ESTIMATION OF THE CAPACITY OF A BASIC FREEWAY AND WEAVING SEGMENT UNDER TRADITIONAL, AUTONOMOUS, AND CONNECTED AUTONOMOUS VEHICLES, USING OVERSATURATED TRAFFIC CONDITION DATA

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DOCTOR OF PHILOSOPHY

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ABSTRACT

Autonomous vehicles (AVs) and connected autonomous vehicles (CAVs) will be the standard in transportation in the future. The use of such vehicles could minimize traffic oscillation and travel time and boost safety and mobility on freeways. An AV is a self-driving vehicle that can make decisions by itself in any situation. CAVs include all the characteristics of AVs and additional communication with other vehicles or the infrastructure (signal system). The use of AVs and CAVs will substantially increase motorway capacity in upcoming decades. Moreover, vehicle dynamics will change as technology and algorithms become more commonplace. In the short term, capacity may have a negative impact on talent; however, as the algorithms become more aggressive, the results will improve.

Highway Capacity Manual (HCM) may need to be updated if freeway system capacity changes. As a result, the manual should focus on enhancing two freeway segments: the fundamental freeway portion and the weaving part (case study on U.S. 101 in Los Angeles, California). A microsimulation program developed by the Planung Transport Verkehr (PTV) in Karlsruhe, Germany, was used to calibrate and evaluate Wiedemann's behavioral car-following model (CFM). The Coexist project from Europe created three types of autonomous cars: AV-cautious, AV-normal, and AV all-knowing.

CFMs are vital because they measure the distance between vehicles. This is crucial for capacity. The capacity of AV cautious vehicles is decreased at all levels and penetrations. When AV-cautious autonomy evolves into AV all-knowing autonomy, the capacity of the weaving section and the BFS may rise by 33% and 36%, respectively.

This study provides a method for evaluating the capacity of freeways, which we estimate using AV levels and penetrations. Transportation planners and traffic engineers may utilize these

capabilities to design better traffic planning and traffic-management technology in the future. For example, highway capacity will be restricted if the AV mix is largely AV-cautious. However, the solution is likely not to expand capacity but to find ways to manage traffic as new technology develops and moves to CAVs. This research aids in the planning and design of how to bring AVs and CAVs to market.

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Furthermore, Dr. Amiy Varma helped me develop the model over the past several years. I want to express my gratitude for their continued faith in me and for guiding me to achieve my goal.

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DEDICATION

I dedicate my dissertation to my beloved parents, wife, and parents-in-law. Without their sacrifice, this achievement would have been impossible.

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LIST OF ABBREVIATIONS

AV .... Autonomous Vehicle

CAV .... Connected Autonomous Vehicle

NGSIM .... Next-Generation Simulation

BFS .... Basic Freeway Segment

CFM .... Car-Following Model

ACC .... Adaptive Cruise Control

CC .... Calibration Component

FFS .... Free-Flow Speed

OPDV .... Opening Velocity Difference

CLDV .... Closing Velocity Difference

HGV .... Heavy Goods Vehicle

SMS .... Space Mean Speed

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1. INTRODUCTION

1.1. Background

The definition of roadway capacity is the maximum durable flow rate at which vehicles can reasonably be expected to travel a point or uniform section of a lane or road in prevailing physical, environmental, traffic, and control conditions over a particular period (Highway Capacity Manual, 2010). This definition of capacity was developed in a standard shape based on discussion and research that began in 1950 to answer the following questions (Roess & Prasssas, Uninterrupted Flow, 2014):

1. In what units should the capacity be measured?
2. Over what period should the capacity be measured?
3. How should the characteristics of the highway be defined, and what attributes of the highway will affect the value of capacity?
4. What operating characteristics define the occurrence of capacity?
5. How should capacity be measured?

Based on the answers, the unit of capacity is the number of vehicles per hour, measured on a saturated section of road that sustains this condition for at least 15 minutes. The original measurement came from the speed vs. flow graph by Greenshields (Greenshields, 1935), where the optimum flow is the capacity. However, the capacity definition has been upgraded and is currently suitable for a 2,400 hr/lane (ln) deterministic value. Some base conditions, such as no heavy vehicles; the driver population, composed primarily of regular users familiar with the facility; and a minimum lane width of 12 ft (HCM, 2010), have also been included in the definition. The Highway Capacity Manual (HCM) sets the capacity value for free flow at 55, 60, 65, and 70–75 mph.

A freeway consists of basic freeway, weaving, merging, and diverging segments. The basic freeway segment (BFS) is the part of the freeway where traffic flows longitudinally with or without lane changing, following the speed–flow relationship; in Figure 1, Lanes 1, 2, 3, and 4 are BFSs. A weaving section forms when a diverging ramp closely follows a merging ramp. In this segment, the vehicle moves from ramp to freeway and freeway to ramp. In Figure 1, weaving is occurring in Lanes 3, 4, 5, and 6, and the vehicles in those lanes are referred to as weaving vehicles, while the others are called non-weaving vehicles. As a result, the ratio of weaving to non-weaving vehicles plays a significant role in weaving flow. Moreover, the length of the weaving section affects assessing capacity.

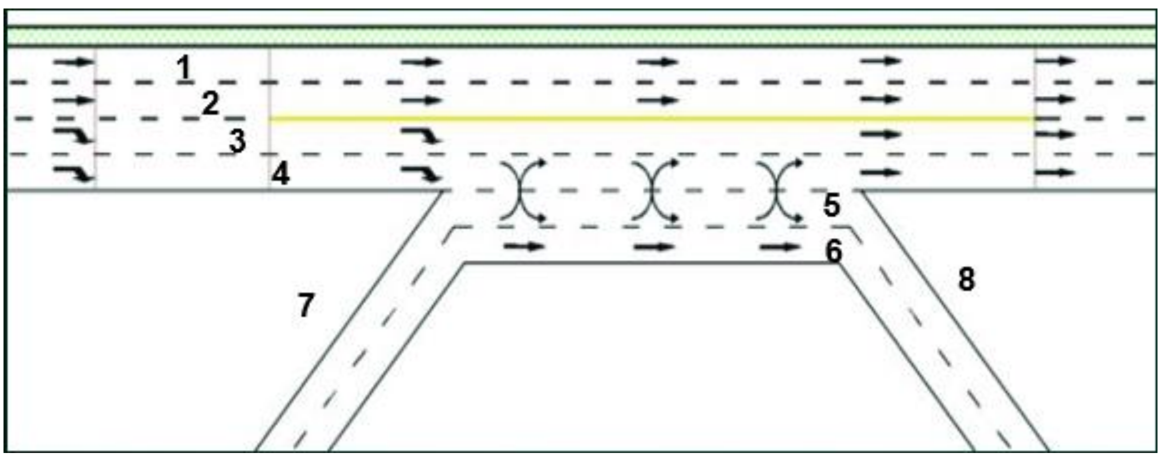


Figure 1. Schematic Diagram of Basic Freeway and Weaving Segments (Wei & Wanjing, 2013)

In the transportation planning, construction, and traffic operation of roads, road and highway capacity is crucial for the safe and efficient movement of goods and people. It determines the maximum throughput of traffic between any two points and hence the efficiency of the transport system. The ability of traffic analysts to forecast where and when congestion will occur, how long it will last, and how much capacity is required in bottlenecks is beneficial for this purpose. Therefore, it is essential to identify capacity precisely for measurement and use in modeling and decision making. An unsaturated or uncongested traffic condition (Figure 2) describes a high traffic flow state and a vehicle speed that is closely around or over posted speed limit. As traffic flow increases, the speed will decrease. At saturation, the traffic speed will be half the design speed, while the flow will be higher. This is the capacity of the saturated section of road. In oversaturated or congested conditions, both traffic flow and speed will reduce. An oversaturated condition is a state of flow where demand is higher than the capacity of the road section. For example, the capacity of a road is 2,400 vehicles (veh)/hr/ln where demand is more than 2,400. Traffic flow will ultimately decrease over time and speed, and it might be zero at one point.

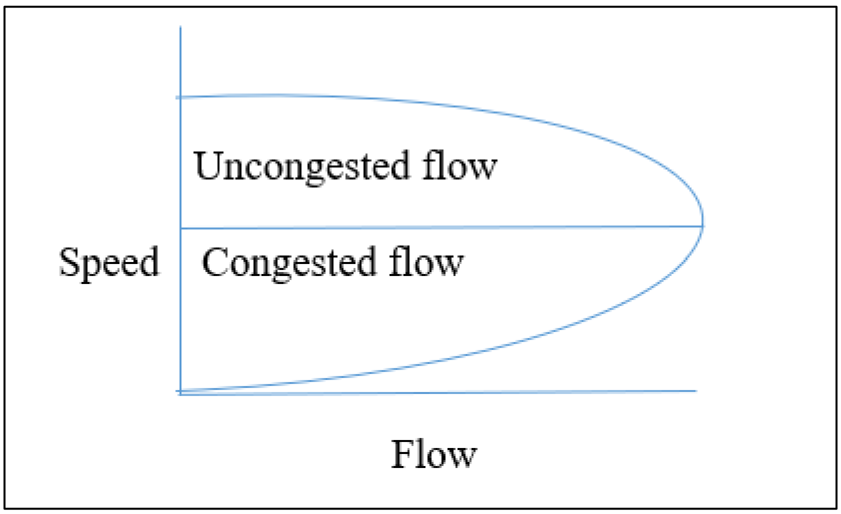


Figure 2. Speed vs. Flow Curve

In recent years, independent vehicles and connected autonomous vehicles (CAVs) have received much interest and attention among researchers worldwide. Autonomous vehicles (AVs) and CAVs are poised to change the way households and individuals own, drive, and operate their vehicles and how the transportation system performs and responds to traffic. The introduction of these vehicles will reduce vehicle headway and reaction time, thereby helping to increase road capacity (Makridis, Mattas, Ciuffo, & Thiel, 2018) and potentially improving traffic safety, as communication systems between vehicles will reduce collision probabilities (Arvin et al., 2018;

Li et al., 2018; Mittal, 2018). Moreover, the capacities of roadway facilities will potentially change; that is, more or fewer cars will be able to use existing roadways with the introduction of AVs and CAVs.

1.2. AVs and CAVs

AVs can drive themselves from Point A to Point B, with driver input ranging from slight to no information depending on the technology. CAVs communicate with the traffic system and other vehicles in the traffic stream. The National Highway Traffic Safety Administration (NHTSA) defines six types of AVs and numbers them from zero to five (NHTSA, 2020).

Table 1. Automation Level of Autonomous Vehicles (AVs)

Level of Automation	0	1	2	3	4	5
NHTSA	No automation	Function-specific automation	Combined function automation, for example steering and acceleration at the same time.	Limited self-driving automation. The driver can safely engage in other activities.	Full self-driving automation. The car can drive itself without a human driver.	-
SAE	No automation (existing equipment such as cruise control)	Driver assistance (existing equipment such as adaptive cruise control)	Partial automation (vehicle can control speed and steering, but the driver should be alert)	Conditional automation (more advanced than previous levels, but the driver should still be alert)	High automation (automated vehicles are capable of driving in all conditions, and the driver does not need to be alert)	Full automation

Level 0 means that there is no automation; the driver performs all driving tasks. At Level 1, the driver has some features that assist them while driving, but the vehicle is under the driver's control. Level 2 includes partial automation; that is, the vehicle has combined automation such as acceleration and steering, but the driver still takes care of all other driving tasks and monitors the environment. Level 3 denotes conditional automation; that is, a driver is necessary but not required to observe the environment. However, the driver should be ready to take control of the vehicle at any time. A Level-4 vehicle has a high level of automation; it can perform under specific conditions, but there must be a driver, who may have the option to take control of the vehicle. Level 5 denotes full automation; that is, the vehicle can perform all driving functions in all conditions.

Furthermore, the Institute of Transportation Engineers (ITE) defines CAVs as vehicles with automation and vehicle-to-vehicle (V2V) connectivity, vehicle-to-infrastructure (V2I) connectivity, or vehicle-to-everything contact (e.g., via mobile, tablet, or other device) through 5G or Dedicated Short Range Communication (ITE, 2021). First, V2V communication is important for, inter alia, understanding the movement of surrounding vehicles during merging, diverging, lane changing, and turning from an intersection. Second, V2I connectivity is essential to reduce delays in an intersection. The vehicle will communicate with a roadside unit that collects all incoming traffic and shares it with vehicles that cross the intersection. Infrastructure also shares signal timing so that drivers can react early to start driving during a traffic light change from red to green, which helps to reduce initial lost time in green. Third, a pedestrian crossing is essential in the intersection area, and this crossing maneuver can be safer using vehicle-to-everything technology. Pedestrians or bikers will receive left- or right-turning vehicles' information through their tablet or mobile, and vice versa, while crossing the road. This will increase non-vehicular movement safety in specific locations where sight distance alone is insufficient.

AVs will potentially improve road capacities through four primary interventions: a reduction in headway between vehicles, the provision of cars that are more responsive to traffic changes, a faster response to changing traffic conditions, and a steadier flow than is possible with traditional cars. The general implication is that current roadways will carry more AVs and CAVs than conventional cars today. However, the definitions provided by the NHTSA and the SAE are broad and do not identify how these vehicles will react to traffic conditions (e.g., how aggressive will the cars be when following other vehicles in traffic?). AVs and CAVs will more greatly reduce the speed and time gaps between vehicles in a traffic stream compared to traditional vehicles today. It is conceivable that when AVs and CAVs are first introduced, the technologies will be less aggressive due to regulations, public trust issues, and a lack of data. The European Union-funded project Coexist (Coexist, 2018) has attempted to define the different levels of aggressiveness in AVs and CAVS, as discussed in Section 1.3.

