maximum benefits for Objective function 1 (Mobility improvement weight = 0.25 and Safety improvement weight = 0.75) were achieved with the platoon configuration of: Intra-platoon headway = 1.0 sec, Inter-platoon Headway = 8 sec, Maximum Platoon Length = 3 vehicles. The objective of this analysis was to present an approach to identify sub-optimal platoon configurations suitable for specific flow rates and AuV market share with specific motivation to assist in multi-objective decision making.

4.6 Conclusion and Future Extensions

The objective of this segment of research was to obtain rationalized insight on mixed traffic movements and evaluate the impact that AuVs will supposedly have on traffic. Whilst the potential of connectivity and automated controls are astounding, the extent of harnessing the benefits depends on discerning their influences on traffic. In this regard, I have proposed a naïve car-following mechanism for mixed traffic and analyzed their motion dynamics to determine the possible improvements. Initially, the location and distributions of AuVs along the traffic stream were discovered to be moving forward with established framework to obtain the highest rewards. The mobility and safety gains obtained from CAV traffic stream were examined for varying traffic flow, AuV market penetration and platoon configurations with the intention of determining the limits of these potential improvements. The final stage of this study was the analysis to obtain optimal platoon configurations to achieve maximum collective improvements.

The findings of the research show that to obtain maximum mobility benefits, close and compact platoons are favorable in roadway sections without side frictions. However, segments with on-ramps, off-ramps, side roads etc. need to be researched in future to account for side frictions and their consequences on collective mobility, safety and environmental gains. Identifying sub-optimal platoon configurations for varying flow rates and market shares of AuVs will assist traffic operation authorities to propose traffic state responsive dynamic platoon structures. Utilizing these platoon configurations will make the best use of AuVs on prevailing traffic conditions to obtain maximum gains. Future research based on this study will account for vehicles with conflicting movements (i.e. lane changing, merging traffic from on-ramps, diverging traffic towards off-ramp etc.) and propose potential improvements. This specific segment of research directly explores partial traffic motion dynamics influenced by the insights obtained from driving behavioral study. However, this study was neutral to including any behavioral variations of HuVs to obtain a standardized benchmark of expected mobility and safety benefits. Additionally, partial motion dynamics were featured in this part due to potential dilution of mobility and safety benefits that could be resulting from inherent complexity of complete motion dynamics. Altogether, exploring partial motion dynamics of mixed traffic to measure mobility and safety gains driven the research one step closer to answer the established research question.

4.7 References

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CHAPTER 5 : MOBILITY AND SAFETY IMPLICATIONS OF MIXED TRAFFIC IN WEAVING SECTION

5.1 Introduction

The rise of automated vehicle (AV) technology, as an essential component of a new generation of traffic infrastructure, has been researched by both academics and industry who recognize its advantages over the existing transportation framework with regards to improved mobility, enhanced safety, and reduced environmental impact. However, large-scale transitions to AV technology-based transportation system cannot happen overnight. Research on the fusion of such technology with the current, human-oriented transportation system that also considers the restraints of current roadways is clearly warranted. Certainly, freeway weaving sections are considered restraints since they act as recurrent bottleneck locations due to inherent vehicle trajectory patterns formed by vehicles changing lanes from auxiliary lanes to mainlines and vice versa. As such, substantial research has established that both mobility and safety of the weaving sections are compromised (Fazio, Holden and Rouphail, 1993; Uno et al., 2003; Golob, Recker and Alvarez, 2004; ho Lee, 2008; Pulugurtha and Bhatt, 2010; Marczak, Daamen and Buisson, 2014; He and Menendez, 2016, 2017).

Although numerous studies have established the eminence of mixed traffic over traditional traffic system from mobility, safety, and environmental perspectives, the exploration of coexistence is primarily limited to partial motion dynamics, most often car-following strategy, of studied vehicle groups (Ghiasi *et al.*, 2017; Seraj, Li and Qiu, 2018; Zhu and Zhang, 2018; Ye and Yamamoto, 2019). This limitation is significant since both traffic operational and regulatory authorities must base their strategic investment as well as informed policy and legislative decision-making on sound, objective facts regarding the numerous levels of AV integration with conventional traffic system. Underpinned by this gap in knowledge, this part my research in the frame of full study addresses the following question: *How can the mobility and safety of varying traffic states in a multilane weaving section be influenced by the shared presence of Automaton driven (AuV) and Human driven vehicle (HuV)s?* In this premise, the two-fold objective of this descriptive research includes: *(i) contriving a comprehensive and realistic modeling framework of mixed traffic with bi-*

directional motion dynamic, (ii) quantifying and clarifying the causal connection between presence of AuVs in traffic with potential shift in mobility and safety benchmarks for a weaving section.

The findings of this study aim to contribute to the existing body of knowledge, which currently lacks substantial evidence to support the effect of AV integration to improve the mobility and safety of weaving freeway sections. Furthermore, the study outcomes can benefit research communities and industries that are actively committed to intelligent transportation systems and who presume that AVs will play a significant role in overcoming flow efficiency limitations and crash likelihood. *The* demand for understanding the implications of AV substantiates the need for more comprehensive research from the mobility and safety perspective. Both of these perspectives play critical role to measure transportation system performance and effects of mixed traffic on planning decisions. From planning and operational standpoint, traffic mobility can be defined as the ability and level of ease of moving goods and services (Götz, 2014). For instance: freeways providing designated high occupancy vehicle lanes to increase overall efficiency of moving people while maintaining the overall number of vehicles. Since elaborate evaluation of mobility shift would require considerable exertion of resources, a few mobility parameters are selected in this study to provide a general overview of potential amendments in traffic mobility. of Traffic safety, on the other hand, can be measured directly from number of collisions, injuries, and fatalities. Since AV are not yet widespread present in traffic, direct measures of potential changes cannot be obtained in most cases. Hence, surrogate safety indicators are adopted to measure positive or negative shifts in overall traffic safety.

5.2 Microscopic Modeling Framework of Multilane Traffic

Last chapter of this thesis provided the framework of microscopic car-following strategy of mixed traffic on a single lane. Founded on that background, this chapter will expand the framework from unidirectional motion to bi-directional motion of traffic which will enable us to develop realistic multilane traffic movements and acquire more reliable estimation of mobility and safety impact. This framework incorporates longitudinal and lateral motion dynamics of both vehicle type for unimpeded movement along the roadway. In addition to mandatory lane-changing, platoon formation among AuVs is also configured within this framework. More definitive conclusions can be drawn from such a comprehensive modeling architecture directly examining the mobility and safety implications of AuVs.

Agent-based modeling was adapted from the MATLAB library to develop the core model structure of this study. Agents of two different types were defined to represent the two vehicle types (i.e., HuV and AuV). These two agents enter and exit a predefined roadway segment with average headway input to maintain average inflow rate and AuV share for each simulated scenario. The roadway segments were defined by giving number of lanes and length of section values as inputs. The driving strategy and vehicle model were similar for both agents apart from acceleration/deceleration conditions, and platoon formation provisions. Irrespective of leading vehicle type, HuVs had an average desired headway of 1.4 sec with standard deviation of 0.3 sec to account for the variability of human driving behavior. The value of desired headway was taken as a log normally distributed variable based on the findings from analyzing real-world driving behavior of SPMD dataset in Chapter 3. While desired headway of an individual vehicle would be fixed (with some exception for forced mandatory lane-changing) throughout the simulation period, the parameter would follow a log normal distribution for overall HuV proportion of traffic. Instead of constant desired headway, the provision of varying desired headway distribution of HuVs within the modeling framework presented the opportunity to incorporate behavioral variation of human drivers. Since the distribution of desired headway was inherited from evaluating real-world driving decisions, the resulting performance from such entry would be more realistic and reliable.

On the other hand, AuVs inherited desired headway from platoon configuration (i.e., inter-platoon headway, intra platoon headway) depending on their position within a platoon. As mentioned in (Seraj, Li and Qiu, 2018), the AuVs are programmed to form platoons amongst themselves. If there is an HuV in front of AuV, the subject AuV would pursue ACC with a smaller desired headway (i.e., 1.25 sec) in the car-following state. However, if the leading vehicle is an AuV, the subject AuV will reduce the desired headway (i.e., 1.0 sec) to form a CACC platoon. The maximum platoon formation length was 3 AuVs in the simulation.

Also, intra-platoon distance is taken as 4 sec to accommodate lane-changing vehicles in between platoons. Hence, if the leading AuV is the 3rd AuV in the platoon, then the subject AuV would maintain 8 sec headways. The platoon structure was selected from 64 platoon configuration tested in Chapter 4 for mixed traffic car-following strategy. As the findings of Chapter 4 suggested that this platoon structure would generate sub-optimal benefits from mobility and safety perspective.

The default driving strategy and vehicle model of the agent-based modeling was customized to develop more realistic vehicle dynamics. Various modeling approaches in the literature established the spatial-temporal anticipation ability of human drivers (Lenz, Wagner and Sollacher, 1999; Knospe *et al.*, 2001; Eissfeldt and Wagner, 2003; Watamaniuk and Heinen, 2003; Lee *et al.*, 2004; Treiber, Kesting and Helbing, 2006; Lindorfer, Mecklenbrauker and Ostermayer, 2018). The anticipative nature of human drivers compensated for higher reaction time than the ACC/CACC system that can generate quicker reaction to an event (Makridis *et al.*, 2018). Hence, for an advanced vehicle control system, incorporating such anticipative intelligence naturally improves driving efficiency and opportunities to avoid a collision. In response, the Model Predictive Control (MPC)-based motion algorithm is chosen for modeling both vehicle types. MPC utilizes present information to predict the future state by controlling the process through the minimization of objective function under constraints. This study aimed at developing a control framework that combined connectivity and automation of AuVs to navigate effortlessly in mixed traffic scenarios. In this modeling framework, I used the MPC framework integrated into MATLAB stateflow model to decide between the different states of the driving strategy.

Each vehicle is assigned a vehicle ID to specify their presence on the road and vehicle type to decide on control provisions. The subject vehicle's longitudinal and lateral control is implemented by computing the current traffic state from input data and predicting its future pattern. A P-step prediction horizon and C-step control horizon are considered for optimizing the control inputs of the subject vehicle. The prediction and control horizon of the MPC is taken as 30 and 3 timesteps respectively. Since, lane changing maneuver takes multiple seconds to complete, the following constraint is included

$$0 \le \delta_r \ or \ \delta_l \le 1 \tag{5.1}$$

which implies that the subject vehicle is allowed to move only once either to the right or to the left lane within the prediction horizon. Some additional constraints are defined to ensure safety and comfort in driving. The speed of the subject vehicle at any time step is bounded by the following upper and lower limit

$$0 \le v_s(k) \le v_{max} = 1.1 \times v_{SL} \tag{5.2}$$

Here, v_{max} is the maximum achievable speed which is 10% higher than the speed limit, v_{SL}=25m/s. Acceleration is bounded by the following boundary constraints

$$-3\ m/s^2 = a_{min} \le a_s(k)\ \le a_{max} = 2\ m/s^2 \tag{5.3}$$

The limits for maximum acceleration and deceleration limits were inspired from extreme acceleration and deceleration pattern analysis on freeway in Chapter 3. Additionally, previous studies on modeling HuV and AuV also aided in choosing the limits to account for driving comfort (Hoberock, 1976; Deng, 2016). To ensure safe driving in traffic by avoiding any collision with other vehicles, the minimum gap constraint is imposed

$$x_{s-1}(k) - x_s(k) - L\ = g_s(k) \ge g_{s,min}(k) = g_0 + h_{0,s}v_s(k) \tag{5.4}$$

Here, Δg_s is the gap between subject vehicle and leading vehicle, $\Delta g_{s,min}$ is the minimum allowable gap for the subject vehicle, g_0 is minimum gap between a vehicle at standstill condition (2.5m), $h_{0,s}$ is the desired headway of subject vehicle. The following nonlinear constraint is introduced to avoid collision risk during lane changing

$$g_{t,lead} \ge\ \theta_t(k) \times \Delta g_{s,min}(k) \tag{5.5}$$

$$g_{t,lag} \ge\ \theta_t(k) \times \Delta g_{s,min}(k) \tag{5.6}$$

$$g_{t,lead}(k) =\ x_{t-1}(k) - x_s(k) - L \tag{5.7}$$

$$g_{t,lag}(k) =\ x_s(k) - x_t(k) - L \tag{5.8}$$

Here, x_{t-1} and x_t are the position of lead and lag vehicles, respectively, in the target lane, L is the average length of vehicle (5m), θ_t denotes current lanes of target lane vehicle and subject vehicle. If the target lane vehicle and the subject vehicle are in the same lane then