1.3. Different Levels of AVs

The European Union-funded Coexist project describes three levels of AV classes: AV-cautious, AV-normal, and AV all-knowing (Coexist, 2018). An AV-normal vehicle behaves like a human driver with the additional capability of measuring the distances and speeds of surrounding vehicles with its range of sensors. In contrast, the cautious driving logic accurately calculates gaps and only merges when gaps are acceptable, and the vehicle slows down when its sensors face blind angles, thus avoiding any surprises. This logic does not require specific devices for vehicle communication and cooperation. In the AV all-knowing class, the vehicle is assumed to have a complete understanding and analysis of environments and other road users' behavior, thereby leading mainly to smaller gaps for all maneuvers and situations. This type of driving logic requires devices for vehicle communication. If the devices fail, the logic may fall back to a cautious driving logic. With additional communication devices and control logic, the driving logic enables cooperation with other CAVs (Coexist1.4, 2018). Therefore, in this analysis, the AV all-knowing vehicle type is what the literature describes as a CAV. The algorithm in AVs and CAVs as well as the vehicles' penetration levels will potentially have an impact on roadway capacities. For example, if there are only AV-cautious vehicles, which is a likely scenario in the introductory phases of AVs and CAVs, they will potentially negatively impact capacities because their algorithms will provide more significant gaps to cars in front of them than traditional cars, hence reducing the throughput of roadways. Moreover, market penetration influences capacity changes. Penetration projection is discussed in Section 1.4.

1.4. AV and CAV Future Market Penetration Projections

In terms of penetration levels, the adoption of AVs and CAVs will not be deterministic. Roadways worldwide will potentially see different ratios of AVs and CAVs to traditional vehicles. In this dissertation, traditional vehicles is defined as vehicles that exist, for the most part, today and require the full attention of the driver from a trip's start to finish. A review of different car manufacturing companies indicates that manufacturer has different timelines for having fully automated vehicles or CAVs.

On the one hand, Daimler aims to produce Level 4 AVs with Bossch, Uber, and NVIDIA. Moreover, Toyota has unveiled the new Lexus LS, and Toyota Mirai—a Level 2 autonomous car—will be released in Japan and the USA in the coming fall (Raynal, 2021). On the other hand, Honda launched a world-first Level 3 AV in March 2021, 100 cars in the amount initially in Japan (Sugiura, 2021).

There is much interest in AVs in the literature, even if they are not currently accessible on the market. Studies (e.g., Arbib et al., 2017; Milakis et al., 2017) are presently being conducted to predict the market penetration of AVs and connectivity in the short and long term (i.e., 2030 and 2050, respectively) based on social, economic, and technological factors. The timeline for the penetration levels of AVs and CAVs is uncertain, and a few studies have attempted to estimate this penetration. One study estimates that AVs will likely take longer than other vehicle technologies to become accepted due to their complexity and cost (Lavasani, Jin, & Du, 2016). Another study that estimated the penetration of AVs and CAVs suggests that it will be at least 2045 before half of the new vehicles are autonomous, and 2060 before half of the vehicle fleets become autonomous (Litman, 2021). Figure 3 shows AVs' and CAVs' market penetration predictions, the amount of travel that will use AVs and CAVs, and the fleet projections over the next 60 years (Litman, 2021). First, the sales trajectory indicates the projected percentage of all new AVs and CAVs for high and low scenarios. According to the high scenario, AV and CAV sales will reach 60% of total sales by 2050. Second, the fleet travel trajectory estimates the amount of travel using AVs and CAVs as a percentage of full vehicle travel for high and low scenarios. Sixty percent of all travel by AVs and CAVs will be achieved a decade after new vehicle sales. This is because older, traditional vehicle fleets will still be in operation. The fleets graph (Figure 3) depicts the AVs and CAVs as a percentage of the total vehicle population. AVs and CAVs will achieve a 60% complete fleet penetration almost two decades after achieving a 60% penetration in new vehicle sales. Fleet turnover plays a significant role in the overall penetration percentages for AVs and CAVs.

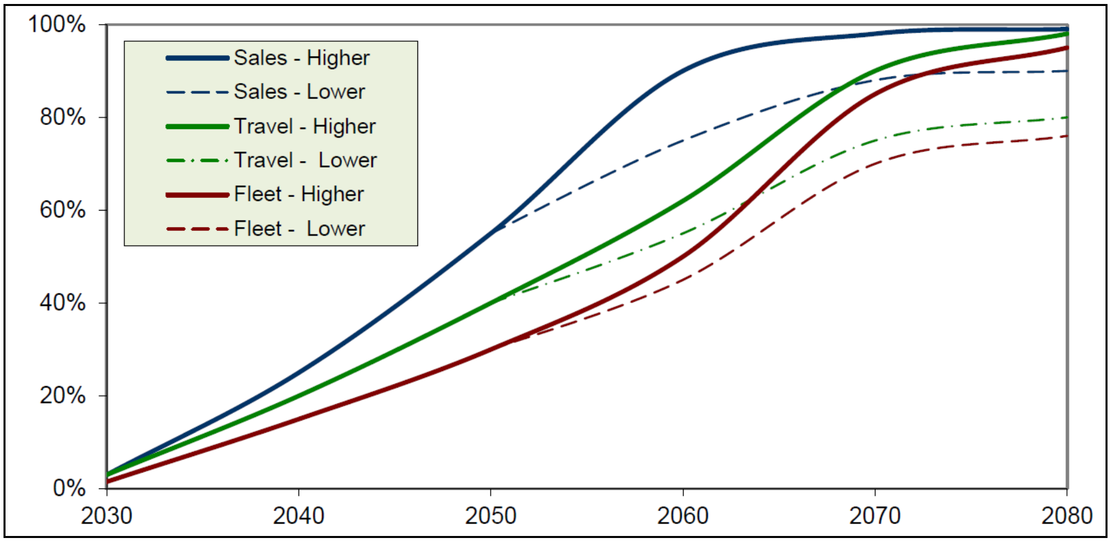


Figure 3. Autonomous Vehicle (AV) Sales, Fleet, and Travel Projections (Litman, 2021)

This mixture (coexist of traditional and autonomous) implies that current generation may not be witness the full capacity benefits of AVs and CAVs until they reach critical mass in the vehicle population. The effect is that transportation capacities will become fluid and change as AVs and CAVs in the general vehicle population change. For example, according to Figure 3, the benefits of such vehicles may only be realized after 2050. Since the planning horizon for most long-range transportation plans is 30 years, it is possible that these full benefits will not materialize within the current long-range transportation plan horizons in the US. Long-range transportation plans are plans that extend 30 years from the base years. On the contrary, there may be more minimum benefits or potentially harmful impacts on capacity. It is thus essential to correctly quantify the benefits of AV and CAVs in terms of capacities to make optimal transportation planning decisions. These decisions require significant time and financial investments.

1.5. State of Practice of Assessing Capacity for the BFS

It has been mentioned before that the BFS capacity value according to the HCM is 2,400 veh/hr at 70–75 mph. Apart from the HCM, other researchers have also developed methods to assess capacity, such as the headway model, the fundamental diagram, extreme value, and the breakdown method. The headway model assumes that driver components can be divided into drivers (followers) and drivers (leaders) in any traffic stream. This model can be generalized by the queuing model (Branston, 1976) and the semi-poisson model (Buckley, 1968). The distribution of control pathways at the road capacity level is expected to be the same as it would be in any safe traffic flow for restricted vehicles. Therefore, capacity = 3,600/headway. The fundamental diagram process proposed by Greenshields in 1938 is based on a relationship between flow and speed.

Nonetheless, the results of the method are based on the curve chosen for analysis. Therefore, adequate data over a wide variety of flow levels must be obtained to allow for accurate curve adaptation (Brilon et al., 2011; Ambuhl et al., 2018). Extreme value is another common type of potential assessment approach that calculates the capacity of the road when the flow reaches a vital point or flattens the flow over the total observation time (Dong et al., 2015). It also assumes that road capacity equals the selected traffic flow maxima overserved during the entire observation period.

Elefteriadou et al. (1995) demonstrated that a breakdown of traffic might be an excellent choice to measure capacity. The breakdown is defined as the point in the speed profile under which traffic speed is stained for a specific time. The breakdown speed threshold is time- and location-dependent. If the threshold is sustained for a particular time, traffic volume during breakdown speed will be the capacity value (Li et al., 2015; Lorenz et al., 2011). Aside from breakdown theory, microsimulation is a popular method for capacity assessment.

1.6. State of Practice of Assessing Capacity for the Weaving Segment

The HCM 2010 defined the capacity equation based on density and demand. The capacity of the weaving segment based on the density reaching 43 pc/hr/ln is estimated as follows:

$$C_{IWL} = C_{IFL} - [438.2\ (1+VR)^{1.6}] + [0.0765\ L_s] + [119.8\ N_{wl}], \quad (1.1)$$

where,

C_{IWL} = capacity of the weaving segment under ideal conditions (pc/hr/ln);

C_{IFL} = capacity of the basic freeway with the same free-flow speed (FFS [pc/hr/ln]);

V_R = volume ratio (weaving flow rate/ total flow rate);

O_{wl} = number of lanes from which a weaving maneuver may be made; and

Ls = length of the weaving segment.

The value of C_{IWL} is converted into the total capacity of the segment using Equation 3.2:

$$C_w = C_{IWL} * N * f_{HV} * f_P, \quad (1.2)$$

where

N = number of lanes within the weaving section;

f_{HV} = adjustment factor of heavy vehicle; and

P_{HP} = adjustment factor for driver population.

The capacities of the weaving segment based on-demand flows are as follows:

$$C_{IW} = 2{,}400/VR \text{ for } N_{wL} = 2 \text{ lanes} \quad (1.3)$$

$$C_{IW} = 3{,}500/VR \text{ for } N_{WL} = 3 \text{ lanes} \quad (1.4)$$

where C_{IW} is the capacity of all lanes in the weaving segment under ideal conditions and is converted into prevailing conditions by using

$$C_w = C_{IWL} * N * f_{HV} * f_P. \quad (1.5)$$

The HCM is commonly used in USA for evaluating the capacity of the sample observed. After processing the observed data, the capacity value of weaving segments is determined using a density equation. However, for mixed situation assessment, we employ a process of microsimulation in this study. Microscopic simulation models usually represent each car in a traffic network. The variables in these models typically include the microscopic properties of each car, such as driver behavior, car characteristics, and road conditions. Microsimulation models use time or car models that simulate how cars work in the real world. Many models, including the optimum speed model, the intelligent driver model, the Gipps model, the speed gap model, and the Wiedemann model, are used in various applications.

1.7. Organization of Dissertation

The rest of this dissertation is organized as follows. First, the literature review examines previous studies on the impacts of AVs and CAVs, the problem statement, the research contribution, Wiedemann's car-following model (CFM), and the lane-changing model are described thereafter. The subsequent data and methodology chapter details the study section, data parameters, calibration, and validation process. Then, the results and discussion chapter discuss the capacity measurements of the base case scenarios, compares them with single class AVs, and presents the percentage changes in mixed case environments. The final chapter includes a conclusion and discussion of the results and recommended future work.

2. LITERATURE REVIEW

In this chapter, we briefly describe previous studies, including how mathematical models or simulation-based models have framed AVs' capacity change, and we identify contemporary research gaps. Thereafter, we explore the state of the art in BFS and weaving segment capacity assessment processes. In this dissertation, the simulation software VISSIM is utilized to create the simulation environment. VISSIM includes Wiedemann's CFM and lane-changing model. These two models are discussed after the state of practice.

2.1. Previous Studies on AVs' and CAVs' Capacity Impacts

AVs and CAVs are projected to enhance highway traffic efficiency, safety, and the environment on the road by detecting, sharing, and applying appropriate control measures. They all stem from CAVs' potential to increase highway traffic capacity by minimizing the distance between cars through communication and automated control technology (Ghiasi, Ma, Zhou, & Li, 2017; Li & Ghiasi, 2017; Kamrani, Wali, & Khattak, 2017). Before starting a new assessment on this topics (impact on capacity), it is necessary to discuss previous research related to capacity assessment on the freeway. In the literature, there are three main frameworks to evaluate and simulate the impacts of AVs and CAVs on capacity assessment: mathematical formulations, simulation methods using simulated data, and real-world data. First, mathematical formulations involve proposing a new equation or modifying a previous equation to measure mixed scenario capacity assessment. Second, the simulation method entails creating a scenario in a simulation environment to produce synthetic data and calculate capacity from those data. Third, real-world data can be employed to assess capacity using a simulation environment. Data are utilized to establish calibration parameters and simulation to determine capacity. Related previous studies are detailed in the following sections (2.1.1-2.1.4).

2.1.1. Mathematical Models

Ni et al. (2012) proposed a framework for analyzing the advantage of highway capacity impact using connected vehicles. To do this, the authors formulated the model based on a rough approximation of the resulting capacity increase, which incorporated the effects of related vehicle technologies on cars following. The authors carried out a simulation analysis to check the model, and, based on an illustrative example, their methods yielded gains ranging from 20% to 50%. Their study offered policymakers and stakeholders a fundamental tool for understanding the accessibility benefits derived from connected vehicle technologies and how those benefits vary with changes in consumer penetration.

Similarly, Friedrich (2016) used a mathematical equation to demonstrate that lower headway and higher penetration levels would raise capacity up to 36%. The author also noted that time headway would change based on the vehicle groups of leader and follower, contributing to the capacity improvement. The author's macroscopic models of traffic flow demonstrate that AVs will, in theory, lead to substantial improvement of capacity and make the current transport system more functional. In particular, two aspects contribute to capacity building. The first aspect is the shortening of headways between vehicles. In this sense, it is vital to retain driving comfort while anticipating the activities of the preceding cars, which allows for less acceleration and deceleration during short time gaps. Second, the speed of the vehicle category is critical in addition to the length of the time delay—the greater the speed, the more significant the traffic volume over a cross-section at a constant density. However, high speed rates can be achieved in solely autonomous traffic while sustaining traffic density.

Shi et al. (2016) modified capacity, maximum service rate, and density to account for CAVs in their studies. By maintaining shorter headways, CAVs significantly influence traffic efficiency during crowded situations compared to uncongested conditions. While performing Monte Carlo simulations inside the traffic stream, the authors conceived a theoretical maximum capacity of 7,200 veh/hr/ln and determined that the capacity increase was minimal if the CAV's headway was equivalent to that of a driver. The quality of traffic flow was unlikely to improve if CAV shares were below 2%.

Chen et al. (2016) established a mathematical framework that defined the effectiveness of the transport network's optimization, the period to be implemented, and the number of AV lanes. The authors found growth in AVs' capacities in the AV-exclusive lane with a shorter headway, which was assumed, but they did not recognize the effect of AVs' existence on traffic flows in terms of capacity. Furthermore, their study was not carried out for mixed traffic situations.

The mathematical formulations present a first step in the evaluation of the impacts of AVs and CAVs. These models must be validated against real-world data to assess their effectiveness, which has not been done in this type of research to date.

2.1.2. Simulation-Based Models with Synthetic Data Literature

Using a simulation environment and synthetic data, numerous studies were conducted to assess freeway capacity. Theophilus et al. (2017) examined the freeway capacity using 100% CAVs by changing the headway value and the demand flow rate in VISSIM. The output revealed capacity increments from 0.46% to 16.54%. The research limitations were as follows: the study considered a single type of vehicle, did not consider heavy vehicles, and avoided mixed traffic scenarios. Furthermore, Tientrakool et al. (2011) investigated capacity benefits using sensors and V2V communication. The authors simulated a vehicle in the network, and their findings indicated that the average inter-vehicle safety is lowered by both sensors and V2V contact, thus increasing road capacity. However, sensors and V2V communication do have a significantly higher percentage of capcity than sensors alone. The highway capacity of each car is approximately 3.7 times the capacity of all manual vehicles at a speed of 100 km/h, where all vehicles have all sensors and communicators. In comparison, the total capacity of all cars is just 1.4 times the capacity of all sensors. In combination with connectivity, as a limited portion of vehicles on a highway are built and used, road capacity is slowly enhanced, followed by traffic volume due to increasingly rapid improvements.

Hartmann et al. (2017) conducted a study to determine the influence of AVs on the German motorway network, using microscopic traffic flow modeling. This study shows that vehicle automation considerably affects capacity when an AV is driving behavior, mainly longitudinal behavior, and their penetration rate is considered. Low penetration rates do not yield significant changes in roadway capacity, but as penetration rates rise, the potential advantages will emerge. Roadway capacity also decreases due to the cautious driving style of AVs. Research suggests that once AVs' headways drop below present restrictions, that they can be used to their full potential (up to a 30% increase in highway capacity), and road infrastructure can be better utilized. This study also found that vehicle automation can boost basic road segment capacity by 45%. The capacity impact of heavy lane changes is substantial, and vehicle cooperation is essential. Partially automated vehicles and highly automated vehicles consequently have a detrimental influence on these locations. Even in the best-case scenario, connected AVs maintain short headways that are inadequate for lane changes. Therefore, the capacity gain is restricted in these locations.

In a study to distinguish between the impacts of connectivity and automation, Talebpour et al. (2016) presented an analytic and simulation-based framework that utilizes different models with technology-appropriate assumptions to simulate different vehicle types with distinct communication capabilities. According to the results, the traffic equilibrium string could be improved by CAVs and AVs. Automation is perhaps more efficient than networking alone to avoid creating and disseminating shockwaves, as proven by simulation results. In comparison, the ability of automation grows almost linearly as sensors are used alone and the number of vehicles installed increases. The simulation findings also revealed that oscillation and collision thresholds increase with a decrease in platoon size or market permeation. In terms of capacity assessment, the authors concluded that AVs provided a higher capacity value than CAVs at a similar penetration rate.

An adaptive cruise control (ACC) system enables a vehicle to slow down when driving behind another vehicle traveling at a lower speed and to speed up to a preset speed when the lead driver accelerates. The predetermined parameters of an ACC scheme are, in theory, the time difference in the lead vehicle and the required vehicle speed. Vehicles equipped with cooperative adaptive cruise control (CACC) may share traffic information through car networks or wireless technologies that allow communication between these vehicles. The influence of automation at a broad perspective and strategic level has also been estimated using macroscopic simulation models. In 2013, Ngoduy (2013) simulated ACC and CACC using a single macroscopic model. For a given model parameter set, the authors created stability diagrams using the linear and nonlinear stability methods. Analytical results suggest that CACC cars stabilize traffic flow better than ACC vehicles under both small and large disturbances. To back up analytical conclusions, the researchers utilized numerical simulations and demonstrated analytically and numerically that the CACC system’s dynamic equilibrium capacity is superior to that of the ACC system. However, the limitations of their research were the use of synthetic data, which are based on assumption.

Previous research has found that CACC systems represent the further evolution of ACC technology that has enabled the exchange of information between vehicles designed to be more precise and quicker in real time. Arem and colleagues proposed the use of a cooperative following paradigm that combines automated longitudinal control with intervehicle communication (Arem, Tampere, & Malone, 2003; Arem, Driel, & Visser, 2006). The traffic flow simulation model MIXIC was used to examine the influence of intelligent vehicles on traffic flow. The authors considered an example of a roadway merging from four lanes into three lanes. Compared to the merging situation without equipped vehicles, data revealed an improvement in traffic flow stability and a minor increase in traffic flow efficiency. The findings of the study have improved the current understanding of the effects of CACC on traffic flow. The idea that CACC can significantly boost roadway capacity has been debunked to some extent. This study was based on simulations only, where real-world observed data and a realistic congestion scenario were missing for performance analysis.

A CACC controller was studied to determine whether the wireless connection had any influence on its performance. The results demonstrate that CACC should be included in a networked control system (NCS; Oncu, Wouw, & Nijmeijer, 2011). Limited bandwidth; several nodes sharing the same media; and other limitations, such as transmission delays and losses, contribute to network-induced flaws in an NCS. Constraints imposed by the networks necessitate a tradeoff between CACC performance and network specifications. Sample-and-hold and network delays due to wireless communication are included in this paper's NCS modeling framework to check the string stability. However, the study was not carried out further for capacity assessment. VanderWerf et al. (2001) created not only an overview for introducing ACC and CACC with their effects but also a mathematical model for both types of cruise control to ensure that ACC systems are implemented such that they improve rather than degrade traffic conditions. To better understand traffic dynamics and capacity, the authors developed a new type of simulation model that includes the crucial features of driver behavior and control system design, which were previously unavailable. After a year, the researchers utilized these models to simulate the three classes of cars and to predict the highway capacity for possible combinations of market penetration of automatic and manual automobiles (Werf, Shladover, Miller, & Kourjanskaia, 2002). The authors employed real-time speed, acceleration, and ACC status information sent between vehicles that were similarly equipped to create a CACC system. Due to its more minor headway (0.5 s), it was believed that the driver would not have to intervene. The drawback of this study was that it did not assess capacity in mixed traffic situations, which will govern the next few decades on the road.

Delisi et al. (2015) investigated the impact of ACC and CACC in a traffic flow study. The second-order GKT model was used as the base model for modeling the effects of ACC and CACC vehicles on dynamic circulation as defined by both approaches. The model describes variations in speed-density dynamics in the context of a so-called balance-speed–density relationship. The numeric solution of the resulting models by developing a high-resolution finite-volume relaxation scheme is essential in the simulation process. The study concluded that CACC provided better stabilization and capacity improvement than ACC. The local capacity in front of a ramp can be automatically increased and moved to other bottlenecks, thus improving traffic operations.

According to existing research, CAV market penetration has also been identified as a significant highway capacity for mixed traffic. There is a considerable rise in roadway capacity with a higher market penetration (Kesting, Treiber, Schönhof, & Helbing, 2017). If inter-vehicle and infrastructure-to-car communication are used, the accuracy of traffic state determination can be improved. Using empirical loop-detector data for an afternoon rush hour as input for the upstream boundary, the authors simulated the full concept on a road stretch with an on-ramp bottleneck. Traffic stability and dynamic road capacity were improved by the ACC vehicles, according to the findings. Ntousakis, K.Nikolos, and Papageorgiou (2015) also attempted a traffic performance analysis study based on various penetration rates of ACC in Aimsun software using ACC-equipped vehicles, varied desired time gaps, and various networks to evaluate their impact on traffic flow characteristics. Moreover, Arnaout and Arnaout (2014) applied an agent-based microscopic traffic simulation model (flexible agent-based simulator of traffic) to study the influence of intelligent vehicles on traffic flow. As they studied the model's lifecycle, they considered metrics such as the flow rate of cars, travel time, and other indicators of traffic congestion. Various amounts of CACC penetration were analyzed, and findings revealed that traffic flow and capacity were better in the CACC-embedded vehicle scenario compared to the scenario without CACC-embedded vehicles. Based on market penetration and the maximum number of cars per platoon, Bujanovic et al. (2018) created an analytical model to forecast the capacity of highway segments. Technologies such as ACC and CACC made platooning possible. The authors built a decision process for a vehicle, to determine the speed it should maintain. There are two possible modes for platoon leaders: CACC mode and ACC mode. CACC vehicles obtain information from their predecessors via V2V communication. Still, they must maintain a wider spacing than if they were part of the same platoon, which would allow them to communicate with one another. Assuming a platoon size of 12, an intra-platoon time headway of 0.8 s, and an interpolation time headway of 1.3 s, the system can move 4,237 vehicles every hour.

Amoozadeha et al. (2015), Steven E. Shladover (2012), Heinovski (2018), Guériau et al. (2016), Bang et al. (2016), Wang et al. (2015), and Milanes et al. (2014) tested a simulation-based CAV platooning protocol and demonstrated a higher roadway capacity due to an extended platoon size and a narrower platoon difference. In another study, Ye et al. (2018) developed a simulation-based, two-lane, cellular automation model on a two-state safe-speed model, which resulted in increased capacity by increasing penetration rate. The authors found a significant impact in road capacity when CAV penetration was more than 30%. They also presented a different study in which a dedicated CAV lane increased capacity to a greater extent than a traditional vehicle. Furthermore, Adebisi et al. (2020) investigated BFS and weaving segment capacity for AVs and CAVs in a simulation environment using two CAV applications on the freeway, namely CACC and advance merging, and developed capacity adjustment factors to use with the HCM capacity value. Heaslip et al. (2020) investigated interstate capacity assessment in mixed traffic scenarios deploying ACC- and CACC-equipped vehicles as AVs and CAVs using a modified MIXIC CFM. According to the results, there was a 28% capacity increase due to AV and a 92% capacity increase due to CAV. In the presence of a heavy vehicle, the results revealed a substantial increase in capacity.

The limitation of the simulation-based models is that they are based on assumptions, which are considered to be real-life situations. While hypotheses are helpful to construct a model and evaluate future traffic performance, a model can only be strengthened through proper validation by real-world data. Nevertheless, a simulation-based model using synthetic data provides a direction for developing a successful model.

2.1.3. Simulation-Based Model with Real-World Data Literature

Fan et al. (2019) attempted to assess capacity in mixed traffic situations using detector data and changing headway values for AVs and CAVs in VISSIM. They demonstrated the potential capacity impact for a BFS, weaving, and ramp junction mixed traffic scenario. In their study, the authors used real-world data to access Wiedemann's car-following calibration parameters, but for AVs and CAVs, real-world data were absent. Instead, the authors used a headway value of 0.9 for AVs and 0.6 for CAVs. Most of the previous studies appear to have implemented only mathematical or theoretical assumptions and simulation-based models for capacity assessment, whereas developing a mixed traffic model using real-world data has been overlooked or scarcely examined. To draw a concrete conclusion about capacity impact, it is necessary to conduct investigations using real-world data. Another shortcoming of model development is the use of point data. Previous studies have used point data (Fan et al., 2019; Manenni et al., 2008; Dong et al., 2015; Gomos et al., 2004) to calibrate and validate the developed model. However, the challenge is that such data cannot distinguish between vehicle types, resulting in improper headway distribution between vehicles. Additionally, point data might not correctly represent a study section. Trajectory data rather than point data should provide a better scenario to construct the model.

2.1.4. Calibration-Based Literature

Calibration and validation play an essential role in microsimulation model development. Moreover, selecting driver's choice speed distribution in VISSIM impacts model development. A detailed VISSIM calibration and validation process based on Wiedemann's CFM is discussed in Chapter 4. For the simulation-based capacity measurement, extensive research has been conducted where proper calibration and validation methodologies have been examined using

Wiedemann's 99 parameters. Wiedemann's CFM has a total of 10 parameters, which are generally calibrated such that only one variable applies to all vehicle types or solely to passenger cars. A prime example of this calibration is the driving behavior parameters in VISSIM, which were calibrated for all vehicles (Saccomanno, et al., 2009; Lu, et al., Freeway Micro-simulation Calibration: Case Study Using Aimsun and VISSIM, 2014; Kan, Ramezani, & Benekohal, 2014). With vehicle-pair trajectory data from the US-101 and I-80 highways, Menneni et al. (2009) calibrated calibration component (CC) 1, CC2, CC3, CC4, and CC5 for all vehicle classes. Jie et al. (2013) published a study in the Netherlands that calculated CC1, CC2, CC3, CC7, and CC8 for passenger automobiles using only vehicle-pair trajectory data. However, the limitation of those studies was an assumption of the exact behavior of all vehicles on highways (Ossen & P.Hoogendoorn; Sarvi & Ejtemai, 2012) even though different vehicles have different following strategies.

The vehicle-following behavior of passenger cars and heavy vehicles differs depending on the type of lead vehicle and speed, according to Aghabayk et al. (2012). The authors made four cases for headway: a car following a car, a car following a heavy vehicle, a heavy vehicle following a heavy vehicle, and a heavy vehicle following a car. Regarding spacing and time headways, the case of a heavy vehicle following a heavy vehicle had the highest values, while the case of a car following a car had the lowest values. In addition, the authors discovered that for speeds below 30 km/h, the case of a car following a heavy vehicle had a more considerable headway and a greater spacing than the case of a heavy vehicle following a car. For speeds greater than 30 km/h, the reverse was observed. Furthermore, Higgs et al. (2011) discovered that truck driver behavior varies depending on the vehicle's speed, based on naturalistic driving. The research suggests that various driving behavior characteristics should be evaluated for different speed levels.