$\theta_t = 1$, otherwise $\theta_t = 0$. This time varying gap constraint defines the permissible gap for lane changing. $\Delta g_{s,min}$ for HuVs were measured by taking safety headway value same as desired headway of the particular vehicle. For the cases of lane changing by any AuV, $\Delta g_{s,min}$ is measured with 1.25 sec as safety headway. Finally, the state of all vehicles in the simulation is updated by the following equations

$$a_{s-1/t/t-1}(k) = f\{\Delta g_{s-1/t/t-1}(k), v_{s-1/t/t-1}(k), \Delta v_{s-1/t/t-1}(k)\} \tag{5.9}$$

$$\delta_{r/l,s-1}(k) or\ \delta_{r/l,t-1}(k)\ or\ \delta_{r/l,t}(k)\ = 0 \tag{5.10}$$

Here, first equation is used to estimate the acceleration of surrounding vehicle and second equation implies that subject vehicle assumes no other surrounding vehicle is changing lane at any time step k. Similar to Chapter 3, the acceleration of HuVs are updated by from an enhanced Intelligent Driver Model (IDM) (Treiber, Hennecke and Helbing, 2000) and model proposed by Hu et al. (Hu *et al.*, 2017) is employed to determine acceleration of AuVs.

$$a_s(k) = \begin{cases} a_{max}\left[1 - \left(\dfrac{v_s(k)}{v_{SL}}\right)^4 - \left(\dfrac{g_0 + \max\left[0, v_s(k) \times h_0 + \dfrac{v(k) \times \Delta v(k)}{2\sqrt{ab}}\right]}{s}\right)^2\right] \\ k_1(g_s(k) - v_s(k) \times h_0 - g_0) + k_2 \Delta v_s(k) \end{cases} \tag{5.11}$$

Through equation 5.10, it is assumed that the vehicles surrounding the subject vehicle (i.e. leading vehicle in current lane $_{s-1}$, leading vehicle in target lane $_{t-1}$and following vehicle in target lane $_t$) are not changing lane at any time step k. The predicted states of all vehicles for ensuring the safety in the prediction horizon needs to be estimated using

$$S(k) = \{S_N(k)\}_{\forall N \neq 0} \tag{5.12}$$

which denotes S as the state of traffic considering S_N as the estimated state of individual vehicle where $S_N(k) = \{\hat{s}_N(k), \dots, \hat{s}_N(k+P)\}$. Since the state vector of individual vehicle includes time varying continuous variables (e.g., position, velocity, current and destination lane of the vehicle) and an integer discrete variable, the optimization of both longitudinal and lateral control decision become computationally demanding and uncertain in obtaining optimal solution within a finite horizon. Therefore, based on the control requirement (i.e., longitudinal, or lateral) at a timestep respective control optimization is considered to estimate the state of the vehicles,

$$longitudinal\ control: J_{long} = \sum_{i=k}^{k+P} [v_s(i) - v_{des}]^2 + \sum_{i=k}^{k+P} a_s^2(i) \tag{5.13}$$

$$lateral\ control: J_{lat} = \sum_{i=k}^{k+P} [v_s(i) - v_{des}]^2 + \sum_{i=k}^{k+P} a_s^2(i) + \sum_{i=k}^{k+P} \theta_t(i) e^{-\alpha_t(i)\left(\frac{g_{t,lead}^2(i)+g_{t,lag}^2(i)}{2}\right)} \tag{5.14}$$

Here, v_{des} is the desired velocity that is equal to speed limit (i.e., 25m/s). The two terms in longitudinal control ensures the vehicles are driving close to desired velocity with little or no acceleration. The third term in lateral control cost function penalizes for unsafe lane changes in the form of Gaussian function. The value of coefficient α_t is measured according to (Kamal, Taguchi and Yoshimura, 2016) which defines the shape of the Gaussian function. Furthermore, planning for a lane change near the end of a horizon limit is not preferred. Since it is more likely that the predicted states of the other vehicles vary in the course, this may force the vehicle to give up on a lane change process before completion. Specifically, minimum steps to initiate a lane change can be imposed by suitably choosing δ and once the vehicle is on course to lane change, the receding horizon approach is applied for successively relaxing δ and finally executing a lane change in a predefined reference trajectory.

In each time step, the subject vehicle is provided with two sets of data: *(i) vehicle's status memory and (i) environment inputs.* The vehicle's status memory includes acceleration, velocity, position, yaw rate, lane position, destination lane information of subject vehicle for last 50-timesteps. Environment inputs include velocity, position, lane position vehicles surrounding the subject vehicle in the weaving section. With those inputs, the subject vehicle decides between longitudinal and lateral control to update the vehicle status. In regard to driver's control decisions, both longitudinal and lateral control decisions contained two states. When only the longitudinal control decision is active, the subject vehicles can be either in the *free-flow* or *car-following* state. The prerequisites of these states are listed below:

- *Free-flow* state is triggered when the upstream area of vehicle is empty, or more than enough safety gap is available for vehicle to drive at 10% higher than speed limit
- *Car-following* state is activated when there is spatial constraint due to the presence of a leading vehicles and that restricts the vehicle to drive under the speed limit

For HuVs, a discretionary lane change is initiated when the vehicle drives at 10% lower than the speed limit for 5 sec. AuVs seek lane-changing opportunities due to the possibility of forming platoons with the leading vehicle in target lane. The lateral control state is active when the subject vehicle attempts to change lane. Discretionary lane changing is omitted for weaving section in this part of the research. Due to the inherent characteristics of weaving section traffic flow pattern, it was assumed that the likelihood of vehicles performing discretionary lane changing in this roadway section would be insignificant. Therefore, only mandatory lane changing occurs based on the destination lane assigned for the vehicle, and the vehicle looking for lane changing opportunities as soon as it enters the weaving section. In the lateral control state, there are two possible scenarios:

- *Initiate* is active when enough gap is available in the target lane to change lane safely
- *Terminate* becomes active when the available gap in the target lane is not enough to safely execute lane changing. In this case, the vehicle is forced to remain in its lane.

Figure 5.1 illustrates the individual vehicle control process at every time step. The subject vehicle is programmed to search for a lane changing opportunity to *Initiate* mandatory lane changing before it *Terminates* the search due to lack of available lead and lag gap in the target lane. The subject vehicle can accept up to minimum gap between vehicles in standstill condition ($\boldsymbol{g_0}$) to execute mandatory lane changing as it approaches the end of the weaving section. Lane-changing duration and reference trajectory for modeling was calibrated by analyzing 631 events of successful lane-changing in freeway from naturalistic driving data obtained from the Safety Pilot Model Deployment (SPMD) project (Bezzina and Sayer, 2015) database. The identified mean lane-changing duration, irrespective of lane-changing type, was 2.3-sec. The duration was measured from the time when the center of gravity of the vehicle had moved from the center of the current lane to the center of the target lane. A reference trajectory was developed for all vehicles to follow during lane-changing maneuver. When the vehicle decided to *initiate* lane changing through MPC based lateral control considering relative gap in target lane, it followed the reference trajectory over the lane changing duration (2.3 sec). Both HuVs and AuVs would follow this trajectory for lane-changing purposes. Behavioral implications of HuVs on lane-changing maneuver had not taken into account in this research. Although the literature has suggested higher lane-changing duration for freeways (Tijerina *et al.*, 2005; Lee, 2006; Toledo and Zohar, 2007; Thiemann, Treiber and Kesting, 2008), the majority of these measurements include waiting time before lane changes to finding suitable gaps. Since this model considered the 5-sec time window for evaluating lane-changing warrants, the smaller active lane-changing duration is justified.

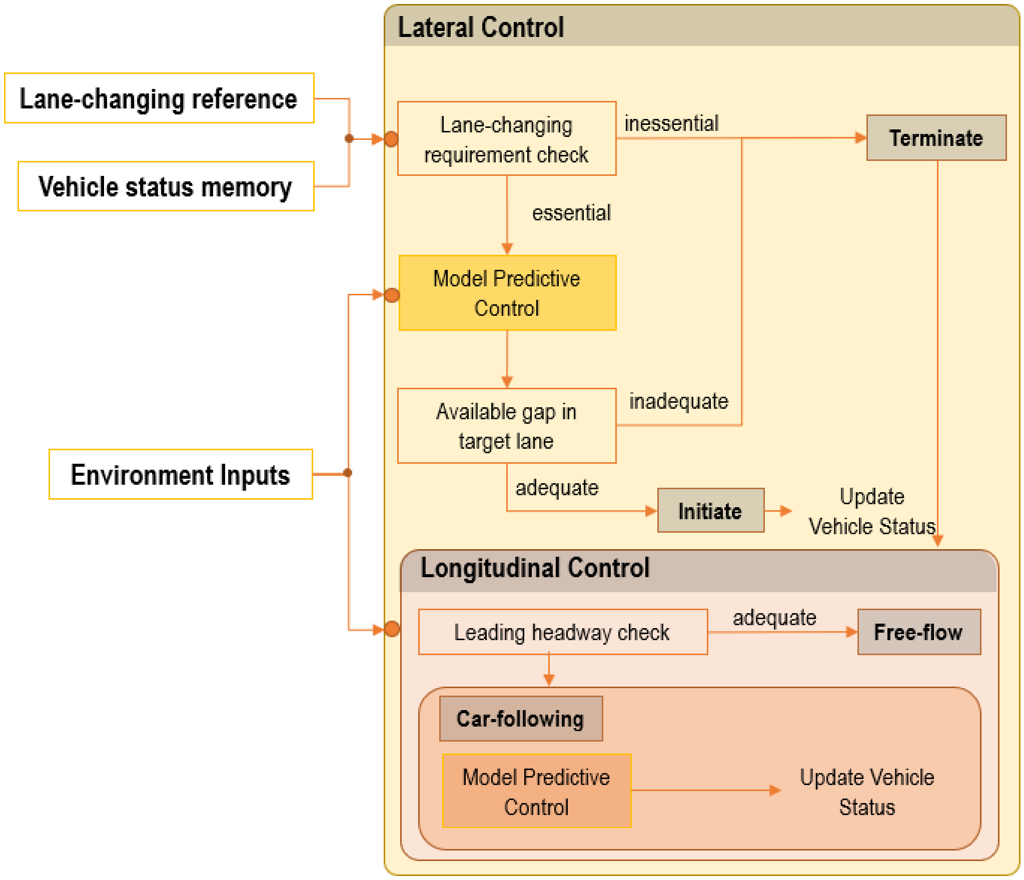


Figure 5.6 Control decision process of individual vehicle at each time step

5.3 Model Validation

According to the Highway Capacity Manual (HCM), the weaving section length varies between 150 m and 750 m. The studied roadway segment is designed as a 600-m long two-lane Type A weaving section of a freeway. The speed limit of the roadway is taken to be 25 m/s (90 kph). The lane-changing vehicle ratio (VR) was assigned to be 10% of flow rate and the destination lane of individual vehicles were assigned randomly during the entry of the simulated roadway segment. The agent-based modeling approach is taken for simulating different inflow rates and AuD shares which provides the opportunity to investigate complex interactions between two distinct groups of vehicles. HCM suggests that the weaving flow rate should not exceed 2800 vphpl for a Type A weaving section as higher inflow rate would be prone to more frequent operational failure. Although this restriction on inflow rate was imposed specifically for roadways containing only HuVs, the maximum inflow rate of simulation model was kept at 2800 vphpl since no specific instruction was provided for mixed traffic inflow rates in HCM. Since it was not established prior to the analysis that AuVs could effectively increase the vehicle movement capability of the roadway segment, increasing inflow rates over the suggested level could induce operational failure due to high inflow rates. Hence, the simulated flow rates were restricted from 1200 vphpl to 2800 vphpl with 100vphpl increment. The varying inflow rate is simulated by adjusting the average headways of vehicle entrance for both types of vehicles. AuD market share is maintained by regulating the number of AuD vehicles present at a time during the simulation. However, each inflow rate and AuD share scenario is simulated 20 times to offset the randomness of vehicle entrance pattern and human driving behavior in the simulation.

To validate the proposed traffic model, the traffic data generated by the model were compared to the standard used in HCM. Numerous simulations were run having only HuV scenarios for varying inflow rate and macroscopic parameters (i.e., flow, density, space mean speed) were recorded. All these recorded data points were then plotted to develop the fundamental diagram (i.e., flow-density diagram) and determine the segment capacity of the simulated weaving section. As illustrated in **Figure 5.2 (a)**, the fundamental diagram of the model weaving section was generated from numerous passes of developed model. **Figure 5.2 (b)** was generated from HCM that illustrates the confirmed capacity of the three-lane Type A weaving section with a 100 kph free flow speed. The capacity term was defined in HCM to be the maximum number of vehicles that can pass a given point under prevailing roadway, traffic and control conditions. Following the definition, the capacity of the simulated section was identified as 2288vph from the flow density diagram. Comparing the obtained capacity of simulated weaving section with **Figure 5.2 (b)** demonstrated that the capacity value falls near the capacity curve for VR=0.10 of the three-lane weaving section with 600 m length. Hence, the developed model was deemed to be consistent with real-world roadway and traffic scenario.