Manenni, Sun, and Vortisch (2008) demonstrated that the speed–flow relation can be utilized as a calibration parameter where authors used detector data and classified the CC parameters value using genetic algorithms following, also illustrates how the CC2, CC4, CC5 value can be measured by drawing the spacing vs. relative velocity graph. Using naturalistic data, Higgs, Abbas, and Median (2011) found that the CC parameters display various values for specific speed ranges. Calibration parameters CC2, CC3, CC4, and CC5 for constant speed differences were subsequently investigated and adjusted because of speed disparity (Manjunatha, Vortisch, & Mathew, 2013). It is comparatively easy to select drivers' choice speed distribution from unsaturated data. This distribution refers to the velocity used by drivers in a free-flow condition (flow less than 1,000 veh/hr). Most previous studies have attempted to construct models using traffic data from unsaturated to oversaturated conditions with FFS distribution (Dong et al., 2015; Lu et al., 2013). Durrani et al. (2016) and Jolovik et al. (2012) attempted to develop a model using oversaturated traffic data, but proper validation and selection of the driver's choice speed distribution were missing. Hence, adequate calibration and validation methods using oversaturated data are necessary to generate valuable data that decision-makers can use to make optimal decisions.

2.2. The CFM

In traffic flow theory, the model-based car-following approach is favored. If a critical breakdown in traffic occurs, the car maintains a certain distance to prevent a collision. Additionally, the following vehicle's speed, acceleration, or deceleration depends on the leader's behavior. Researchers have investigated this behavior in recent decades and have developed several CFMs.

In 1953, Pipes demonstrated a model that denotes the movement of vehicles controlled by a “law of separation,” where the considered vehicle maintains a specific following distance from the preceding vehicle (Pipes, 1953). According to this model, safe distance headway and speed have a linear relationship.

Furthermore, the Forbes model states that the gap between two successive vehicles should be greater than or equal to the reaction time for the following vehicle. Having a leader in front to perceive the need to decelerate and apply the brake is considered (College, 2019).

In the contemporary situation, the General Motors CFM received the maximum attention (Chakroborty & Kikuch, 1999). This stimulus-response model assumes that the following vehicle will respond to a apprehensive speed between the leading vehicles. The model also assumes that a given stimulus influences the response, depending on the distance headway between the leading and following vehicle and the following vehicle speed.

Later in 1981, Gipps proposed an accident-free model by denoting the safe distance maintained by the follower vehicle to avoid a collision. Safety distance has three components: reaction time, braking distance, and additional distance to the leading vehicle smaller than the minimum gap (M.Treiber & A.Kesting, 2013). The concept underlying the model is that every driver prepares their speed to safely stop even in the case of sudden braking of the leading vehicle.

The intelligent driving model is another simple time-continuous CFM that measures the acceleration of the following vehicle in each phase according to its velocity, gap, and relative speed. This acceleration has two parts: desired acceleration without having a leading vehicle and braking acceleration without having a leading vehicle. In free-driving mode, the acceleration reaches zero as the vehicle approaches the desired speed; in an urban situation, the vehicle's gap is contrasted with the desired gap, and acceleration is zero when the actual gap is the desired gap (M.Treiber et al., 2013).

Wiedemann's car-following theory is a collision-free model that addresses speed, space gap, time gap, and acceleration between two successive vehicles with four driving regimes, namely free flow, approaching, following, and braking. According to this model, a vehicle's response is triggered by the difference in speed between the lead and trailing vehicles (e.g., acceleration or deceleration). The following driver's regulation is controlled by perception thresholds of large and small relative speeds. Total 10 calibration parameters represent that four regimes that starts from CC0 and end at CC9. Out of nine, two parameters are space-related, two are time-related, and three are speed- and acceleration-related. This model is a complete scenario of freeway traffic movement that is included with all necessary parameters. For this reason, we chose Wiedemann's CFM for further analysis.

The purpose of using Wiedemann's CFM is to cover every situation in the following process (four regimes defined by Wiedemann) from the braking situation to the free-flow situation. Furthermore, different regimes are separated with thresholds, as illustrated in Figure 4. The overall model structures deal with speed, distance, acceleration, and relative speed. When developing equations for diverse conditions, this model is designed to be accident-free.

2.3. Problem Statement

Based on the literature review above, a few shortcomings have been identified concerning capacity estimations for AVs and CAVs. The AV and CAV capacity literature used theoretical frameworks or synthetic data to calculate capacity in a mixed traffic environment. A model must thus be developed based on real-world data. While theoretical frameworks or artificial data-related models are a useful starting point, they cannot aid in assessing capacity for a particular location explicitly. A simulation-based model is more acceptable and vital to use by traffic engineers if real-world data are created. Previous studies have used either synthetic data or unsaturated traffic condition data to replicate field situations in the simulation environment. This practice is widely used for model development or case study purposes, but there are challenges when using only oversaturated traffic data. These challenges arise when choosing the driver's choice speed distribution and speed range, which play a significant role in model calibration and validation. A driver's choice speed refers to a vehicle's driving speed based on the driver's choice rather than the roadway conditions; it is similar to or higher than the posted speed limit. This situation is seen in unsaturated conditions, but in saturated or oversaturated conditions, the driver drives the vehicle according to traffic flow. Considering only oversaturated data usage, challenges have previously been overlooked and highlight another shortcoming. Using oversaturated data and an improper driver choice distribution will result in an unacceptable calibration, validation, and overall capacity assessment in traditional, mixed traffic situations.

Aside from considering unsaturated to saturated data types, most previous studies have also used a single Wiedemann 99 CC to build the capacity assessment model; however, there was no separation between vehicle types (i.e., car, bus, truck, and motorcycle). This distinction is necessary, as all vehicles do not maintain the same space and time gaps from the leading cars. For example, passenger cars maintain a smaller gap with leading passenger cars, but a more significant gap with leading trucks or buses. Similarly, a vehicle maintains a varying gap if the leading vehicle is a car or truck. The main reason for this shortcoming is that most studies have used detector data that are readily available. Detector data are collected from a study section via a detector embedded under the pavement or through the use of a roadside data collection device, which detects several parameters such as vehicle number, timestamp, speed, and occupancy at the detector's location. However, detector or point data do not capture the road traffic conditions of a roadway or study section that represents the whole study section and cannot differentiate between vehicle types. Thus, vehicle type segregation is necessary to define the field scenario in simulation, and it has been identified as a shortcoming of previous studies. Low-scale calibration is provided by a single vehicle and detector data, resulting in a low-profile match between the field and simulation scenarios. It is not easy to build a robust model when parameters match invisibly.

Specifically, three major shortcomings have been discussed, namely the driver's choice speed distribution from oversaturated traffic data, single-vehicle calibrating components, and the use of detector or point data sources for developing the model, In light of these shortcomings, this research aims to answer the following research questions as stated below

1. What are the appropriate data for these studies, and what methodology should be applied to fit the data set into microsimulation tools such as VISSIM?
2. What penetration levels of AV-cautious, AV-normal, AV all-knowing vehicles lead to a significant change in capacities?
3. How will capacity percentages change under mixed AV, CAV, and traditional vehicle scenarios for saturated conditions?

This study addresses these research questions by setting up a microsimulation-based model analysis using Wiedemann's car-following theory on a trajectory data set with proper calibration and validation.

2.4. Research Objectives and Research Contributions

The main objective of this research is to evaluate the capacity impacts of AVs and CAVs for a BFS and a weaving segment under a mixed vehicles condition, including traditional AVs and CAVs, by simulating different penetrations for various mixing levels of AVs and CAVs and classic cars. To achieve this main objective, the following tasks are identified:

1. We utilize Wiedemann's car-following behavioral model to estimate the capacity impacts of AVs and CAVs in mixed settings. To this end, we employ NGSIM trajectory data for the traditional vehicle. This data set is oversaturated.
2. Merging traditional and AV and CAV CFM parameters with simulation-based traffic, we build this model to assess the capacity of an essential freeway and weaving segment for single-class AV and mixed scenarios (in the presence of traditional, AV-cautious, AV-normal, and AV all-knowing vehicles). We then compare the capacities to traditional vehicles to evaluate their impacts on freeway capacities.

On the basis of the previous studies' gaps, the main contributions of the present research are as follows:

1. A step-by-step process-building of model calibration and validation using oversaturated data to assess freeway capacity—especially the process of calibration parameters from given trajectory data.
2. A planning horizon of capacity changes with mixed levels of AVs and CAVs over the next few decades for better understanding by the planners.

2.5. Summary

In this chapter, we presented an extensive review of previous literature on how AVs and CAVs will affect capacity. The major gap of mathematical and theoretical-based models indicates that changing a few parameters cannot result in capacity change for a particular location in a broad sense. The synthetic data-based simulation model provides a platform for creating a simulation environment to assess capacity. However, as data are imaginary, the model still does not provide a capacity change of a particular location. Moreover, we mentioned gaps related to calibration validation, such as problem-associated detector data and single-vehicle type CC parameters in VISSIM. Thereafter, we stated the problem of this research along with the research objectives and contributions. Finally, we discussed the state of practice of the BFS and the weaving segment.

3. VISSIM MODEL SETUP AND DATA COLLECTION

3.1. Introduction

PTV Planung Transport AG has developed PTV VISSIM in Karlsruhe, Germany, as a microscopic multimodal simulation software package. First established in 1992, PTV VISSIM is now a world leader and is widely used by practitioners and academia to simulate traffic at the micro-level. Microscopic simulation in transportation means that every entity (vehicles and pedestrians) in a study area is simulated individually (i.e., represented in the simulation by a corresponding entity, considering all the relevant properties). This study used VISSIM software with the Wiedemann 99 CFM and VISSIM lane-changing model to build the capacity assessment model for a freeway.

The car-following algorithms in AVs and CAVs and the roadway FFSs, geometries, and conditions will significantly affect capacities. If these algorithms have cautious car-following algorithms that leave more significant gaps than average regular cars, their introduction will decrease abilities and potentially reduce throughput. The more aggressive they are, the higher their impacts will be on increasing capacities to optimal for different FFSs. Thus, the aggressiveness of the algorithm in AVs and CAVs with a car-following parameter as one of its measures will determine how the vehicles impact roadway capacities. The hypothesis here is that the car-following technologies in AVs and CAVs will significantly impact capacities. The speed of technological development, testing and regulatory approval, consumer travel, housing preferences, development practices, quality, affordability, and public policies are some of the factors that will affect the car-following algorithms of AVs and CAVs.

Using AV and CAV naturalistic data, the Coexist project has made significant contributions to mixed AV and CAV scenario studies (Table 12) using VISSIM as a platform.

The PTV Group in Germany created VISSIM, a commercially accessible software program for simulating microscopic traffic flows. In the 1970s, Wiedemann and others developed accident-free psychophysical driver behaviors, considering four driving regimes, namely free driving, approaching, safe gap, and braking, which consider speed, distance, acceleration, and time between the leading and following vehicle. Later, the University of Karlsruhe included this CFM into the VISSIM software. We used VISSIM as the simulation software to build the model for capacity estimation.

3.2. Wiedemann's CFM

VISSIM, a microsimulation software, deploys model-based, psycho-physical car-following theory to simulate real-world scenarios. It is a type of microsimulation focused on Wiedemann's understanding of the driver. There are two models integrated into this software: Wiedemann 74 and Wiedemann 99. It is generally recommended to use Wiedemann 74 in the merging stage of the traffic stream, such as highway merging points, signalized intersections, arterial analysis, and network analysis. In contrast, Wiedemann 99 is recommended for freeway analysis, as it has four driving states known as free driving, approaching, safe gap, and braking.

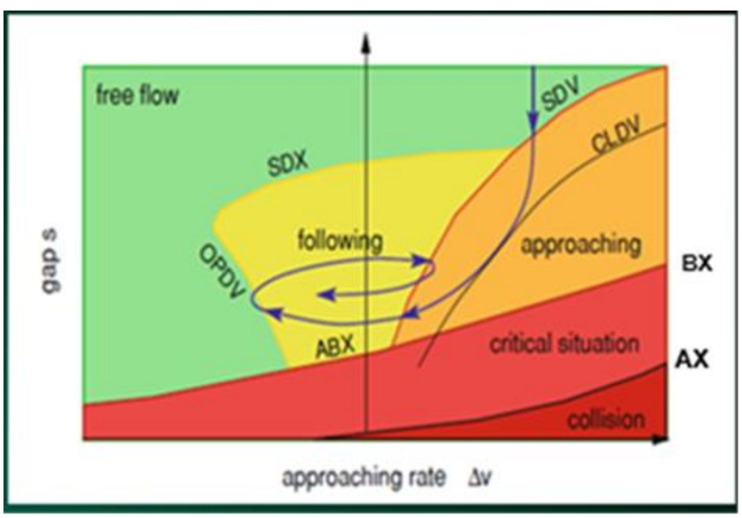


Figure 4. Wiedemann's Car-Following Model (CFM; Higgs, Abbas, & Median, 2011)

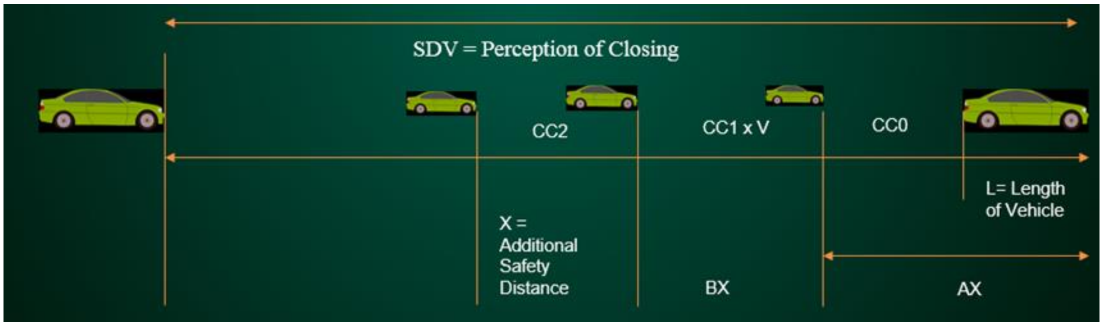


Figure 5. Different Location of Leading Car and Following Car

Understanding the regime of parameters is important in the tuning calibration and validation of these models to accurately represent real-world conditions. Figure 4 illustrates the relationships between the parameters in Wiedemann's CFM. The boundary between a collision and a critical situation is AX (Figure 4), which is the sum of the standstill distance (the distance traveled during a stop situation) and the length of the leading vehicle. BX is the point between a critical situation and the additional safe gap after AX. The relationship between the parameters and thresholds mentioned by Aghabayk et al. (2013) are used below:

$$AX = L + CC0, \tag{3.1}$$

where CC0 is the distance between the rear bumper of the front vehicle and the front bumper of the following vehicle in a stop condition, and L is the car length (Figure 5). The next parameter is CC1, which is a time gap between two successive vehicles:

$$BX = AX + (CC1 \text{ x } V), \tag{3.2}$$

where BX is the speed-dependent safe distance range, CC1 denotes a time gap between two consecutive vehicles with additional differences after CC0, and V is the relative vehicle's pace. Next is CC2, which is again a distance parameter but in the unconscious following region:

$$SDX = BX + CC2, \tag{3.3}$$

where SDX is the upper end of the unconscious region. When the following vehicle approaches the leading vehicle, it continuously decelerates until it reaches zero relative velocity, and the following driver tries to maintain low acceleration or deceleration. Data points close to zero relative speed with spacing constitute an unconscious following region. Additionally, CC2 is the extra protective distance that the driver must retain throughout the next unconscious cycle. The subsequent parameters are CC3 and CC4, which are related to time and relative velocity (negative), respectively:

$$SDV = \frac{\Delta x-(SDX)}{CC3} - CC4. \tag{3.4}$$

SDV is the perception point of the driver while approaching the leading vehicle. Starting the closing process, the following vehicle detects slow-moving vehicle. Using perception and reaction time, the follower driver decelerates to maintain zero relative velocity. Moreover, $\underline{\Delta}$X is the space gap between vehicle pairs, and CC3 is the time elapsed from the beginning of deceleration to the beginning of the following unconscious relative velocity during the unconscious process. The next parameter is CC6, which refers to speed oscillation:

$$CL\mathrm{DV} = -\frac{CC6}{17000} * (\underline{\Delta}\mathrm{x} - \mathrm{L})^2 - \mathrm{CC4}, \tag{3.5}$$

where CLDV is the perception point when driving from a short distance, and CC6 is the speed oscillation that varies when the following vehicle is close to the lead vehicle. The next parameter is CC5, which denotes a positive relative velocity:

$$O\mathrm{PDV} = \frac{CC6}{17000} * (\underline{\Delta}\mathrm{x} - \mathrm{L})^2 - \mathrm{CC5}. \tag{3.6}$$

Here, OPDV (opening velocity difference) is the limit of the unconscious region, where the distance between the follower and the leader decreases over time. Furthermore, CC5 is the ultimate positive relative speed in the resulting unconscious process, CC7 is the mean of acceleration in the corresponding unconscious phase, CC8 is the typical overall acceleration after pushing the car from the stationary condition, and CC9 is a 50-mph automotive acceleration.

3.3. Lane-Changing Model

We utilized the VISSIM lane-changing model only for weaving segment analysis in this study. Vehicle lane-changing models are used to understand the behavior of vehicles during lane-changing times. Drivers usually find a comfortable gap between trail vehicles or lead vehicles in the new lane with proper acceleration and deceleration during lane-changing time. VISSIM incorporates a lane-changing model that works with the free-lane rule, which means vehicles may overtake in each lane; the slow-lane/fast lane rule follows the German traffic code. Both rules included vehicles' maximum and accepted deceleration, diffusion time, minimum clearance, safety distance reduction factor, and maximum deceleration for cooperative braking. All parameters are described below (Vissim, 2020).

Maximum Deceleration: This refers to the upper bound of deceleration of the own vehicle (the vehicle that wants to move to a new lane; B in Figure 6) and the trail vehicle (the vehicle that is already in the new lane but behind the vehicle that seeks to move to a new lane; A in Figure 6) during the lane change. A higher absolute value denotes more aggressive lane-changing behaviors.

Accepted Deceleration: This is the lower bound of deceleration of the own and trail vehicle during the lane change.

Diffusion Time: This is the maximum amount of time a vehicle can wait at the emergency stop distance for a necessary change of lanes. A lane change during normal traffic flow might require a greater minimum distance between vehicles to maintain speed-dependent safety.

Minimum Clearance: This is the gap that must be maintained between two vehicles after a lane change.

Safety Distance Reduction Factor: This factor concerns the safety distance of trail vehicle and lane changing vehicle, whether a lane change will occur.

Maximum Cooperative Deceleration: The trail vehicle will decelerate or brake cooperatively to allow the preceding vehicle to change lanes and move into its lane. The higher the value, the stronger the braking, and the greater the probability of changing lanes.

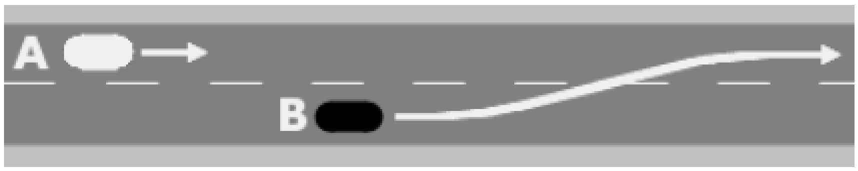


Figure 6. Lane-Changing Scenario (VISSIM, 2020)

To the best of our knowledge, few studies have attempted to calibrate VISSIM lane-changing parameters to reflect a study area. For the German freeway system, lane-changing parameters for the BFS as well as the weaving, merging, and diverging segments were determined for free-lane selection and right-side rule (Leyn et al., 2015). The Wisconsin DOT has determined the maximum deceleration for state-wide purposes (WisconsinDOT, 2018). However, none of the studies have elaborated a step-by-step direction to determine values for a case study area.

3.4. Study Area Description

Next-generation simulation (NGSIM) is an open data source developed by FHWA in a trajectory format (USDOT, 2016). The data used for this study was collected on June 15, 2005, from 7.50 to 8.35 AM on US10 in Los Angeles, CA, from Lankershim Boulevard to Cahuenga Boulevard using video cameras mounted on top of 36 story buildings. The length of the Study section was 2100 feet with five main lanes, one auxiliary lane, one on-ramp, and one off-ramp. The Complete vehicle trajectory was transcribed at a resolution of 10 frames per second. Figure 7 shows the diagram of US 101 that was used in this study.

The study section is signed at 55 mph. The first 15 minutes of data show that lane space mean speeds are below 26.5 mph, indicating oversaturation conditions. The second 15 minutes data is lower than 1st 15 minutes, which also indicates an over-saturated state. For analysis purposes, the entire section was divided into three sections. 0-500 ft is framed as 1st section, 500-1270 ft framed as 2nd section, 1270-2100 ft framed as 3rd section (figure 7).

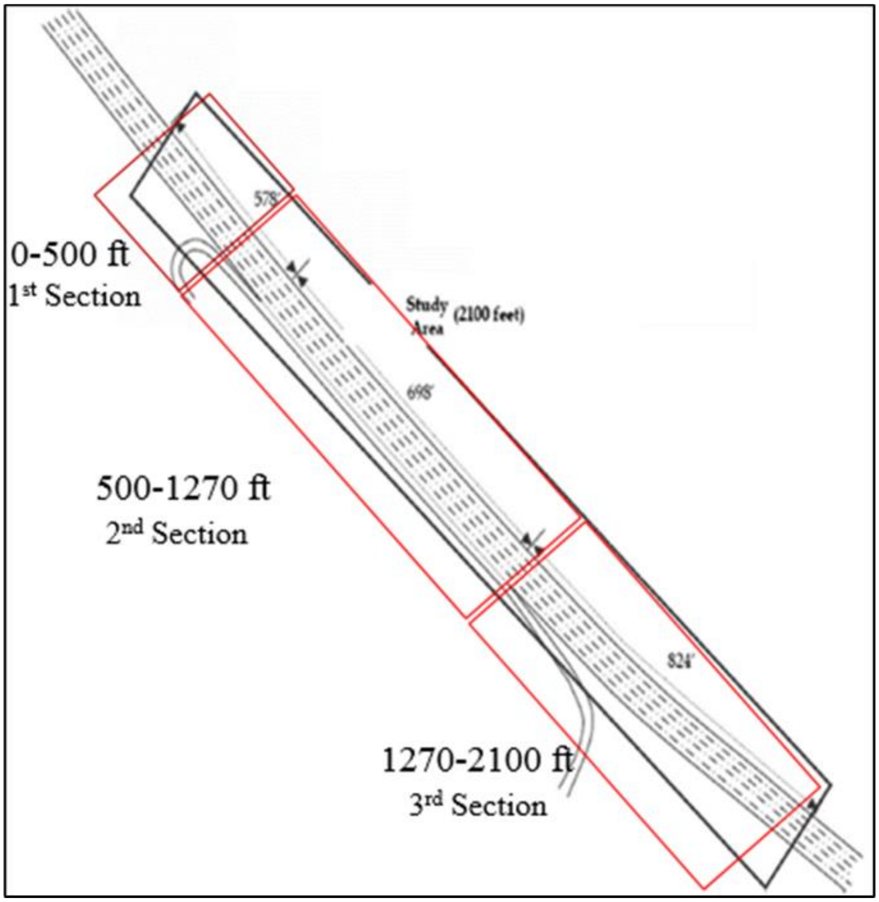


Figure 7. Schematic Diagram of US101 (Systematic, 2005)

The oversaturated traffic condition is critical in the traffic flow because demand is higher than capacity, resulting in reduced traffic flow and speed. In Figure 2, the flow curve from optimum point to zero point is the oversaturated traffic condition. The study section took traffic data during the morning peak period, which was an oversaturated traffic condition. It is challenging to develop a capacity assessment model to select proper driver's choice speed distribution when oversaturated traffic. An improper selection of distribution will lead to improper calibration validation of the model and a wrong capacity assessment. So, working with the most critical condition data and finding the ultimate result was one of the vital challenges of this research, and therefore oversaturated data is considered.

The Lane numbering starts from the rightmost side of figure 7. Lane 1 to lane 5 is through lanes in this section. Lane 6 is an auxiliary lane that begins from the endpoint of the on-ramp and ends at the start point of the off-ramp. On-ramp is lane #7 and Off ramp is lane #8. A detail about the speed, flow of each lane has been mentioned in Appendix A. For basic freeway segment analysis, lane 1-4 has been considered for all three sections. For weaving segment analysis, lane 1-6 of the 2nd segment (500-1270) has been considered.

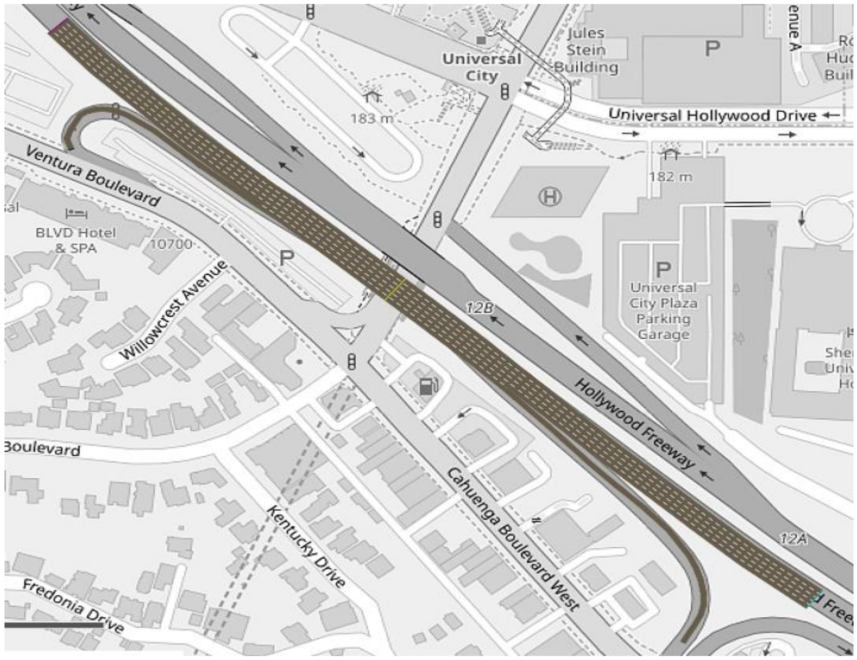
The segment can be used to generalize to other traffic locations. The primary requirement before developing a model is the collection of appropriate traffic data from the basic freeway and weaving segments. This study location is suitable for data collection. It covers all the requirements to construct a freeway capacity assessment model, such as sufficient length of study link, number of lanes, vehicle variation, and traffic operation parameters. The study location consists of the basic freeway, merging, a diverging and weaving section, a complete picture of the freeway system. Moreover, traffic data was collected during oversaturated conditions which are defined as the most critical situation. Besides, the dataset includes all required parameters to apply Wiedemann’s car-following theory, such as vehicles velocity, acceleration, space, and time headway. This segment can be generalized as an excellent example for data collection due to the reasons described above.

VISSIM requires a detailed and complete description of the layout of the geometries of the test site for meaningful output. This process has been described in the last part already.