To further consolidate the model validity, the Level of Service (LOS) criteria established for the freeway weaving segment in HCM was matched with obtained model output. As stated in HCM, the capacity of a weaving segment is the result of flows that causes the density to reach Level of Service (LOS) E/F for freeways. **Table 5.1** outlines the different lane density ranges that are reported in HCM for the distinct LOS of weaving sections in freeways. The model-generated fundamental diagram exhibited the capacity at 23.81 vpkpl density level. According to **Table 5.1**, this density value falls under LOS E for freeway weaving sections and therefore complies with the requirement stated in HCM. Since the results from both analyses were found to be consistent with the expected outcome, the developed microscopic model was regarded to be an effective representation of real-world traffic and could therefore be applied for future analysis.

Table 5.1 Different Level of services depending on freeway weaving section lane density

LOS	Lane Density (vpk)	
	Freeway weaving section	Multilane and Collector-Distributor Weaving section
A	≤ 6.0	≤ 8.0
B	> 6.0 -12.0	> 8.0 – 15.0
C	> 12.0 – 17.0	> 15.0 – 20.0
D	> 17.0 – 22.0	> 20.0 – 23.0
E	> 22.0 – 27.0	> 23.0 – 25.0
F	> 27.0	> 25.0

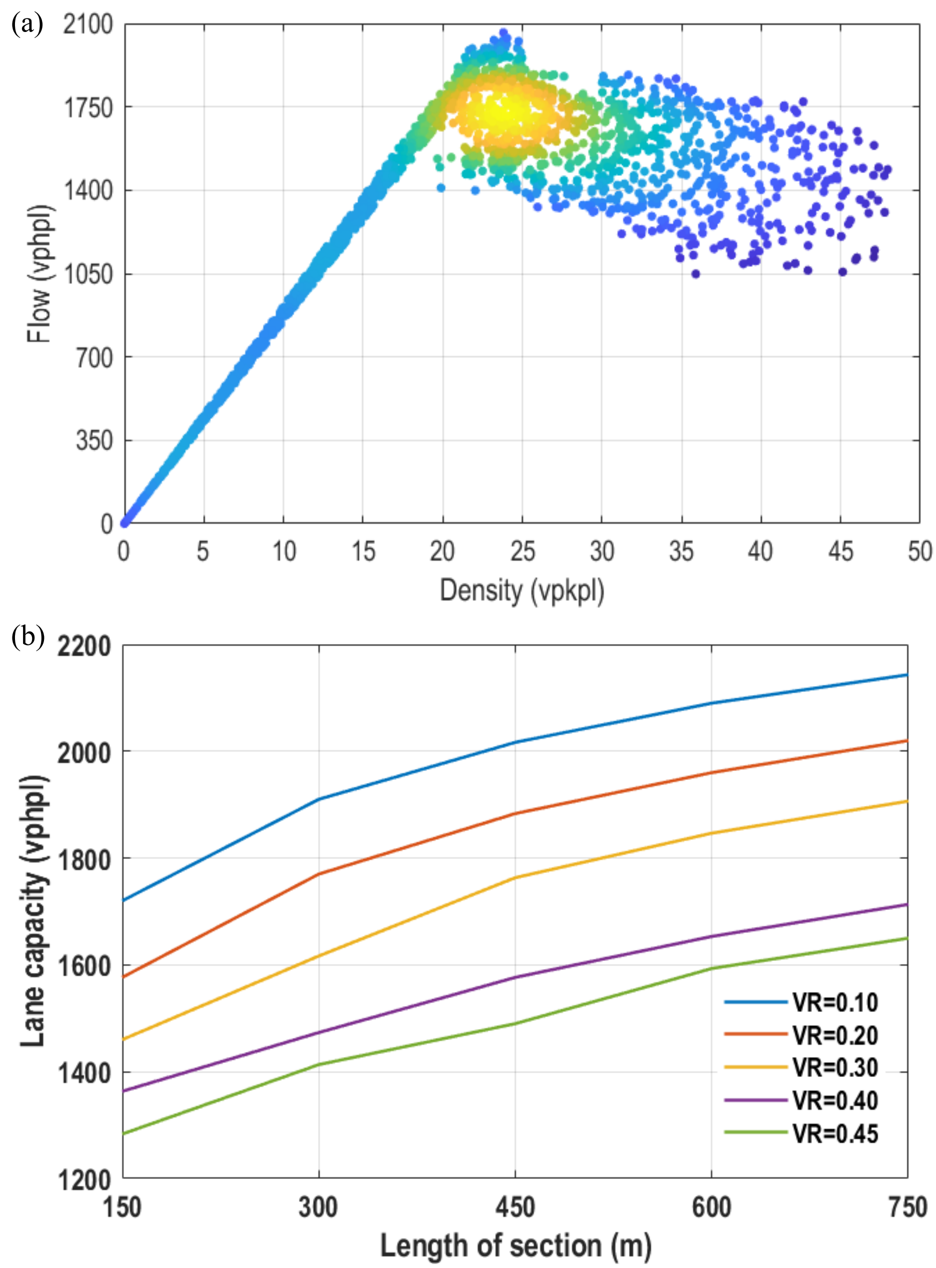


Figure 5.7 (a) Flow-density diagram from simulation runs with HuVs only, (b) Lane capacity at varying length and VR of weaving section

5.4 Mobility Implications

Chapter 4 of this thesis presented the mobility implications from mixed traffic car-following strategy through average travel time and average travel distance of all the vehicles in traffic. While both parameters were exceptionally competent in envisioning the mobility impact due to AuVs, sometimes comprehending the effective shift in mobility become complicated due to contrasting nature of these parameters. As a result, two alternative macroscopic parameters were chosen in this part of the study to quantify mobility shifts resulting from mixed traffic in weaving section. The mobility consequences resulting from mixed traffic movement was measured considering two key parameters: (i) Maximum throughput, (ii) Average speed of traffic. The inflow rate varied from 1200-2800 vphpl with 100 vphpl increment in each step. Similarly, the AuD share was increased from 5% to 95% with a 5% increment in each step. As a result, 323 unique scenarios of mixed traffic movement were generated. To account for the fluctuations resulting from driving behavioral variations of human driver as well as AuVs' location and distribution (as established in Chapter 4) on measured parameters, each simulation scenario (i.e., Inflow rate, AuV share) were repeated 20 times. The analyzed outcome from these scenarios were compared with base case (0% AuD share) to compute the consequences of mixed traffic movements. To compute the chosen mobility parameters of each scenario, the simulation period (18000-timesteps =30 minutes) was divided into six 5-min intervals and maximum/average parameter value was measured for each interval. Finally, the maximum parameter value was chosen by taking maximum of the interval values for maximum throughput and average of the interval values for the average speed of traffic.

5.4.4 Maximum Throughput

While much effort have been made (Chang and Lai, 1997; Vander Werf *et al.*, 2002; Ni *et al.*, 2010; Tientrakool, Ho and Maxemchuk, 2011; Fernandes and Nunes, 2012; Shladover, Su and Lu, 2012; van den Berg and Verhoef, 2016; Chen *et al.*, 2017; Ghiasi *et al.*, 2017; Liu *et al.*, 2018; Tilg, Yang and Menendez, 2018) to specify the impact of AuD vehicles on the maximum throughput of freeways, the variability in results kept is as an open and debated issue. Hence, this study has attempted to confront the issue with a precise scope of estimation for Type-A weaving section with 90 km/h speed limit and restricted inflow rates. The simulated scenarios varied the AuD vehicle shares from 5% to 95% to maintain mixed traffic environment and compared the performance with a base case to appraise potential changes. As portrayed in Figure 5.3(a), the variation in maximum throughput was non-linear and much greater due to variations in AuD vehicle share than inflow rate changes. Maximum detriment in throughput was experienced at 10% AuD share (-3.88%, 1981 vphpl@ 1400 vphpl inflow rate) and maximum gain was attained at 65% AuD share (80.49%, 3720 vphpl @ 2200 vphpl inflow rate) in comparison to base case (2061vphpl). We compared our attained results with Tilg et al (Tilg, Yang and Menendez, 2018) where they evaluated the effects of automated vehicles in the capacity of freeway weaving sections. Their study found that the maximum throughput of the simulated weaving section increased from 1700 vphpl @0% AuD to 3300 vphpl @100% AuD (94.12%). Although a comparable level of increase was observed in this study, the maximum increase in throughput was observed at a lower AuD share (65%). Recently, Rezaei and Caulfield (Rezaei and Caulfield, 2021) drawn similar conclusion from their study where optimal mobility was achieved for both off-peak and peak traffic scenarios at 60% AuV shares. Attained maximum throughput for increasing AuD shares were further compared with the analysis of Liu et al. (Liu *et al.*, 2018), which estimated theoretical capacity of homogenous freeway sections resulting from mixed traffic. The following equation was applied to calculate the theoretical capacity at varying AuD shares:

$$Q_{max} = \frac{3600}{P_{AuD(l)} \times HW_{AuD(l)} + P_{AuD(f)} \times HW_{AuD(f)} + P_{HuD} \times HW_{HuD}}$$

$$P_{AuD(f)} = \delta \times \delta$$

$$P_{AuD(l)} = \delta(1 - \delta)$$

$$P_{HuD} = 1 - P_{AuD(f)} - P_{AuD(l)}$$

Here, $P_{AuD(l)}, P_{AuD(f)}, P_{HuD}$ are the probability of any vehicle being AuD vehicle platoon leader, follower, and HuV, respectively; $HW_{AuD(f)}, HW_{AuD(l)}, HW_{HuD}$ are average safety headways of AuD vehicle platoon leader (i.e. 1.25 sec), follower (i.e. 1.0 sec), and HuV (i.e. 1.5 sec) respectively; δ is AuD vehicle share. Comparison between the theoretical capacity with the highest maximum throughput value for specific AuD share displayed a similar pattern up to 65% AuD share (Figure 5.3(b)). While theoretical capacity showed an increase, the simulation results demonstrated a steady decline. This phenomenon can be explained by the fact that our inflow rate was bounded at 2800 vphpl based on the HCM guideline that could restrict potential gains. Additionally, in the simulation, both vehicle types were designed to lane-change in same trajectory with similar acceptable gap and safety headway conditions that could play a critical role in restricting maximum throughput after a threshold AuD share. At higher AuD shares, platoons formed by AuD vehicles reduced lane-changing scopes for the remaining HuVs and forced them to form larger gaps between platoons to execute mandatory lane changes in weaving sections.

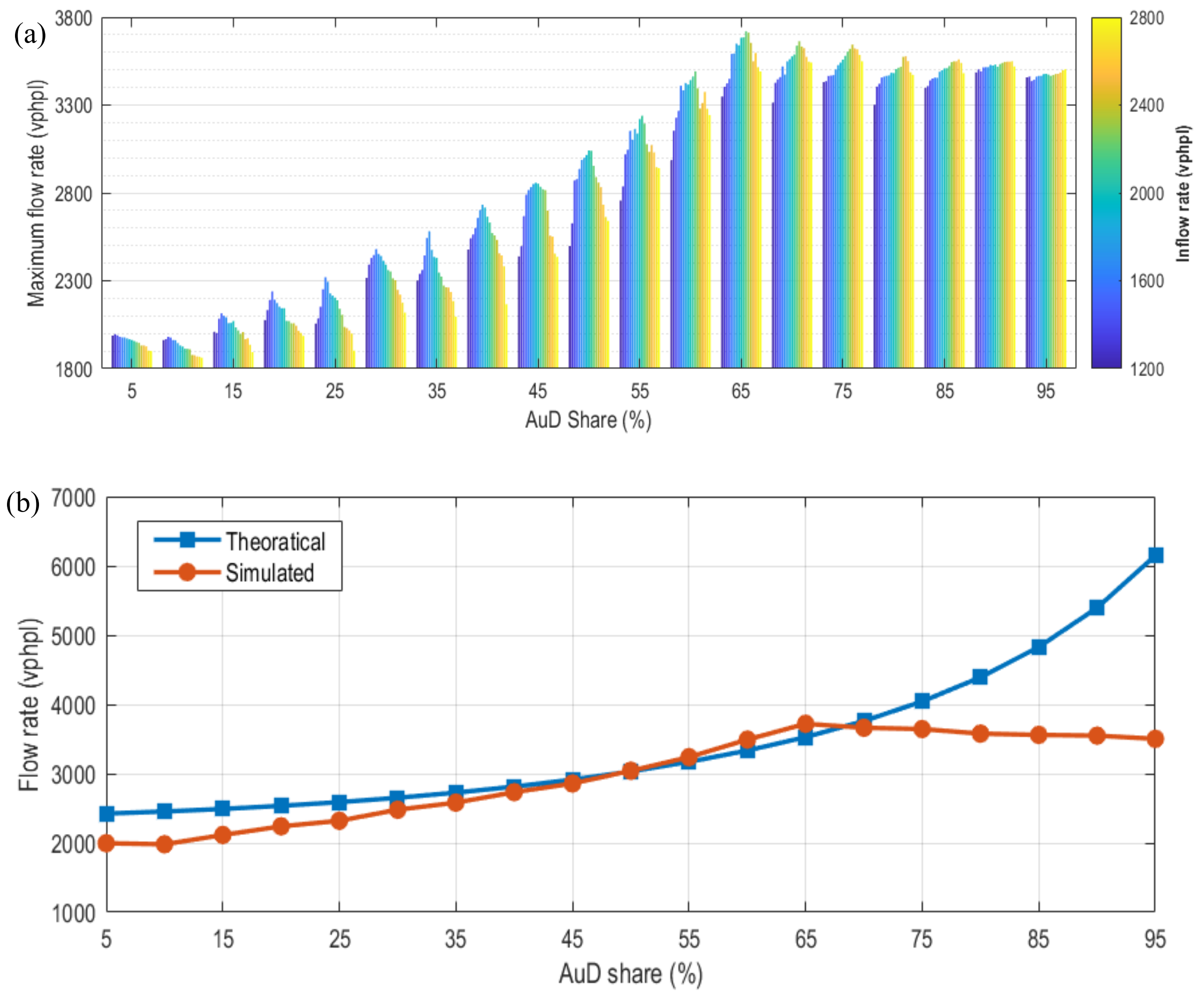


Figure 5.8 (a) Maximum flow rate through weaving section at various traffic state, (b) Comparison between theoretical and simulated maximum flow rate for mixed traffic