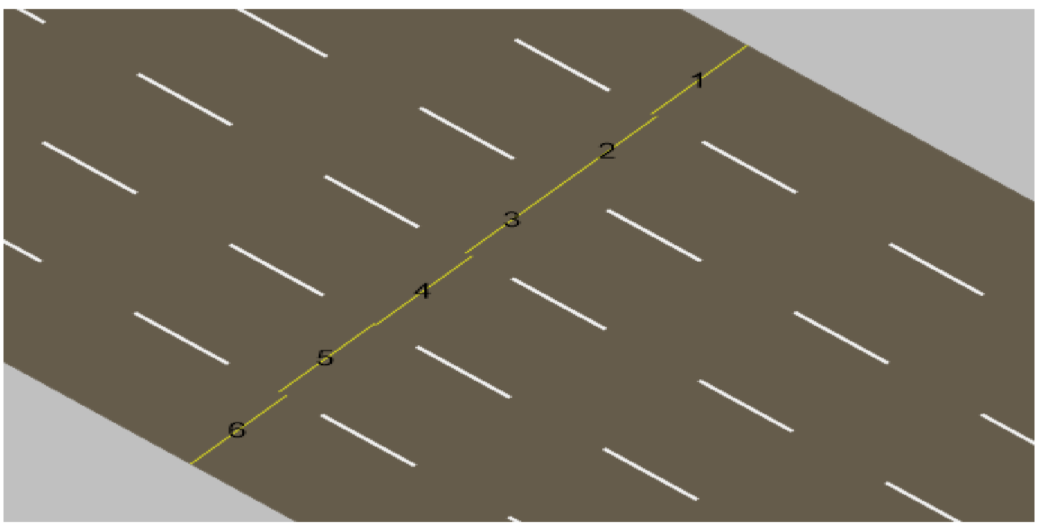
3.5. Setting Up the VISSIM Model for the Study Area

VISISM needs to prepare to run the simulation of estimating capacity of the study area. There are a few steps in VISISM microsimulation that have been described below.

1. The study location for this dissertation was applied to US 101, LA, California, as NGSIM data was collected from there. An overlapped geometry was drawn in VISSIM for five through lanes, one on-ramp, one off-ramp, the auxiliary lane with similar lane width as a field. In Figure 8 (a), the brown color road part indicates the drawn 5 through lanes, auxiliary lane, on and off-ramp roadway on VISSIM while keeping the default map behind.
2. Next, five types of vehicles were selected. Car and heavy goods vehicles (HGV) are considered traditional vehicles, AV cautious, AV normal, AV All-knowing were selected as AV vehicles. For all types of vehicles, driving behavior was determined as Freeway (free lane selection).
3. Desired speed was customized as a requirement. In this dissertation, a total of 6 types of speed distributions were selected with lower and upper bounds. The calibration, validation, and simulation setup for various free-flow speeds describe a detailed speed distribution.



(a)



(b)

Figure 8. VISSIM Screenshot of US101 Location (a) and Data Collection Positions (b)

4. The next part includes vehicle composition, where the percentage of traditional/AV classes composition is necessary to run the simulation. In the vehicle input part, traffic demand needs to be set as input. Calibration validation has a specific traffic demand which is borrowed from Cambridge Systematic (2005). This demand value was counted

from the field during observation. For capacity calculation, traffic demand was kept at 13,000 vehicles. In both cases, the first 5 minutes were spent for warm-up, which means running different vehicles initially and counting for the next 15 minutes.

5. Finally, the simulation parameter set up and evaluation parameter set up was completed to get the result. A total of six data collection points was set up in the middle of the brown color road (yellow color horizontal lines in Figure 8 (b)) to get the VISSIM output.

This process was followed to set up the simulation to assess the capacity in mixed traffic environment.

3.6. Traffic Demand

Traffic demand is one of the significant inputs to VISSIM. Traffic demand is the number of vehicles that are using a transportation system over a preset period. This research shows the number of vehicles that traverse the roadway section described previously over 15 minutes; traffic demand value was used in three categories in this dissertation. The first category includes traffic demand input for calibration. The first 15 minutes of traffic data were used to divide five minutes, which was used as calibration input traffic demand. The second category includes traffic demand input for Seconds 15 minutes, which is part of validation. Third category traffic demand was used to measure capacity. For all three types, initial five minutes (0-300 sec) were used for simulation warm-up where demand was kept below the field observation. Vehicle output was counted for the next fifteen minutes with five minutes breaks. A detail about traffic demand has been given in table 2. The Highway Capacity Manual (HCM, 2010) suggests a single lane capacity of 2,400 veh/hr/lane for highways for saturated conditions.

The literature and VISSIM manual suggest that increments of 15 minutes be used for the demand period in the models. It means that the HCM single lane capacity is 600 veh/hr/lane. A total of 5 through lanes, one auxiliary, on-ramp off-ramp each was used to replicate the roadways used in this study, as shown in table 2 for the basic freeway segment. For the weaving segment analysis, five lanes and auxiliary lanes were used in this dissertation. According to the HCM capacity manual, the five lanes can carry a maximum of 12,000 vehicles for all five lanes in the weaving section.

For this dissertation, however, since the objective was to evaluate traffic impacts in oversaturated conditions, the traffic demand was increased to 13,000 veh/hr for all four lanes during capacity analysis. It is worth noting that the actual number of vehicles that will use the network during the study period will be lower. The number of vehicles using the network in a microsimulation setting can never exceed the physical capacity of the roadway network.

Table 2. Traffic Demand (Veh/hr) Input for Various Categories.

	Calibration		Validation		Capacity Analysis	
	BFS	Weaving	BFS	Weaving	BFS	Weaving
0-300 seconds	4000	4000	4000	4000	4000	4000
300-600 seconds	6912	9240	6228	8364	13000	13000
600-900 seconds	6672	9012	6276	8352	13000	13000
900-1200 seconds	5472	7404	5232	7056	13000	13000

3.7. Summary

In this chapter, details of the VISSIM Wiedemann car-following model, lane-changing model, a brief discussion of data type, data obtaining, and preparing system have been discussed. A short description of the data collection area, the timetable for data collection, VISSIM simulation preparation for the assessment have been discussed with equation and description. In addition, the traffic demand for the VISSIM inputs were also described. The next step is the calibration and validation of the model which will be detailed in next Chapter.

4. VISSIM MODEL CALIBRATION

4.1. Introduction

The market penetration of AVs/CAVs will have an impact on capacities. An essential question that planners and traffic engineers have right now is how capacities will change with different penetration and AVs and CAVs algorithms compared to traditional vehicles as we see today. As AVs and CAVs get introduced, their algorithms will be very cautious, as seen in the current Tesla (Tesla, 2021) and other car models (Waymo, 2021) that perform self-driving functions under specific scenarios. As data from their introduction and penetration levels increase, the algorithms will get more aggressive with a headway reduction. Thus, we may have a period when we face lower capacities than traditional vehicles as AVs/CAVs get introduced and their market penetration increases. Capacity gains will occur as their algorithms get better and their market penetrations increase. It is essential to estimate these impacts to prepare our transportation systems to introduce AVs and CAVs at planning and operations levels.

The AV/CAVs literature suggests improving capacities by over 30% under the right circumstances. Transportation planners develop models that forecast traffic and its impacts on the transportation supply. The output of these models is used to create short and long-range transportation plans. With the potential effects of AVs/CAVs on capacities, transportation planners and decision-makers are constantly asking if the capacities used in these models are wrong. For example, a transportation planning model could predict that traffic on a hypothetical roadway corridor that currently has four lanes will increase by 30% over the next 15 years. The impact of this increase in traffic could call for the addition of the roadway's capacity to six lanes given traditional vehicles. However, if AVs/CAVs are introduced, the capacity implications could potentially change. The additional lanes might not be warranted given the correct estimation of capacities. Therefore, it is necessary to assess freeway capacity under mixed traffic scenarios where the traditional vehicles, the autonomous vehicle will exist together.

On the other hand, the impacts of this 30% could be more significant with the introduction of AVs/CAVs than traditional vehicles. This could happen if the technologies in most AVs/CAVs in the traffic stream are less aggressive than conventional cars. If the algorithm in AVs/CAVs limits the spacing and headway between vehicles in traffic in comparison to traditional cars. Automatic Cruise Control and level one autonomy vehicles leave more significant gaps and headway than conventional cars. The implication could be that the proposed six-lane roadway will still be deficient in handling the 30% increase in traffic for the hypothetical road. There are several ongoing efforts to quantify the capacity impacts of AVs/CAVs under different traffic conditions, roadway types, and AV/CAV levels.

The mix of AVs/CAVs and classic cars will also impact capacities. It is plausible that we may have Cautious, Normal, and AV All-knowing cars driving simultaneously on the same roadway as traditional cars. The impacts will be different for a situation where there will be 100% AV cautious cars. The different penetration levels of each of these AV/CAVs will have impact capacities differently. The capacity impacts for a scenario with 80% AV cautious and 20% all-knowing will be different for a system with 80% AV all-knowing and 20% AV cautious. AV-cautious, for example, at lower penetrations may have minimal impact on capacities. As their penetration increases concerning the total cars on the roadways, their capacities will also change to 100% penetration.

On the other hand, AV All-Knowing will perform more aggressively and have lower headways and gaps, increasing capacities more than AV Cautious vehicles. Its impacts on capacities will be positive at perhaps most levels of penetrations and speeds. The hypothesis here is that different mixes of AV/CAVs will have other implications for highway capacities.

To test these hypotheses, a simulation analysis based on microsimulation within the VISSIM software was performed as shown in Figure 9. First, the baseline capacities using NGSIM data were built to calibrate and validate the baseline model. Next, models with single classes of AV/CAVs are built and the capacity impacts are measured followed by models with mixed types of AVs. Different penetration levels and different mixes of AV/CAVs were used for the modeling.

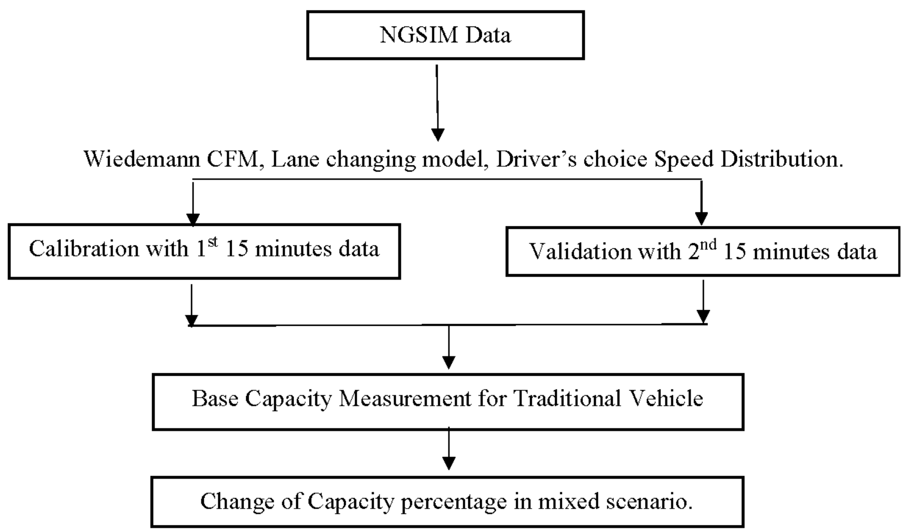


Figure 9. Flow Chart of Methodology

To achieve an effective model, calibration and validation is needed and detailed in this chapter. Calibration is adjusting the model input parameters so that the model closely replicates observed data, validation compares the model output data to observed data using data not used to calibrate the model.

4.2. Wiedemann Car Following Model Behavioral (CC) Parameters Data Collection, Calibration, and Validation

The basic freeway and weaving segments have been selected to assess this study's capacity in the mixed traffic situation. A microsimulation-based model will be built using trajectory data after proper calibration and validation. The next section will discuss the calibration and validation of the basic freeway and weaving segment separately.

4.2.1. Calibration of the Basic Freeway Segment

Calibration means comparing a parameter value provided by a device/ software with known real-world values. The purpose of calibration is to replicate the field scenario in a simulation environment using the proper layout of the road, adding traffic volume with proper speed distribution so that the observed traffic parameters match with simulation output. For accurate calibration, a set of CC parameters, speed distribution needs to be selected. Whether this selection is appropriate, a validation process needs to do with different day/ time traffic data where both traffic patterns are similar. The simulation software VISSIM contains calibration components (CC) parameters. Wiedemann 99 model includes a total of 9 parameters. These parameters are based on the space, time, speed, and acceleration of the following vehicle according to the reaction of the leading vehicle. The calibration process starts with finding appropriate CC parameters for passenger cars and heavy vehicles, then compares observed and simulation output using space mean speed (macro-level) and cumulative speed distribution (micro-level). Finding proper CC parameters is an iterative process. It means, initially, the CC parameters value with a range has been determined from the dataset using logic. From the range, a single value has been picked up and put into the VISSIM. A simulation ran to get space mean speed data as an output using that particular set of parameters. This process was continued until the space mean speed from simulation output was matched with the observed value.

The four leftmost lanes between 7.50-8.05 AM were considered for this research's Basic Freeway Capacity component. There are three vehicles type available in the Dataset, passenger cars, heavy vehicles, and motorcycles. Only Passenger cars and heavy vehicles are used for this research as the percentage of the motorcycle was 1%, which is negligible. CC values were determined based on these two vehicle types, as shown in

Table 3. Figure A.7 in Appendix A is a snapshot of the data used for calibration and developing the base model of only traditional vehicles. This snapshot file includes 20 columns with the most essential variables discussed next.

The data collection provides unique ids for all cars in the traffic stream. These IDs are used to identify and track the vehicles in the traffic stream and their characteristics as they drive through the roadway section. The IDs can deter whether cars are driving in the traffic system by following each other. For example, in the first column, the vehicle ID of Figure A.7 is 726, which is the following vehicle, and the preceding vehicle is 709. After a certain period, the prior vehicle number becomes 714. The following vehicle means the vehicle which is following while having a leading vehicle. There are eighteen attributes in the original data set, but only the following attributes were used for this study. The features that have been used from these files are vehicle length (v_length), vehicle width (v_width), vehicle class (v_class, car = 2, HV= 3), vehicle speed (v_vel), vehicle acceleration (v_acc), lane ID, Space headway (Space_hdwy = space gap from the front bumper of the leading vehicle to the front bumper of the following vehicle), Time headway (Time_hdwy = time gap from the front bumper of the leading vehicle to the front bumper of the following vehicle). The last two columns of the snapshot are the previous vehicle velocity (pre-veh_vel) and previous vehicle class (PreVeh_Class) that has been created manually using the v_lookup formula in Microsoft excel. To discover the different CC values, different logics have been applied and are described next.

4.2.1.1. CC0 Standstill Distance

CC0 (space gap) is the distance the following vehicle keeps away from the leading vehicle in a standstill situation. It is the distance between the rear bumper of the front vehicle to the front bumper to the following vehicle in a stop condition. L is the vehicle length. To assess CC0, only 0-10 mph speed (v_Vel) range were considered using the filter in MS excel for the following/considered vehicle, and the corresponding space headway (AX in Figure 5) column was checked. The max and min space headway was noted, and average vehicle length was subtracted from the values. The average length of a car (L) from the entire file used in this study was 14.5 ft, and the heavy vehicle length was 32.5 ft. It is mentioned before that CC0 stands for standstill distance between vehicles; however, there was no space headway found in zero mph speed, which is why speeds between 0-10MPH were considered standstill speed.

4.2.1.2. CC1 Headway Time (sec)

CC1 is the time gap between two successive vehicles that are in motion. It is time for the following vehicle to reach the lead vehicle's position in a traffic stream. This is an additional gap after CC0. More than ten mph speeds for the following vehicle were considered to determine this value, and the corresponding headway range was considered. Then (The length/Velocity) value was subtracted from the Time headway value to get CC1.

To figure out the CC2-CC5 values, the graph of spacing vs. relative velocity (Figure 10) was drawn considering different vehicle pairs where,

$$\text{Relative velocity} = \text{Speed of (following vehicle – Leading Vehicle)} \qquad (4.1)$$

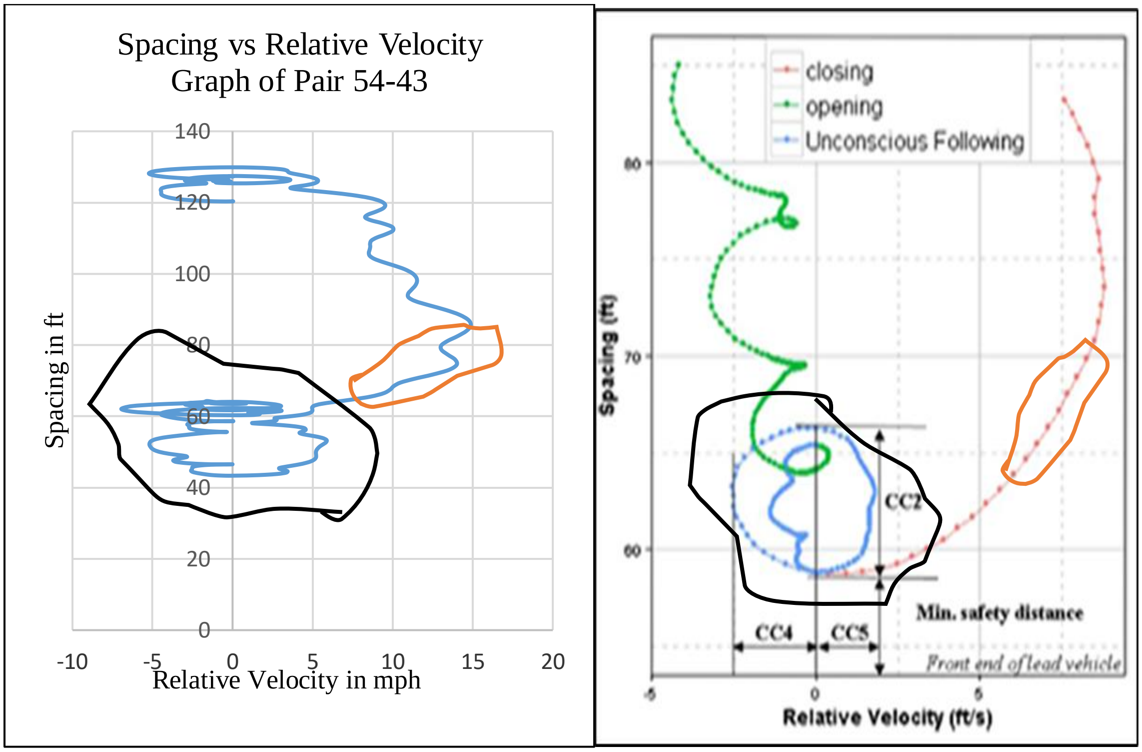
Here, Spacing = Space headway- length of the Leading vehicle. This process has been done with several steps. The first step was using the filter option in MS excel. The choosing the following vehicle number. Suppose in the file, the vehicle with vehicle ID 51 has four preceding vehicles (34,40,47,49) in different time frames while crossing the study section. Considering a single pair, for example, 51-40, a space vs. relative velocity graph was drawn, and data were extracted using a previous research result that was done by (Manenni, Sun, & Vortisch, 2008) Figure 10 (b). In such a way, randomly, 177 pairs were considered to draw and extract the CC2, CC3, CC4, and CC5 values. A sample of a graph of pair numbers 54-43 has been drawn in Figure 10 (a).

4.2.1.3. CC2 Following Variation

CC2 (unconscious following zone) is the extra protective distance that the driver needs to maintain throughout the ensuing cycle of the unconscious. The unconscious following zone can be described following way: When a leading vehicle drives at a constant velocity, at that situation if the following vehicle approaches the leading vehicle, it continuously decelerates until it reaches zero relative velocity, and the following vehicle's driver tries to maintain low acceleration/ deceleration with an ideal gap. This is when relative velocity changes from positive to negative. The following unconscious region is the data points close to zero relative speed corresponding to low acceleration/deceleration. We selected a pair of vehicles following each other from the data set, then drew a spacing vs. relative velocity curve that will look the same as Figure 10 (b). CC2 is the difference in spacing indicated in the Y-axis distance in Figure 10 (b) (black color circle). For example, from Figure 10(a), the CC2 value is 18 ft (60-42 = 18 difference in Y-axis). Overall, Figure 10 represents spacing vs. relative velocity.

When the following vehicle has a higher velocity than a leading vehicle, it comes closer, and spacing decreases. This is called the closing situation, which makes a slope in the graph.

Orange circles in both graphs are the zone of closing. When leading and the following vehicle has a comparatively lower gap while having relative velocity around zero, it creates an area indicated with a black boundary in both graphs. This is called a following unconscious region.



(a) (b)

Figure 10. Spacing vs. Relative Velocity of Paired Vehicle (Manenni et al., 2008)

4.2.1.4. CC3 Time from Start of Deceleration to Start of Unconscious Process

CC3 is the time elapsed from deceleration to the beginning of the following unconscious process for the following vehicle. It is the perception threshold for the following vehicle during the closing time (close to the leading vehicle). Selecting a pair of vehicles followed by drawing spacing vs. relative velocity graph, a slope would appear the same as the red color curve in Figures a & b, which is indicated in orange color in both figures, indicating closing to unconscious region. The slope was measured as spacing divided by Relative velocity. Only slope values were taken from those pairs that showed in the graph. From the graph Figure 10 (a), the CC3 value was found 1.5.

4.2.1.5. CC4-CC5 Negative and Positive Relative Velocity for Following Vehicle

I selected a pair of vehicles following each other from the data set, then drew a spacing vs. relative velocity curve that will look the same as Figure 10(b) (same as CC2 process) that retrieve CC4, CC5 values. These values are the two boundaries that represent negative and positive relative velocity. For example, from Figure 8 (a) CC4, CC5 value was found -6, 6. The same procedure was followed for other pairs also.

4.2.1.6. CC6 Speed Oscillation of Following Vehicle

CC6 represents how the following vehicle's speed oscillation varies during closing time by the following vehicle to the leading vehicle. Oscillation is the repeated change, usually in time, between two or more distinct states of some measure about a central value (often a balance point). CC6 was kept as default since we could not find any explanations for estimating CC6 even after contacting the software vendor.

4.2.1.7. CC7 Acceleration during Unconscious Following Process

CC7 is the acceleration during the following unconscious process, which means acceleration during the CC2 range. During the measure of CC2, the corresponding acceleration range value of the following vehicle was considered.

4.2.1.8. CC8 Acceleration of Vehicle from Stationery State

CC8 is the acceleration after the vehicle starts moving in a stationary situation. Therefore, 0 - 22.5 ft/s threshold was set to get corresponding acceleration. The following vehicles' speed range was selected from the 0-22.5 ft/s, and the corresponding acceleration range was considered.

4.2.1.9. CC9 Acceleration of Vehicle Driving Over 50 MPH

CC9 is the acceleration of a vehicle driving at or above 50 mph. Therefore, the following vehicle has considered 74 ft/s and above 50mph to get the corresponding acceleration range.

Each of the vehicle pairs needs to be considered to estimate the extracted value. Some of them might not show proper figures due to insufficient data. Table 3 shows simulation calibration component parameters used for this study based on the observed vehicle speed. From the range of each parameter, the value was selected for each CC and tested.

Table 3. Calibration Parameter Values for Traditional Vehicle

Parameters	Default	Car	Heavy Vehicle	Unit
CC0	4.92	8	18	Ft
CC1	1.5	1	2	Second
CC2	13.12	11	25	Ft
CC3	-8	-3	-3	Second
CC4	-0.35	-1.12	-1.8	m/s
CC5	0.35	1.5	1.80	m/s
CC6	11.44	11.44	11.44	1/ (m.s)
CC7	0.82	0.47	1.70	ft/s^2
CC8	11.48	5.80	6.0	ft/s^2
CC9	4.92	0.51	1.25	ft/s^2

4.2.1.10. Driver's Choice Speed Distribution

One of the key facts of setting up a simulation is evaluating driver choice speed distributions, as the improper selection may lead to a fragile structure of the model. The meaning of the driver's comfort speed has been described in the problem statement part. For this dissertation, it wasn't easy to get driver choice speed distribution for the entire segment because it was oversaturated from the beginning of the data collection period. During the simulation, a bottleneck started from the middle of the 2nd section and propagated to the 1st section. Therefore, the research region's third section (1270-2100 ft) (Figure 8) was used to get driver preference speed distribution. It was assumed drivers travel at their choice of speed after the third-second section. The range of the third section is the starting point from diverging point to the end of the entire section. The observed data set found a speed range between 35 to 60 mph (FFS 55 mph for the study section). The following cumulative distribution was used as input to VISSIM for calibration, validation, and capacity analysis, as shown in Table 4.

Table 4. Drivers Choice Speed Distribution Used in the Simulation

Speed in mph	Cumulative Distribution
35.00	0.00
37.67	0.19
42.02	0.66
49.30	0.91
60.00	1.00

Figure 11 shows the comparison of the observed and simulated speed distributions for the third section. Again, a visual inspection shows that the simulation speed distributions match the observed speed distributions very closely. This meant the selected drivers' choice speed distribution was accurate and correctly represented in the model.

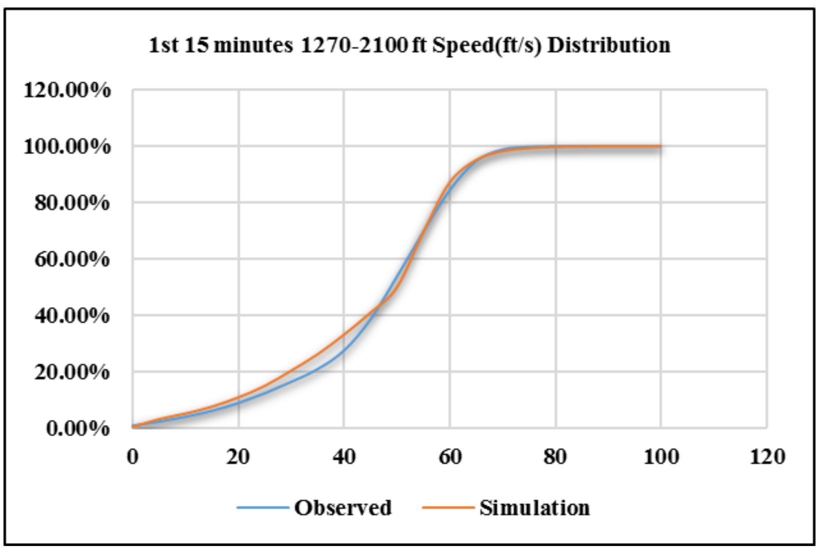


Figure 11. Comparison of Observed Vs. Simulated Drivers' Choice Speed Distribution

Due to the analysis, the segment being in a saturated state at the start of the data collection, it is not feasible to use a 35-60 mph range for speed which means upper bound 60 mph and lower bound 35 mph. The reason is that the first segment flow affects the second segment's flow. At the beginning of the study section (first segment), the speed distribution was tested to obtain the correct speed scale. The range of the speed for calibration purposes that was used was between 25 and 50 mph (25 mph difference same as driver's choice speed difference) where upper bound was set 50 mph, lower bound was set 25 mph and keeping the distribution same as the driver's choice speed distribution.

4.2.1.11. Calibration Measures of Effectiveness – Macro and Micro Level

Several parameters are used to compare observed and simulation data to measure how well the model replicates real-world data. The comparison includes traffic flow matching less than 15% difference and lower GEH statistics value, comparing modeled vs. field speed, comparing visually acceptable lane utilization (Crossing, 2006). In this study, speed comparison has been tested where both visual and statistical tests are performed to compare the model output to the observed data. Speed is a unique parameter collected from the field and can be directly obtained from simulation.

For visual tests, graphs at the macro (space mean speed) and micro-level speeds (cumulative speed distribution) compare the simulated output to the observed data. VISSIM allows for the placement of data collection metrics within the roadway network during simulation. The metrics were set in the middle of the entire section, which collection traffic flow value as a representative point of the section and a bottleneck location. However, field data were collected using eight video cameras mounted on top of 36 storied buildings, and data was processed later. There is no similar process in VISSIM available except putting a data collection point on the road. In the VISSIM simulation, the built-in data collection points were selected from the index and placed at the midpoint of the second segment of lanes 1-4 from the left of the travel direction ion to examine traffic speed output. At the macro level, space mean speeds evaluate whether the simulated speed output pattern matches the observed data. Space means speeds are obtained from the detector for the simulation model. Though lane 1 data has a difference of around six mph, the other lanes show relative value and patterns. Space means speed comparison between the modeled output and the observed speeds for each of the four lanes are shown in Figure 12.