Analysis of maximum throughput fluctuations due to varying inflow rates at a specific AuV share identified the highest variations at 45% AuV share, which gradually receded with gradual increase of AuV shares. In addition to behavioral variations of human drivers, which represented by desired headway parameter of HuVs, the competing lane-changing opportunity searches by both vehicle types reached maximum level once the traffic reaches at equitable shares of AuVs and HuVs. This explains the highest variation at 45% AuD share and lower variations at higher as well as lower AuD shares.

5.4.5 Average Speed of Traffic

One of the key indicators of mobility is the average speed of traffic since an increase in average speed of traffic can be interpreted as a reduction in travel time for the traffic and vice versa. Furthermore, an experimental study conducted by Jiang et al. (Jiang *et al.*, 2018) specifically with AuVs forming a 51-vehicle platoon indicated that traffic (in)stability could be better reported through average traffic speed than traffic density or spacing. In this regard, the average space mean speed of the weaving section was measured for each simulated scenario. Figure 5.4 illustrates the obtained average speed outcomes for different simulated scenarios. As observed in Figure 5.4 (a), the average speed of traffic resulting from various inflow rates were highly dispersed at the lower AuD shares (5-20%). Each black dot for a specific AuV share represents the average speed at a specific inflow rate. The average speed value of a certain scenario (i.e. inflow rate, AuV share) was obtained by taking average speed of all the repeated simulation run for that scenario. On the other hand, with increasing AuD shares, the resultant average speed became increasingly concentrated, shifting towards the speed limit. The dispersion of average speed at lower AuV share indicated instability in traffic flow resulting from sparsely spaced AuVs in traffic. The instability of traffic at lower AuV shared were also translated into lower maximum throughput at similar AuV share, as presented in last sub-section. However, with gradual increase of AuVs brought more stability which was perceivable from more compact average speed distribution of traffic. Figure 5.4 (b) provides a clearer demonstration of interaction between inflow rate and AuD shares with average speed of traffic. Although, the changes in average speed of traffic at the lower inflow rate was negligible, reductions in the average speed at lower AuD shares was prominent at high inflow rates. The comparison of mixed traffic scenarios with base case average speed (82.75 kph) obtained a maximum reduction of 11.53 kph at 20% AuD share and 2700 vphpl inflow rate and a maximum increase of 7.22 kph at 95% AuD share and 2400 vphpl inflow rate. It should be noted that both types of vehicles were simulated to attain the desired speed, which was the speed limit (90 kph). Therefore, the maximum possible increase in average speed was 7.25 kph within the design framework.

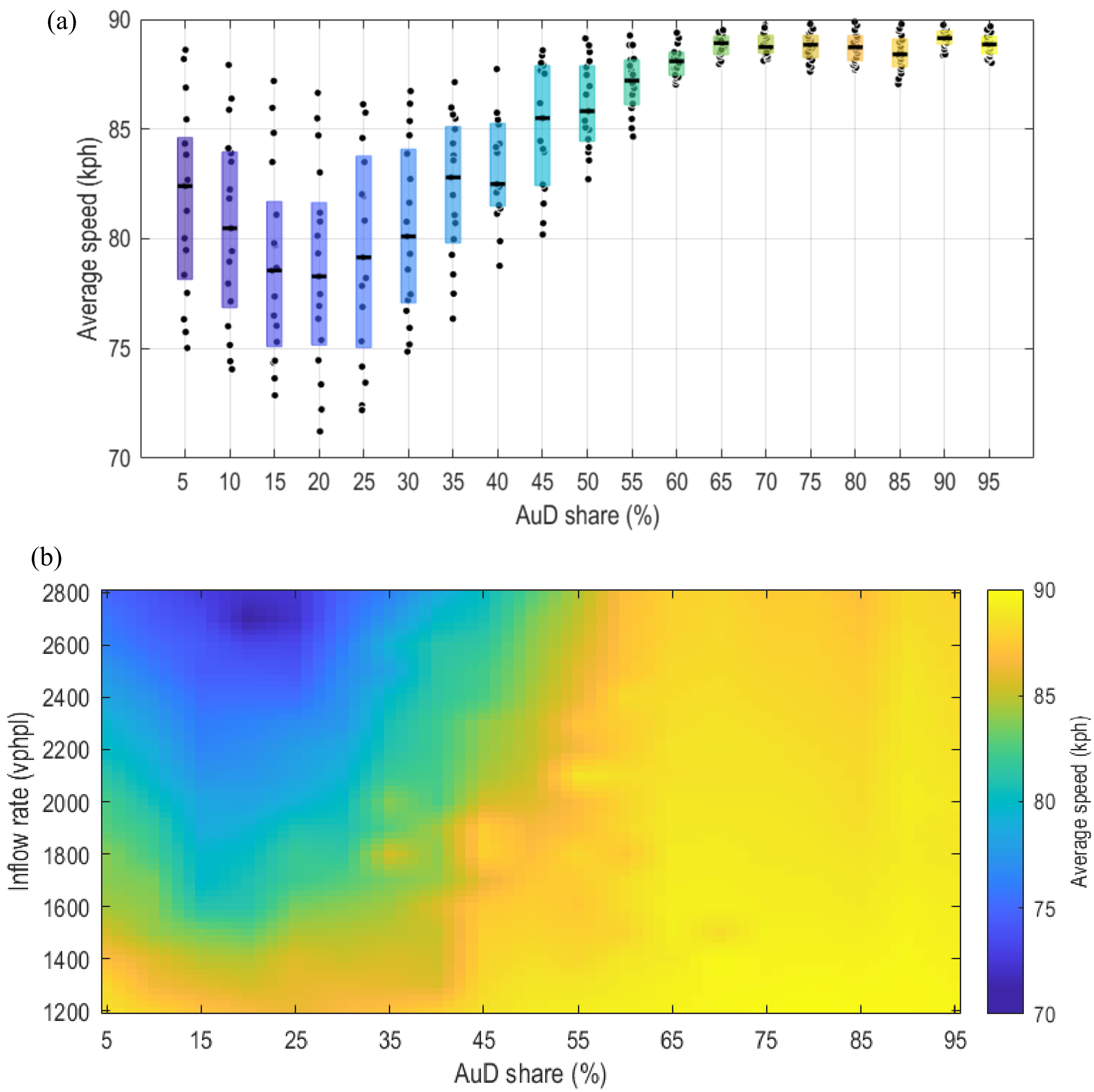


Figure 5.9 (a) Average speed of weaving section for simulated mixed traffic scenarios, (b) Average speed heatmap for varying inflow rates and AuD shares

Liu et al. (Liu *et al.*, 2018) noted an insignificant improvement at lower market share compared to drastic improvement at higher market share. However, the study considered market share at 20% increments, which limits the understanding for AuD shares with more nuanced increments. In contrast to Liu et al, the findings from this study experienced slower traffic movements at lower AuD shares in high traffic demand. These events could have been triggered by dispersed positioning of AuD vehicles in traffic that were unable to form closely spaced CACC platoons with other AuD vehicles. As a result, these isolated AuD vehicles had to maintain ACC driving principles while accommodating lane changing vehicles at high inflow rate. Tilg et al.(Tilg, Yang and Menendez, 2018) mentioned that these gap-searching vehicle, specifically HuVs, related to speed attenuation until they engaged in successful lane changing maneuvers. The gradual increase of the AuD share improved platoon forming probability that lead to more stable traffic movement and is analogous to the findings by Talebpour and Mahmassani (Talebpour and Mahmassani, 2016). Those authors demonstrated the instability in traffic flow resulting from lower connected and automated vehicle shares. On the other hand, Spiliopoulou et al. (Spiliopoulou *et al.*, 2018) concluded that almost all congestion of the studied corridor could be eliminated at 60% market penetration. Our study also demonstrated a similar pattern since the average speed over the simulation duration of most scenarios beyond 60% market share was close to the speed limit.

5.5 Safety Implications

Traffic safety assessment is vital when analyzing unfamiliar transportation system performance. The developed microscopic simulation framework provides the opportunity to perform elaborate safety implications analysis on simulated mixed traffic scenarios without physically implementing the AuD vehicles in transportation system. However, two major limitations of simulation models are the discounting of collision events among simulated vehicles and the inability to simulate human drivers' distraction and misjudgment errors. Hence, the safety analysis of simulated models is dependent on interpreting and comparing surrogate measures of safety. In this research, we have used Time-to-collision (TTC) as the primary measure of effectiveness for safety as its use in the capacity has significant precedence in the literature. Safety critical TTC events were detected from simulated scenarios with maximum throughput and then translated into relatable safety parameters such as potential conflict events and rear-end crash potential.

There are four types of vehicle interaction scenarios in a mixed traffic environment: HuV with HuV (potential) leader (HuV-HuV), HuV with AuV (potential) leader (HuV-AuV), AuV with HuV (potential) leader (AuV-HuV) and AuV with HuV (potential) leader (AuV-AuV). However, any commonly accepted threshold of surrogate measure of safety is yet to established for AuV in the literature. Hence, in this study, author only examined the interactions of HuV with other HuV and AuV leader for potential conflict identification. Since the market share of AuVs changes with different scenarios, the crash risk rate for HuVs, along with conflict frequencies are used to identify safety implications of AuV in mixed traffic environment.

5.5.1 Potential Conflict Events

TTC, defined as the expected time for two vehicles to collide if they remain on the same path at the same speed, is a widely used surrogate safety measure. The Surrogate Safety Assessment Model (Gettman *et al.*, 2008) suggests 1.5 sec TTC as the threshold value for identifying potential safety concerns from a simulation environment; this which was adopted in our research to extract the number potential conflict events from simulated scenarios. The identified potential conflict events were classified into two collision groups: (i) rear-end and (ii) lane changing. To classify the potential conflict type, the driving state of the subject vehicle was checked. If the TTC value fell below the threshold during *free-flow* or *car-following* longitudinal control state, then it was classified as rear-end conflict event. On the other hand, if the TTC value fell below the threshold during *initiate* lateral control state, then it was classified as lane-changing conflict event. The following equations were used to measure and identify a potential conflict event:

$$CE_s(k) = \begin{cases} 1 & if\ TTC_s(k) \leq 1.5 \\ 0 & otherwise \end{cases}$$

$$TTC_s(k) = \frac{x_{s-1}(k) - x_s(k) - L}{v_s(k) - v_{s-1}(k)} = \frac{g_s(k)}{v_s(k) - v_{s-1}(k)}$$

Here, $CE_s(k)$ is the conflict event count of the subject vehicle, *s* at time step *k*. x_i, v_i, g_i represents *i* vehicle's position, velocity and lead gap (current lane) respectively. Since the simulation was repeated several times for specific traffic flow scenario (i.e. inflow rate, AuV share), the average conflict events from all the repetition was reported for the specific scenario to reduce the stochastic effects resulting from behavioral variation of HuVs as well as placement changes of AuVs. Since the threshold TTC value for identifying the conflict events were lower than the desired headway of AuVs (i.e., ACC = 1.25 sec, CACC platoon = 1.0 sec), the conflict events emerged from AuVs were disregarded from total conflict events computation. Hence, the identified conflicts were generated exclusively from HuVs interacting with other HuVs and AuVs in vicinity.

Figure 5.5 showed the pattern of traced potential conflict events at varying traffic states. It is evident that as the AuD share increased, there was a clear and significant decrease in conflict event counts. The summation of potential conflict events, irrespective of inflow rates, was found to be 94.28% lower at 95% AuD share (186 conflict events; 42 rear-end, 144 lane-changing) in comparison to the base case (3249 conflict events; 1238 rear-end, 2011 lane-changing). The gradual decline of conflict events experienced an exponential pattern with AuD share expansion [Figure 5.5(a-f)]. While larger shares of the conflicts were found to be lane-changing (base case: 38.1% rear-end, 61.9% lane-changing), presence of AuD vehicles were relatively more proficient in mitigating rear-end type conflicts (95% AuD share: 22.6% rear-end, 77.4% lane-changing) by HuVs.

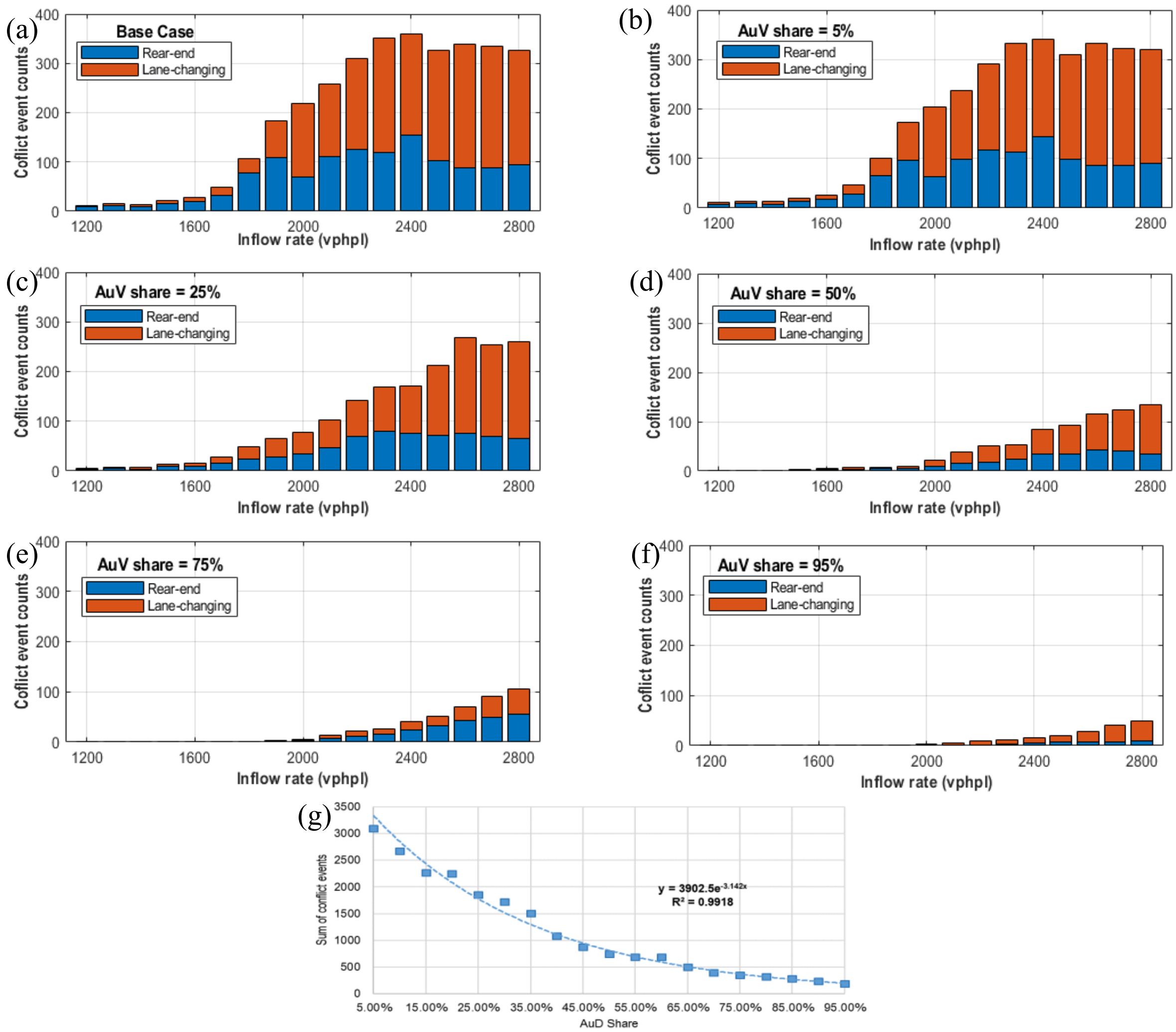


Figure 5.10 Counts of detected conflict events at (a) base case (0%), (b) 5%, (c) 25%, (d) 50%, (e)75%, (f) 95% AuV share, (g) Pattern of total detected conflict events at increasing AuD share

The potential conflict events were further explored by the proposed methods of Oh and Kim (Oh and Kim, 2010) to estimate the crash risk index (CRI) from the TTC values in the analyzed roadway segment. While obtaining deterministic control state of each individual vehicle was possible under the current modeling framework, the probabilistic estimation of lane-changing decisions was retained to maintain the novelty of the proposed method. The following equations were used to determine the crash risk index of a certain traffic scenario:

$$P(Cr_s)(k) = P(NLC_s|X_s)(k) \times P(NLC_{s-1}|X_{s-1})(k) \times P(C_s|TTC_s)(k)$$

$$\mathrm{P(NLC_s = 1|X_s)(k)} = \frac{\exp[f(X_s, \beta)]}{1 + \exp[f(X_s, \beta)]}$$

$$= \frac{1}{1 + \exp(11.476 - 0.045v_s(k) - 0.083v_t(k) - 0.046g_s(k) + 0.023g_t(k))}$$

$$\mathrm{P(C_s|TTC_s)(k)} = \exp\left(-\frac{1}{c}\left(\frac{g_s(k)}{v_s(k) - v_{s-1}(k)}\right)\right)$$

$$\mathrm{P(Cr_s)(k)} = \left[\frac{\exp[f(X_s, \beta)]}{1 + \exp[f(X_s, \beta)]}\right] \times \left[\frac{\exp[f(X_{s-1}, \beta)]}{1 + \exp[f(X_{s-1}, \beta)]}\right] \times \exp\left[-\frac{1}{c}\left(\frac{g_{s-1}(k)}{v_s(k) - v_{s-1}(k)}\right)\right]$$

$$CRI_i = \frac{\sum_{s=1}^{S}\sum_{t=1}^{T} P(Cr_s)(k)}{K \times S}$$

Here,

- x_i, v_i, g_i represents *i* vehicle's position, velocity, and lead gap (current lane) respectively
- $P(Cr_s)$ is the probability that the subject vehicle would be involved in a rear-end crash
- $P(NLC_s = 1|X_s)$ is the probability that the subject vehicle will not change lanes (NLC) under adjacent (i.e., *s-1, t, t-1* vehicles) vehicle conditions [Figure 5.6(a)]
- $P(C_s|TTC_s)$ is the probability that the subject vehicle would collide with the front vehicle given the current TTC
- CRI_i is the crash risk index of scenario *i*
- K is the total time steps of analysis
- S is the number of vehicles passing through the weaving section

Further details and parameter values are available in (Oh and Kim, 2010). Applying this method, the CRI values for each of the mixed traffic simulation scenarios (i.e., Inflow rate, AuD share) was measured from identified potential conflict events. TTC values more than the threshold TTC (i.e., 1.5 sec) were discarded from the CRI calculation. For each traffic state (i.e., inflow rate, AuV share), the simulation instances with maximum numbers of potential conflict events were chosen to measure CRIs and plotting them, illustrated in Figure 5.6. As is evident in Figure 5.6(b), the overall CRI showed non-linear downward trend with increasing AuD shares. The maximum CRI was experienced at 5% AuD share (average =0.0207 standard deviation = 0.0143), which reduced significantly at 95% AuD share (average= 0.0019, standard deviation = 0.0014). At 5% AuD share, the average reduction in the CRI from the base case (Average CRI = 0.0218, standard deviation = 0.0149) was 4.82% that gradually increased to a 91.35% reduction at 95% AuD share. For specific AuD shares, the CRIs experienced an upward trend with increasing inflow rates. Findings from this analysis were conform to the findings of Papadoulis, Quddus, and Imprialou (Papadoulis, Quddus and Imprialou, 2019),Ye and Yamamoto (Ye and Yamamoto, 2019), and Rahman and Abdel-Aty (Rahman and Abdel-Aty, 2017) who all concluded, based on different sets of parameter analysis, that increasing AuD vehicle share could greatly improve traffic safety conditions.

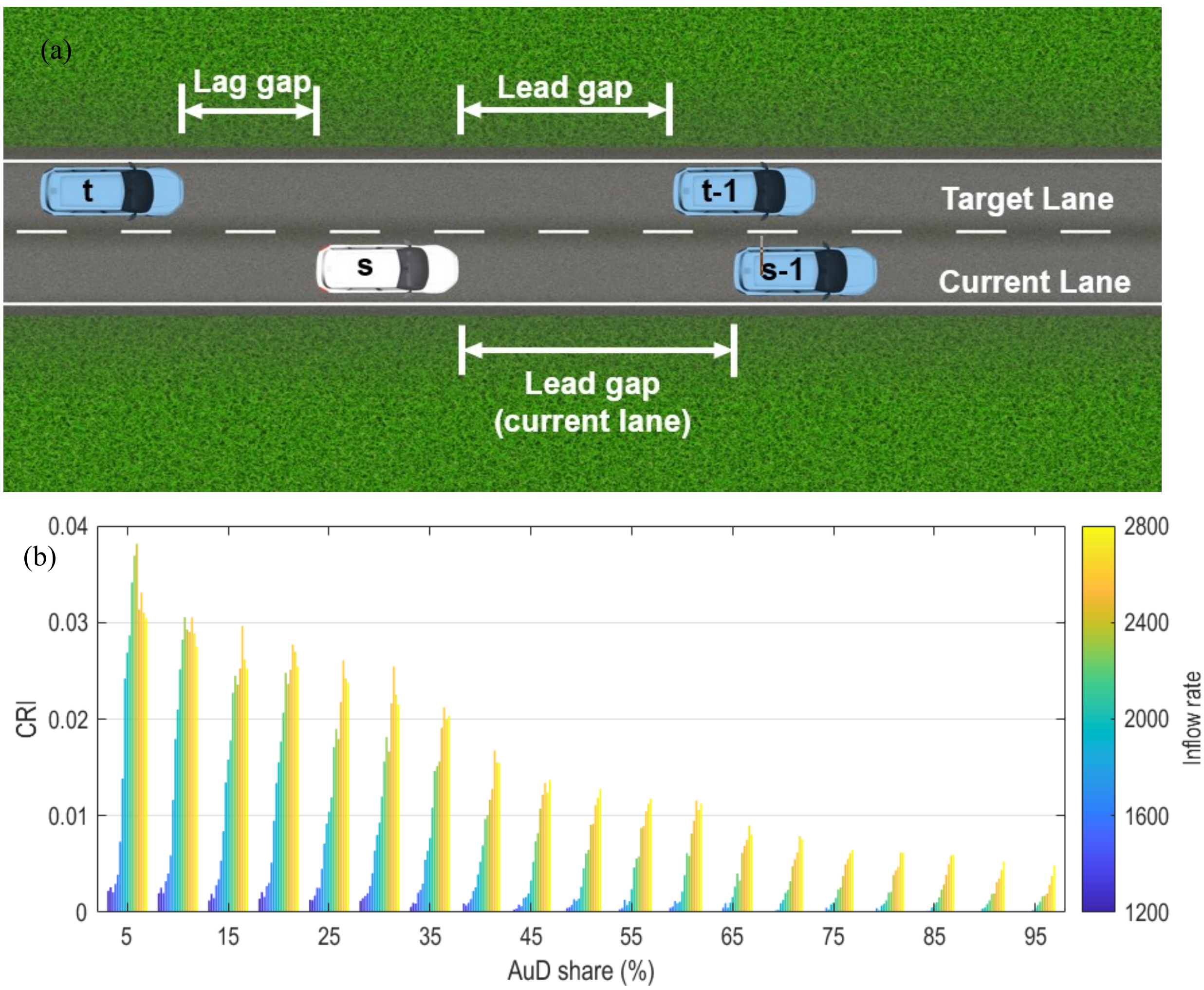


Figure 5.11 (a) Subject vehicle's perspective of decision parameters, CRI values for simulated traffic states considering (b) all vehicles

While both analyses so far showed significant improvements in overall traffic safety with gradual increase of AuV shares, the findings were incomprehensible when it comes to determine the implications of AuVs on HuVs' perceived safety. Since the movements of AuVs were regarded as safe, irrespective of TTC values, due to their instantaneous response capability, overall reduction of potential conflict event and crash risk of entire traffic with increasing AuV shares were anticipated. Hence, an adjusted CRI values were measured by considering only the number of HuVs passing through the weaving section to obtain more profound insights. The analysis results are presented in figure 5.7. As portrayed in this figure, the CRI from human drivers' perspective did not present as straight forward improvements as the pervious analysis. While the pattern of higher CRI with increasing inflow rate persisted for a specific AuV share, the reduction of CRI with increasing AuV share was renounced. Minimum average CRI for HuVs' were experienced at 70% AuV share (0.0083) with minor changes until this point. However, the HuVs encountered substantially higher safety issues at high inflow rate from 75% AuV share and upwards. (at 5% AuV share), The maximum CRI at 95% AUV share was 0.0966 that occurred at 2800 vphpl inflow rate which was more than two-times higher than maximum CRI (0.0401) at 5% AuV rate. While the overall reduction in CRI until 75% AuV share was rather moderate, the increment in CRI for HuVs were more drastic at high inflow rate with higher AuV shares.

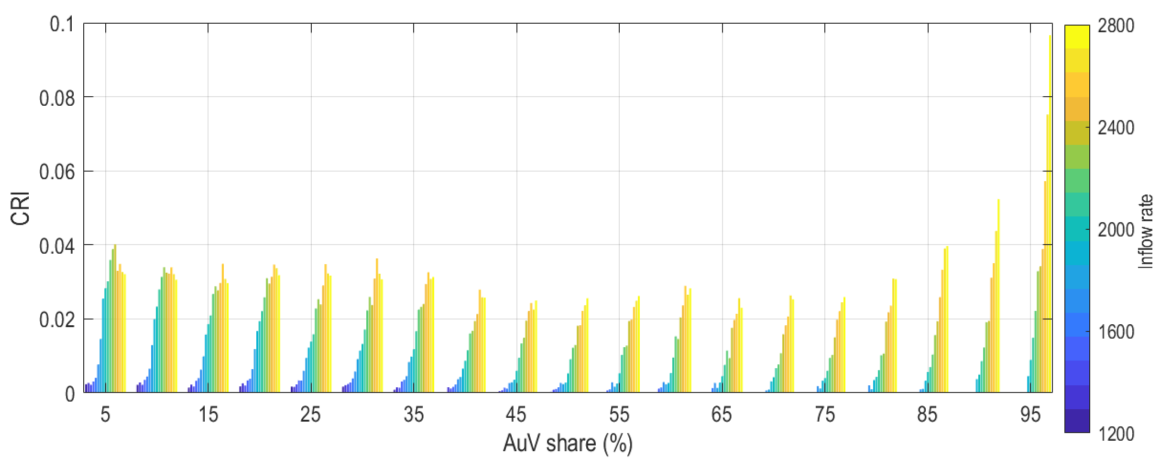


Figure 5.7 CRI values for simulated traffic states considering HuVs only

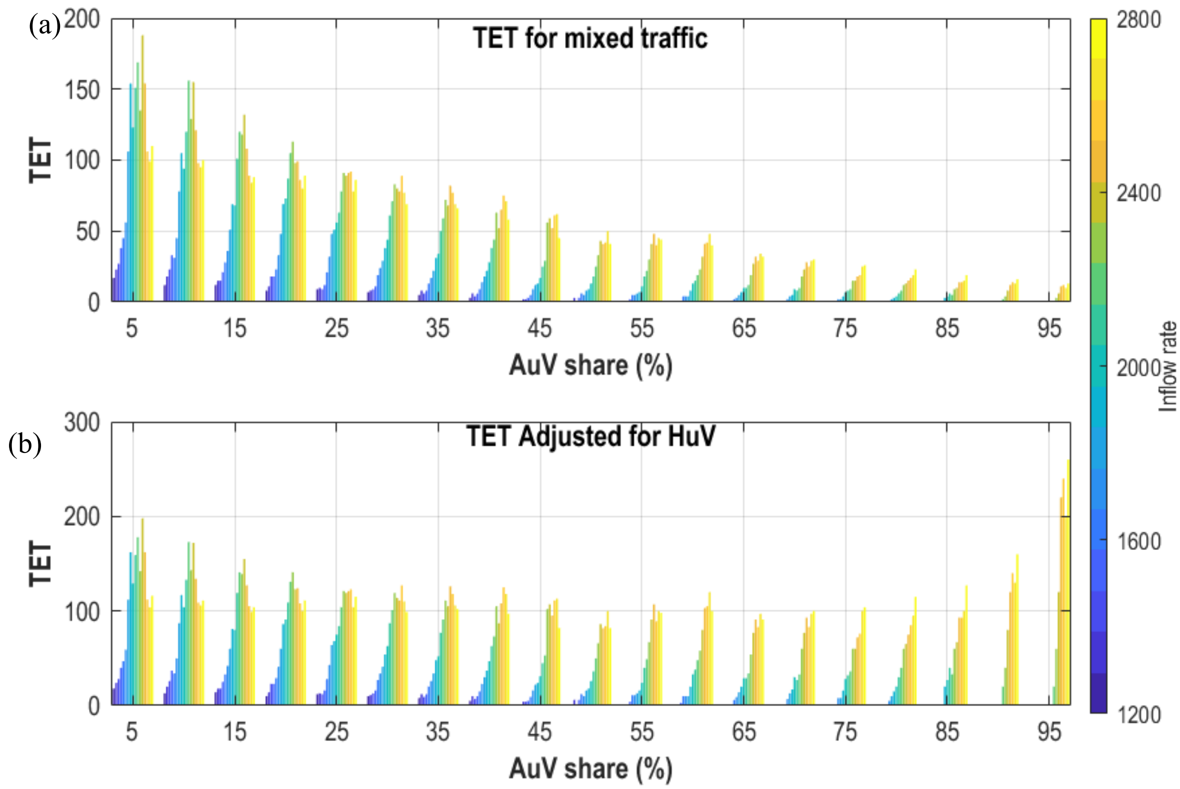
5.5.2 Rear-end Crash Potential

As presented in Chapter 4, Time Exposed Time-to-collision (TET) and Time Integrated Time-to-collision (TIT) are derived from TTC to perform as surrogate measures of safety for vehicles at risk for rear-end crash. TET and TIT was introduced by Hayward, Minderhoud and Bovy (Hayward, 1971; Minderhoud and Bovy, 2001) and being widely used in traffic safety literature to evaluated rear-end crash potential at a traffic scenario. TET is the summation of instances where TTC are lower than threshold value. In previous sub-section, the conflict events were identified in similar manner. However, the difference between the identified rear-end conflict events and TET measurement for rear-end crash potential stems from the fact that multiple consecutive TTC values of subject vehicle lower than threshold TTC was counted as single potential in conflict event identification process. On the other hand, individual time step is considered TET calculation. Therefore, higher TET value could be observed with lower rear-end conflict events which would indicate higher safety concerns. TIT measures the value of TTC lower than threshold TTC. Similar to TET, lower TIT value is expected at safer traffic conditions. The values of these parameters were measured using the following equations:

$$TET_i = \sum_{s=1}^{S} TET_s, \quad TET_s = \sum_{k=1}^{K} \delta_k \Delta k, \quad \delta_k = \begin{cases} 1 & \forall\ 0 < TTC_s(k) < TTC^* \\ 0 & else \end{cases} \tag{3.9}$$

$$TIT_i = \sum_{s=1}^{S} TIT_s, \quad TIT_s = \sum_{k=1}^{K} [\frac{1}{TTC_s(k)} - \frac{1}{TTC^*}] \,.\, \Delta k \quad \forall\ 0 < TTC_s(k) < TTC^* \tag{3.10}$$

Here, TET_i and TIT_i are the TET and TIT values for traffic scenario (i.e. inflow rate, AuV share) i, TET_s and TIT_s are the TIT and TIT values for subject vehicle s, TTC^* is threshold TTC (1.5 sec according to (Gettman *et al.*, 2008)) , $TTC_s(k)$ is TTC of subject vehicle *s* at time step *k*. Aligned with previous safety analysis, this analysis measured the TET and TIT values of simulated traffic for all 323 studied scenarios. For each scenario, the simulation instance with maximum throughput was considered for analysis. Both TET and TIT were not only counted for mixed traffic volume over the duration but also adjusted for changing HuV proportions of traffic to make equitable comparison. As observed in figure 5.8 (a, c), both TET and TIT of mixed traffic gradually decreased with increasing share of AuVs. Generally, on a specific AuV share, TET and TIT for mixed traffic increased experience increasing pattern with increasing inflow rates. This pattern for a specific AuV share persisted through adjusted TET and TIT (Figure 5.8 b, d) which were made to account for gradually diminishing shares of HuVs in traffic. Nevertheless, the changes in adjusted TET and TIT due to increasing AuV shares were dissimilar to what was noted for mixed traffic scenario. Although the TET and TIT was reduced considerably from the perspective of mixed traffic volume, these parameter values rather increased once considered from the perspective of only HuVs, particularly at high AuV shares.



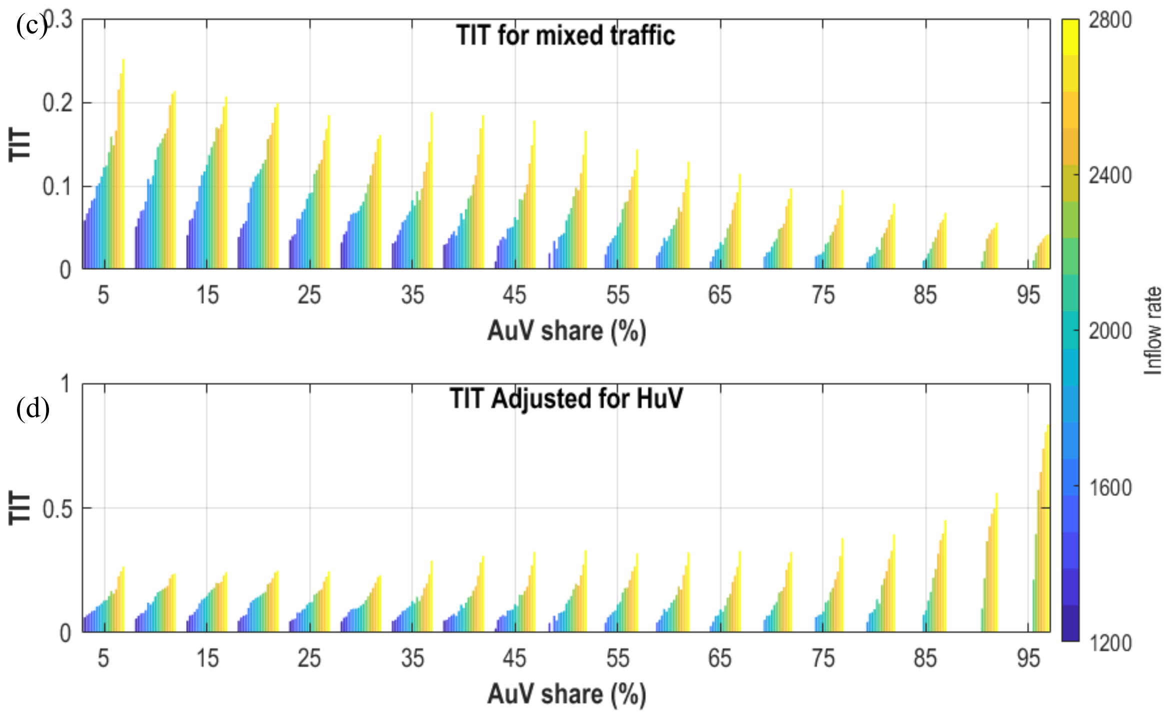


Figure 5.8 TET and TIT values in different traffic states for (a, c) total traffic, (b, d) HuVs only

This analysis demonstrated the dichotomy of crash potential due to change in perspective. In plain sight, both TET and TIT showed significant reduction (from average TET =100 and TIT = 0.1318 at 5% AuV share to average TET= 3.3 and TIT = 0.0124 at 95% AuV share) for the mixed traffic passing through the weaving section. However, in-depth observations to these parameters from HuVs' perspective revealed stark dissimilarity at higher AuV shares (from average adjusted TET = 105 and TIT = 0.1388 at 5% AuV share to average adjusted TET = 65.88 and TIT = 0.2472 at 95% AuV share). It is also important to note that rear-end crash potential was nonexistent for majority (1200 – 2100 vphpl) of the simulated inflow rate. Hence, the increasing trend in rear-end crash risk by HuVs were pushed by extensive AuV presence at high inflow rates. Moreover, the analysis disclosed the ineffectiveness of AuVs to influence perceived safety of HuVs at high inflow rates in weaving section, even with leading market share.

5.6 Maximizing Combined Mobility and Safety Implications

Due to complex correlation of simulated traffic scenarios (i.e., inflow rates, AuV shares) with mobility and safety implications, developing a closed form of objective function to attain combined optimal benefits is considerably convoluted and time consuming. Hence an alternative approach of iterative search with meta-modeling is taken in this study. Meta-modeling is a macro-modeling method of used in literature (Vlahogianni, Karlaftis and Golias, 2005; Forrester, Sobester and Keane, 2008; Boschian *et al.*, 2011; Vlahogianni, 2015) that aims to build simple and computationally inexpensive models that replicates the correlations that are observed when samples of a complex, high-fidelity model or simulation are drawn. Meta-models are often referred as approximation, surrogate, response surface models. Different meta-modeling techniques include generating analytically inexpensive approximation of computationally intensive true response through different machine learning methods such as: polynomial interpolation, support vector regression, kriging, neural network etc. (Hussain, Barton and Joshi, 2002; Queipo *et al.*, 2005; Jakobsson *et al.*, 2010; Gosavi, 2015). This approach has been commonly used for solving simulation-based optimization and analytical dynamic equilibrium problems in transportation applications. The goal of including this modeling in this research is to produce faster and simpler approximation of a simulation generated results to make multi-objective optimization, design space exploration etc. feasible.

Mobility and safety scores were calculated for the range of simulated traffic scenarios from the attained parameter values of chosen mobility and safety parameters. To attain a balanced mobility benefit, both the average travel time and average travel distance were leveraged to calculate mobility scores. Safety scores were achieved by measuring the reduction of CRI from the base case. The following equations were used to measure the mobility and safety scores of each inflow rate and AuD share scenario:

$$MS_{(i,j)} = \sum_{t=1}^{T} \left[\rho_{(i,j)}(t)\left[v_{SL} - v_{i,j}(t)\right] - \rho_{(i,0)}(t)\left[v_{SL} - v_{(i,0)}(t)\right]\right]$$

$$SS_{(i,j)} = CRI_{(i,0)} - CRI_{(i,j)}$$

Here, $MS_{(i,j)}, SS_{(i,j)}$ are mobility and safety scores for inflow rate *I* and AuD share *j*; $\rho_{(i,j)}(t), v_{i,j}(t)$ are the traffic density and average traffic speed at the weaving section at timestep t for inflow rate I and AuD share j; $\rho_{(i,0)}, v_{(i,0)}$ are the traffic density and average traffic speed at the base case (0% AuD share); v_{SL} is the speed limit of weaving section. For a better performance by the machine learning algorithm, both scores were scaled within 0 to 1 range as they would be supplied as training and testing samples of a neural network. The neural network was developed in MATLAB with Inflow rates and AuD shares as input and corresponding mobility and safety scores as output. 70% samples were used for training and remaining samples were used for testing purpose. A Bayesian regularization algorithm was chosen with 20 hidden layers. The performance of each iteration was measured by mean squared error. Final model comparison between predicted vs expected values showed $R^2 = 0.9884$ for training samples and $R^2 = 0.9786$ for testing samples. The purpose of developing such meta-models were to regress the response surface that characterizes the correlation between decision variable inputs (i.e., inflow rates, AuV shares) and simulation outputs (i.e., mobility, safety score).

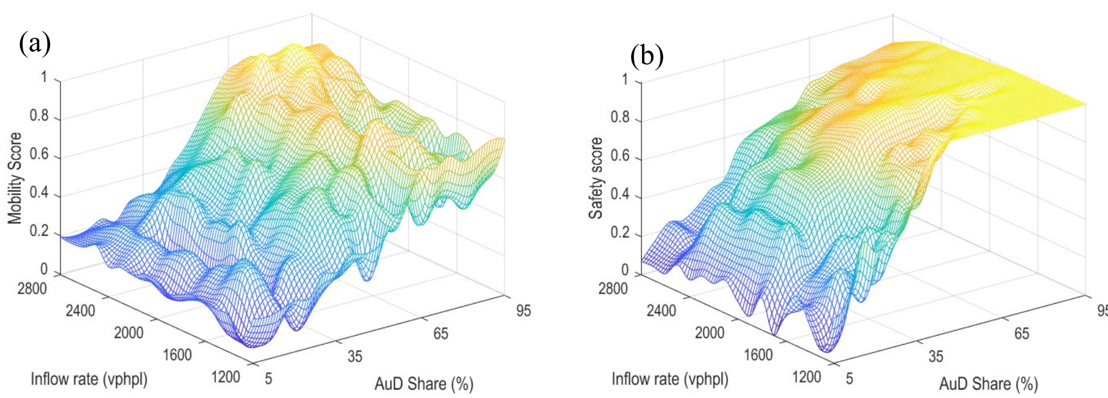


Figure 5.9 (a) Mobility scores, (b) Safety scores for varying inflow rates and mixed traffic scenarios

The finalized training model was then applied to obtain scaled mobility and safety scores for specific inflow rates and AuD shares in the weaving section. Furthermore, the model imparted optimal AuD share information to achieve maximum combined mobility and safety benefits for the specified inflow rate. Suppose the upstream average flow rate of the weaving section 1760 vphpl and AuD share of the traffic is 46%. The model provided the expected mobility and safety scores, which were $MS_{(1760,0.46)} = 0.5651$ and $SS_{(1760,0.46)} = 0.8810$. For the same upstream average flow rate, the combined mobility and safety impact would be maximized by AuD share of 64.5% ($MS_{(1760,0.645)} = 0.7849$, $SS_{(1760,0.645)} =$

0.9385). This information would be critical for traffic operation and management authorities to impose controls enabling inflow rates and AuD share to attain more efficient flow and safer traffic movements through weaving sections that could act as potential bottlenecks of the freeway network.

5.7 Conclusion

This chapter proposed a microscopic modeling framework of mixed traffic that was applied to a freeway weaving section. Multifaceted traffic scenarios of mixed traffic were simulated for the weaving section, a combination rarely explored in the literature so extensively. The modeling framework built on MPC-based decision-making principles that accounted for the anticipative aspects of human drivers. This modeling capability can be attributed to lateral control decisions and control model transitions of both vehicle types. Specifically, the anticipatory lane-changing decision while perceiving the future status of neighboring vehicles and reference lane changing trajectory built upon empirical observations were the cornerstone of reproducing realistic traffic states for a multilane roadway. In this study, the simulation results contributed to understanding the effects of AuD vehicles on traffic mobility and safety as well as validating the findings from previous relevant studies, such as Tilg et al. (Tilg, Yang and Menendez, 2018), Liu et al. (Liu *et al.*, 2018), Spiliopoulou et al. (Spiliopoulou *et al.*, 2018), Papadoulis, Quddus, and Imprialou (Papadoulis, Quddus and Imprialou, 2019), Ye and Yamamoto (Ye and Yamamoto, 2019), and Rahman and Abdel-Aty (Rahman and Abdel-Aty, 2017). While the findings were consistent with these research efforts, this research contributes to the body of knowledge by several issues including dichotomic interaction between mobility and safety in mixed traffic, pseudo safety perception with higher AuV shares and meta modeling to attain equitable mobility and safety advantage from AuV presence in weaving section.

Analysis results revealed that low AuD vehicle share at high inflow rates could have an adverse impact on mobility of the weaving section. This finding was critical for the weaving section due to the distinct and preemptive lane-changing activity experienced in this freeway segment. Safety features of traffic in weaving sections were found to be exponentially associated with AuD vehicle shares. While increasing traffic demand could raise safety concerns at any level of AuD vehicle presence, the range of potential conflict levels was found be substantially reduced with higher AuD vehicle shares. Finally, the simulation results were assembled together to develop an assistive application for traffic operation and management authorities that can aide traffic state evaluation from both a mobility and safety perspective; the application can also seek optimal levels of AuD vehicle presence to maximize the impact. Altogether, the analysis results were reported with the goal to provide some clear insights into the implication of AuD vehicles on weaving section traffic mobility and safety as well as clarify the transformation of mixed traffic flow dynamics with the gradual adoption of AuD vehicles under the current traffic system.

Future research includes further expansion of human driving behavior and the identification of resulting variations. Furthermore, we will continue the research by considering different platoon strategies as well as distinguishing the impact of different platoon structures and varying human behavior. While this study examined the mobility and safety implications for traffic containing two types of vehicles, the mixed traffic scenario will be enhanced to address HuVs with an advanced driver assistance system that aims to improve driving efficiency without absolute reliance on automaton.

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CHAPTER 6 : CONCLUSION

6.1 Research Summary

According to SAE level of automation, full automation can only be achieved at level 4 and 5 of automation where the vehicle will be in full control. In other levels of automation human driver has the capability to intervene or the responsibility to take driving decision. Therefore, driving behavior identification is extremely essential to reach level 4 and 5 of automation. Furthermore, in mixed traffic stream (i.e., traffic stream that contain both autonomous and human driven vehicle), human driving behavior identification is important for automated vehicles to anticipate potential hazardous situation as well as to adapt with human driving pattern while sharing the road. In this premise, the entire research is divided into three distinct phases. The first phase of this thesis examines naturalistic driving behavior of human drivers to obtains insights about variations and complexity involving human counterpart of mixed traffic. Additionally, novel driving behavior classification method was proposed for two distinct duration perspective by combining longitudinal and lateral control decisions of human drivers. The analysis was performed using different sensory data, so the results don't take into account the quality of the signals, but more likely the quantity of available data. Author assumed that available dataset that was collected for analysis from USDOT website was checked and rectified for any deficiencies. The threshold-based labeling was performed in scaled driving feature (i.e., jerk, yaw rate, leading headway) data. The ranges of these features vary with different road class and exogenous factors. The choice of the threshold value was made through observations and informed assessment from literature review of similar approaches of behavioral classification (Langari and Won, 2005; Won and Langari, 2005; Murphey, Milton and Kiliaris, 2009; Vaitkus, Lengvenis and Zylius, 2014; Shi *et al.*, 2015; Wang *et al.*, 2017). Finally, the author proposed a human-machine interface to transmit the classification information with the aim to positively influence the control decision making of the driver. The backhaul communication architecture was not considered within the scope of this research.

In the second phase of the research, the foundation of microscopic simulation framework was laid to evaluate mobility and safety implications of mixed traffic movements. This part of research was focused on dominant maneuver in vehicle motion dynamic (i.e., car-following) and proposed a strategy to execute mixed traffic movement in a single stream of traffic. The authors attempted to identify the impact of AuVs location and distribution on remaining HuVs acceleration characteristics. Furthermore, different platoon structures were examined to evaluate the influence of varying platoon configurations on expected mobility and safety benefits. Maximum Platoon Length was restricted by several factors such as: DSRC communication range, platoon stability, V2V communication structure, lane changing maneuverability etc. While Maximum Platoon Lengths can be up to 10 or 20 vehicles by minimizing communication delay and optimal design of vehicle control system, the requirement to provide enough lane changing gaps in later part of the research restricted the parameter value (i.e. maximum platoon length) (Shladover et al., 2015). To evaluate mobility implications due to AuVs, two key parameters were used in this phase, average travel time and average travel distance. Due to conflicting characteristics of these two parameters, a mobility score was established to assess the combined impact through a single parameter. Results from mobility analysis indicated positive correlation between platoon structure (i.e. intra-platoon headway, inter-platoon headway and maximum platoon length) with mobility improvement. Hence, roadway segments with predominant car-following maneuver could be benefitted operationally from closely spaced platoons formed by AuVs. On the other hand, the safety implications were measured by time-to-collision, time exposed time-to-collision, time integrated time-to-collision parameters which represents rear-end collision expectations due to car-following. Afterwards, a single parameter, named as safety score, was established to capture the overall safety impact of AuVs on simulated traffic. Analysis results suggested that smaller platoon lengths with widely spaced AuVs would induce greater safety benefits from mixed traffic. Finally, a method to identify sub-optimal platoon structure from candidate structures was applied to attain balanced mobility and safety benefits from mixed traffic movement.

Final phase of the research incorporated complete motion dynamics of both vehicle types to estimate expected mobility and safety implications. Additionally, the focus of the research was concentrated to a specific configuration of weaving section, in order to deliver fairly accurate evaluation as well as contribute to the body of knowledge by examining a congestion prone yet rarely studied roadway segment. This part of thesis included lateral motion dynamic with already established longitudinal strategy of mixed traffic. Insights obtained regarding behavioral variations of human drivers were integrated in motion dynamics of HuVs to reproduce comparable real-world inconsistency in simulated environment. Afterwards, developed model was validated through highway capacity manual suggested macroscopic parameters for similar roadway configurations. The developed model was simulated for several combinations of HuVs and AuVs to get an enhanced understanding about mobility and safety implications on studied roadway section. To reduce the complexity of interpreting the results, the traffic volume ration between mainline and ramps were kept invariable throughout the simulation scenarios. Changing this ratio could generate dissimilar outcome from the same simulation model. The mobility implications of the simulated scenarios were measured through maximum throughput and average speed of traffic. Results of maximum throughput analysis indicated that maximum benefits from AuVs presence could be obtained at 65% AuV share in traffic. While theoretical computation of maximum throughput (Liu *et al.*, 2018) showed gradual increase with increasing AuV shares, the restricted inflow rate, due to suggested guidelines by Highway Capacity Manual, could induce limiting maximum throughput at lower AuV share. In addition to maximum throughput analysis, average traffic speed analysis provided impartial assessment of AuVs' mobility implications. Results of the analysis indicated speed harmonization of traffic at higher AuV market shares (> 60%) with some level of disturbance at lower market shares (5-20%). Since the inherent characteristics of weaving section demands higher than normal lane-changing maneuvers among the vehicles, some level of disturbance due to the presence of AuVs were expected due to unfamiliar attributes of both vehicle types. On the other hand, safety implications were measured through two parameters: potential conflict events and rear-end crash potential. Potential conflict events were identified for each simulation scenarios (i.e. Inflow rate, AuV shares) to identify the pattern and extent of prospective implications. Results from these analyses illustrated progressively reduced conflict events with gradual increase of AuV market shares. Finally, a machine learning-based method was put forward to identify the AuV share corresponding to maximum combined mobility and safety benefits for prevailing inflow rate in the studied weaving section. The method was developed from recorded mobility and safety implication results obtained simulated traffic flow scenarios which finally provided estimates of expected mobility and safety benefits from existing AuV share in current traffic flow rate.

6.2 Fundamental Contributions

The value of the research depends on significant contribution made by the findings from research to the body of knowledge as well as for practical application. Each phase of this thesis aimed at making meaningful contribution to the existing literature and practice as well as paving the road of advancing AuVs integration with traditional roadway and transportation system. The following two sub-sections have listed the key scientific and practical contributions made through this research.

6.2.1 Scientific Contributions

In the first phase of this research (Chapter 3), the analyses were initially focused on determining the behavioral heterogeneity of human drivers with the intention to rationalize the significance of anticipating such inconsistencies while estimating expected benefits from AuVs in mixed traffic scenarios. Neglecting such key aspect of HuVs could lead to erroneous assessment of AuVs impact on traffic and eventually results in improper policy decision making as well as resource allocation. While several previous studies identified and classified behavioral variations of human drivers, handful of studies analyzed for naturalistic driving data of such extent with different road classes as well as accounted for bi-directional control behavior of human drivers. Selecting features to represent car-following and lane-changing behavioral pattern of human driver and leveraging these feature profiles to classify driving behavior on different classes of roads allowed this research to make novel contribution to existing literature. Behavioral classification of human drivers was extended further with this research effort by considering two different time scales to apprehend the process of instantaneous driving behavior becoming driving habit with passing time. Previous research efforts were limited to identifying individual trip behavior of human drivers and often overlooked the gradual progression of trip behavior towards driving habit. Reviewing this progression of driving behavior is important from mixed traffic perspective, since AuVs might persuade the driving behavior of human counterpart to bring positive changes for short and long-term driving behavior.

Second phase of this research (Chapter 4) dealt with achievable mobility and safety implications derived from shared presence of AuVs and HuVs. In this part of the research car-following maneuver of vehicle motion dynamics was the sole consideration. Although car-following alone is unable to completely explain the complexity of driving conditions in mixed traffic scenarios, this maneuver formulates the majority share of driving task in naturalistic driving conditions. As a result, a car-following strategy was proposed in this phase for mixed traffic to evaluate the impact on overall mobility and safety. While the car-following strategy was adapted from a previous study, the application of this strategy to quantify mobility and safety impact was a novel contribution. The foundation of microscopic modeling was laid by developing the framework for two vehicle types traversing an uninterrupted roadway section without passing each other. At this phase, human drivers were regarded to demonstrate identical car-following behavior since the behavioral influence of human behavior would impose a unique challenge in estimating obtainable benefits from mixed traffic. Therefore, the obtained variations in mobility and safety was generated exclusively from positional and configurational difference among the studied vehicle types in the simulation which highlighted the warrants to consider this component of expected implications into consideration. Majority of the previous studies either disregarded the impact resulting from vehicles' orientation or accumulated with human behavioral component while estimating the AuVs effects on mixed traffic. To expand the analysis from vehicle component, this part of the research also explored the influences of AuVs placement in traffic stream on overall traffic flow efficiency. Different complex platoon structures formed by AuVs were reviewed and influences of these platoons were measured to identify suitable AuVs placements and platoon configurations to attain favorable impact on mobility and safety at different traffic flow scenarios (i.e. inflow rate, AuV share). This study confirmed reciprocal correlation between mobility and safety benefits resulting from increasing AuV presence in traffic. However, it's worth pointing out that the estimated mobility and safety implications were calculated disregarding the expected behavioral variations of human drivers. Due to the absence of complex behavioral heterogeneity, the derived results from analyses were easily interpretable and justifiable. Excluding the human behavioral component at this stage of the research allowed us to appraise the importance of behavioral variation in estimating the potential benefits in the final phase of the research.

The final phase of this research (Chapter 5) centered around a specific roadway section (i.e. weaving section) of freeway in transportation network which is usually vulnerable to recurrent congestion due to the natural traffic flow characteristics of this section. Despite numerous efforts in the literature to identify the impacts of AuVs on freeway mobility and safety, insufficient documentation was available prior to this study about the implications on this pivotal component of freeway system. In addition to emphasizing on a critical roadway segment, this study also incorporated complete motion dynamic of both vehicle types to formulate a complete microscopic modeling framework with CACC-based platoon formation among AuVs. Insights obtained from first phase of the research on human driving behavior was also integrated at this phase. Developing such comprehensive modeling framework offered the opportunity to in-depth exploration of mobility and safety consequence of AuVs on numerous traffic flow scenarios. This research proposed an approach to demonstrate the variations in potential effects of AuVs on weaving section operation from both mobility and safety perspective while considering the variations in driving behavior by their human counterpart. To the best of author's knowledge, no prior effort was made in this specific direction of research. Hence, this research provided a direction to move forward for the future research attempts as well as some benchmarks for mobility and safety parameters to compare the research output with complex real-world traffic operations.

This research effort was a unique approach in integrating real-world complexity with numerical simulation to attain valuable insights about potential implications of AuVs on freeway weaving section mobility and safety performance. The findings obtained from this research will impact both academic and industrial progression of AuV progression in the future.

6.2.2 Practical Contributions

Besides the contributions of this thesis on scientific sector, the findings from this research also make valuable contributions the society and practice. The results of this research can be deemed beneficial for policymakers, transportation planners, roadway infrastructure designers, traffic operation authorities and road users.

The integration of naturalistic driving behavior and realistic CACC-platoon structure within a singular microscopic modeling framework provides an effective simulation to to evaluate mobility and safety impact of AuVs in various traffic scenarios. This transferrable numerical simulation structure can be calibrated to replicated traffic characteristics of different freeway segments including multiple driving modes which is advantageous for policymakers and traffic operators to examine the consequences of introducing various levels and configurations of CACC-platoons in mixed traffic before promoting this technology for large scale deployment.

The estimated mobility implications at different AuV market shares are fundamental and of significant importance for transportation planning and management authorities. Given that studied mobility parameters (i.e., Maximum throughput, Average speed of traffic) illustrated strong reciprocity with AuV presence in traffic, roadway operator may consider proactive management strategies to adapt the flow characteristic. Additionally, transportation planners and operator can contrive strategies to artificially increase AuV shares given that adverse mobility impact was observed at low AuV shares. Meanwhile, roadway infrastructure designers may need to adjust the geometric design of roadway segments to maintain homogeneity in roadway capacity considering the different levels of capacity increments resulting from AuV presence.

The combined implications of AuVs on mobility and safety can be communicated to road users for clarifying the significance of this technology in overall improvements of traffic operations. The speed homogeneity and increased capacity achieved at higher market shares of AuV can offer more reliable travel experience for road users. Furthermore, the benefits derived from reduction of rear-end crash probability at any level of AuV share and traffic demand are undeniable. Successful interpretation and communication of the insights obtained from this research can educate road users to be more receptive to this new technology while being mindful of potential shortfalls.

6.3 Key Limitations and Future extension opportunities

Most of the research efforts are constrained by some form of systemic limitations. This research was not exempted from such limitations. Although this research made some valuable contribution to the body of knowledge, there are a few key limitations that restricted the far-reaching applications of the obtained knowledge. Some of the key limitations of the study is listed below:

- First major limitation of the study sets the premise of future stuides which is the lack of field experiment opportunity. Large scale operation of AuVs is still unachievable. Furthermore, small scale experimentation with AuVs is highly restricted within access-controlled testing locations. As a result, this study adopted features and characteristics assumed in other AuV studies to simulate the motion dynamics of AuVs in mixed traffic scenarios.

- The dataset used for behavioral classification contained 63 different features of individual driver at each time step. Among these features, only three features were carefully chosen to represent drivers' intentions and control decisions. Incorporating more features in the analysis would definitely increase the complexity of the process with the odds of refining the classification process. An approach of incorporating multiple features in driving behavior classification process was undertaken by Tawfeek and El-Basyouny (Tawfeek and El-Basyouny, 2020).
- In the second phase of this research, a synthetic leading vehicle trajectory was developed to perform numerical simulation which might not be representative of the real-world scenario. However, the purpose of the proposed trajectory of the leading vehicle of the traffic stream was to explore different driving scenarios (i.e. acceleration, steady state, deceleration) experienced by the vehicles in a traffic stream.
- The proposed microscopic modeling framework for mixed traffic disregarded few implications in real-world motion dynamics such as: string stability, concave-convex car-following pattern, cut-in vehicles, inconsistent gap-acceptance from individual human driver etc. By ignoring these phenomena of real-world traffic movement, the research focused in more wholistic and system level approach.
- In the communication state between vehicles, it was assumed that the vehicle status could be communicated among vehicles instantaneously without any error. Therefore, real-world impediments like vehicle actuation delay, communication delay, lost data packet issues were disregarded.

6.4 Conclusion

This research is the outcome of recognized gap in existing literature to obstruct the progress of Connected-Automated vehicle technology for the future of transportation system. While this technology comes with promises to overcome major limitations of traditional transportation system and infrastructure, the actual effects depend on planned implementation and integration with existing transportation system. This research explored the influence of AuVs on mobility and safety for mixed traffic operation in a freeway weaving section which was uncharted in the literature and contributed to the knowledge base. The modeling framework built in this research can be implemented for other roadway segments for mixed traffic simulation. Integration of behavioral component of human drivers in the modeling framework by studying naturalistic diving behavior is an added feature of the developed model which can generate more scattered but realistic evaluation of mixed traffic operations.

The findings from this research enhanced the appeal of Connected-Automated vehicle technology from both mobility and safety perspective. The mobility improvements measured through the increase in capacity and average speed of traffic. Overall mobility improvements at high market shares of AuV is encouraging for policymakers to support this technology. This also pointed out some mobility detriment at lower market share since adjustments were required to be made by both AuVs and HuVs to accommodate each other. Hence, transportation authorities and policy makers can prepare for these initial obstacles while integrating and expanding the technology with traditional transportation system. On the other hand, the inclusion of AuVs in traditional transportation system advertently improved the safety performance of traffic. This study only analyzed potential rear-end type conflicts resulting from mixed traffic movements to evaluate safety performance. Analysis results indicate substantial reduction of potential conflicts with the increasing AuV shares in traffic. Findings regarding safety is favorable to introduce AuVs in existing transportation system to avail safer traffic movements.

Although the generalized findings of this research deemed favorable towards AuVs, the outcomes of this research are subject to the developed modeling framework and assumptions made in the simulation scenarios. Future research efforts can extend this premise by challenging the model assumptions, addressing the limitations, and focusing on experimental data collection to examine the findings of this research. Additionally, new control strategies and AuV control dynamics can be tested to address the adverse mobility implications of mixed traffic at lower AuV shares. This study can be further extended by introducing assisted driving vehicles in mixed traffic scenarios where human drivers can utilize advanced driver assistance system to make more informed control decision while driving. Since, the behavioral pattern of assisted driving system is still unknown, this type of driving system was disregarded in this study. In summary, this study unlocked the possibilities to prolong this direction of research in multiple dimensions and provide answers to the unknowns about this new technology.

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