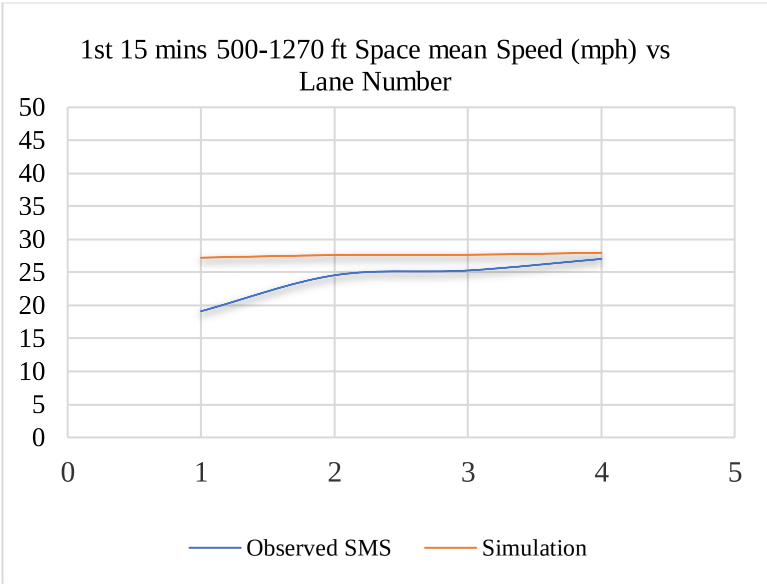


Figure 12. Speed Comparison for Calibration in Macro Level (a) and Micro Level (b)

At the micro-level, the cumulative speed distribution for the second segment was compared to the observed incremental speeds (Figure 13). Cumulative speed distribution is a distribution of the speed of a specific range called Bin (5 mph range in this case), then it finds the total frequency of that bin followed by the percentage of frequency. Adding percentages together cumulatively creates an S shape line. In this study, the field observed value matches with the calibration output in Figure 13, but the aim was not to do a perfect match rather than matching the pattern and similarities in how data looks. Both spaces mean speed and cumulative speeds comparison are satisfactorily calibrated to the observed speed distributions as graphs are showing good matching through eye measurement

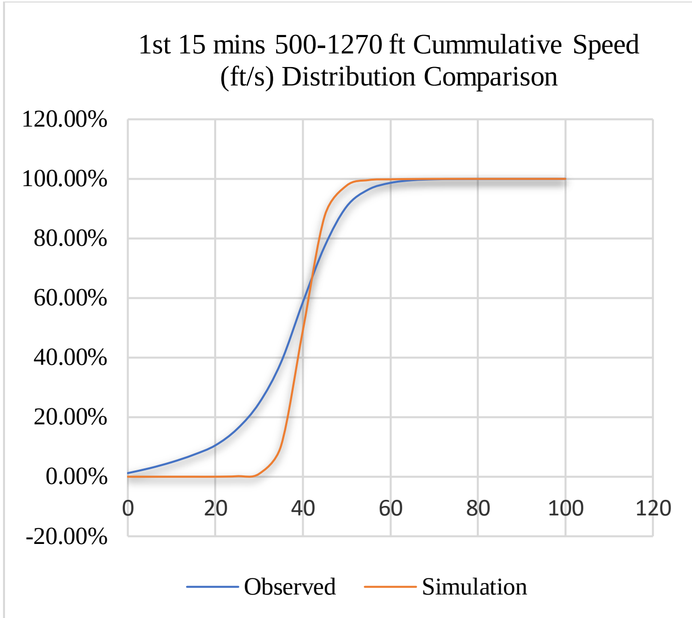


Figure 13. Comparison of Cumulative Speed Distribution Between Modeled and Observed Speeds

In addition to the visual tests, statistical tests were performed for the macro level to verify whether the simulation output was significantly different from the observed data. A paired t-test was performed at the 95% confidence interval where the null hypothesis was no difference between the means of the observed and simulated SMS. The two-tail P-value shows 0.102966 that is greater than 0.05 with only four observed data existing, which means there's insufficient evidence in favor of the alternative hypothesis that the means differ. The equation used to find to estimate the T-value and value is given below.

$$t_c = \frac{m}{s/\sqrt{n}} \tag{4.2}$$

Here, m is the mean difference, n is the sample size, s is the standard deviation of data set Excel output has been given in Table 5

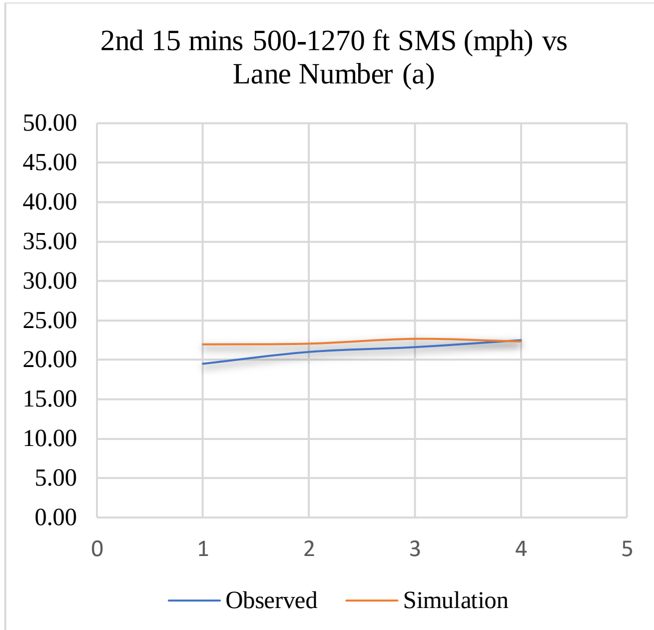
Table 5. Excel Output of Space Mean Speeds T-Test for BFS in Calibration

	Observed	Simulation
Mean	24.00	27.62
Variance	11.64	0.09
Observations	4	4
Hypothesized Mean Difference	0	
df	3	
t Stat	-2.32	
P(T<=t) one-tail	0.05	
t Critical one-tail	2.35	
P(T<=t) two-tail	0.10	
t Critical two-tail	3.18	

4.2.2. Base Model Validation for the Basic Freeway Segment

The next step in the modeling process was to validate the model against real-world data for another period, not calibrating the model. Validation typically involves using visual comparison tools and statistical tools. Thus, the model is validated at the micro and macro levels.

Space mean speed (SMS) from lanes 1-4 from the left side and cumulative speed distribution of the middle section were compared to the observed data as shown in Figure 14. Cumulative speed distribution indicates the entire study section's speed output, which is called microanalysis. On the other hand, space means the speed of each lane rather than the whole section compared to the macro-level analysis. It is noteworthy to mention that the 2nd 15 minutes. For validation purposes, the second 15 minutes were chosen. SMS was lower than the first quarter (compared to the observed speed value 1st and 2nd 15 minutes). The Speed spectrum from 20-45 mph (25 mph difference) is extended for validation using the same distribution used in calibration.



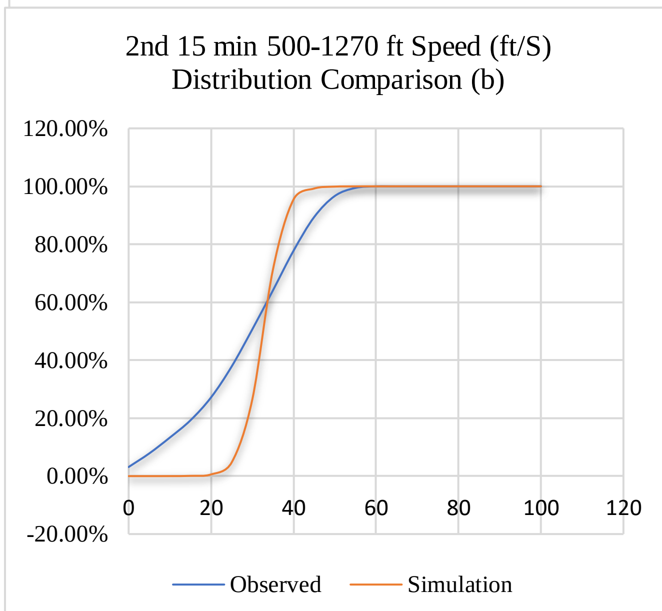


Figure 14. Speed Comparison for Validation in Macro Level (a) and Micro Level (b)

The macroscopic comparison (SMS comparison) shows a similar match between observed and simulation data, a close straight line in testing. On the other hand, cumulative speed data distribution showing an S curve matches the observed data pattern.

A paired t-test of two samples was performed to compare the observed and modeled SMS means for statistical validation. The null hypothesis was no difference in mean speed values between the observed and modeled SMS. The P-value of two-tail was found at 0.13383at the 95% confidence interval. This value is greater than 0.05, with only four observed data existing which means there's insufficient evidence in favor of the alternative hypothesis that the means differ. Detailed Excel result has been given in Table 6.

Table 6. Excel Output of Space Mean Speeds T-Test for BFS Validation

	Observed	Simulation
Mean	21.15	22.24
Variance	1.58	0.09
Observations	4	4
Pearson Correlation	0.66	
Hypothesized Mean Difference	0	
df	3	
t Stat	-2.04	
P(T<=t) one-tail	0.06	
t Critical one-tail	2.35	
P(T<=t) two-tail	0.13	
t Critical two-tail	3.18	

4.3. Calibration and Validation of Wiedemann Car Following Model for the Base/ Traditional Vehicles at Weaving Section

4.3.1. Calibration of Weaving Segment

The weaving segment begins at the point of the study section, where it merges with the standard freeway on the highway and proceeds to the point of exit from the road. This study used lanes 1-6 from Figure 8, the midsection (500-1270) from 7.50-8.05 AM time, to calibrate the weaving segment. A detailed traffic flow and related calculation of weaving and non-weaving have been provided in Appendix B. The set of data features three classes of vehicles. Only cars and heavy vehicles were considered; the motorcycle was excluded, as previously explained. Depending on certain types of vehicles, CC values were calculated and calibrated. A similar procedure has been followed to find CC parameters, as explained in the basic freeway segment.

Table 7 shows the CC parameters for both cars and heavy vehicles compared with the default values given in VISSIM used in this study for the weaving area.

Table 7. Car Following Calibration Parameters Values for Weaving Section.

Parameters	Default	Car	Heavy Vehicle	Unit
CC0	4.92	8	18	Ft
CC1	1.5	1	2	Second
CC2	13.12	**9**	25	Ft
CC3	-8	**-1.9**	-3	Second
CC4	-0.35	**-1.46**	-1.8	m/s
CC5	0.35	1.46	1.80	m/s
CC6	11.44	11.44	11.44	1/(m.s)
CC7	0.82	**3.85**	**1.70**	ft/s^2
CC8	11.48	**4.13**	**3.59**	ft/s^2
CC9	4.92	**2.56**	**4.92**	ft/s^2

CC parameters value for weaving section is almost similar for the gap, time, and relative speed, but differ for acceleration (CC7-CC9). In this section, the acceleration value during the unconscious following (CC7) region for the car is higher than the basic freeway segment. The acceleration value for vehicle speed over 50 mph representing CC9 is higher for both vehicles than the basic freeway segment. The higher value is lane changing for merging or diverging as it governs in the entire section.

4.3.2. Calibration of Lane Changing Parameters

Besides the car-following parameters, lane-changing parameters also need to be calibrated to represent ground truths. The second section of the study area (500-1270) (figure 7) and data from 7.50 to 8.05 were considered for this calibration. At the very beginning, only those vehicle IDs have been identified that changed lanes from ramp to freeway and freeway to ramp and those vehicles which did not change lanes (details in Appendix A). Therefore, the following parameters have been calibrated for the lane-changing model.

- Max deceleration: This is the upper bound of the deceleration range of the considered vehicle (B in Figure 6) that wants to change lanes. Consider a driver who wants to change lanes; for example, that driver perceives the speed of the vehicles in the lane they want to change into, they will adjust their speeds based on the speed of the vehicle ahead of them in the lane they are moving into. Before changing the lane, the upper bound from the acceleration column from the data set was identified. At the same time, the trail vehicle ID of the new lane was obtained from the data set (A in Figure 6 and corresponding deceleration of that trail vehicle before considered vehicle change lane was identified. As a result, the value of similar lane-changing vehicles was determined -11.2 ft/s2 for own and -8.62 ft/s2 for trail vehicles.

- Accepted Deceleration: The steps were the same as max deceleration, but a lower bound of deceleration was considered from the data set for own and train vehicle ID. The value was determined -0.88 ft/s2.
- There is no previous research or even VISSIM 2020 manual that describes a step-by-step work to find value for other lane-changing parameters from a given dataset. That is why all the other parameters were kept as default for this study.

Table 8 describes the values that are used for lane changing calibration in VISSIM are given below.

Table 8. Lane Changing Calibration Parameters Values

Parameters	Own	Trail
Max deceleration (ft/s^2)	-11.2	-8.62
(-1) ft/s^2 per distance	200 ft	200 ft
Accepted Deceleration	-0.88	-0.88
Waiting time before diffusion	60 s	
Safety Distance reduction factor	0.6	
Max Deceleration for Cooperative Braking	-8.62	
Min Clearance	1.64 ft	

Evaluation of driver comfort speed distributions is one of the main aspects of a simulation setup, as the improper choice of distribution will result in the wrong assessment of capacity. It was challenging for our analysis to get preferential driver allocation for the whole section because it was excessively saturated from the data collection time. The third segment (1270-2100 ft.) of the testing area (figure 7) was used to get driver preferential speed distribution. After the end of the diverging point, we assumed drivers were driving in their choice of direction. A speed range between 35 to 60 mph (FFS 55 mph for the study section) of separate distribution was used, as shown in Table 9

Table 9. Drivers Choice Speed Distribution Used in Figure 14

Speed in mph	Cumulative Distribution
35.00	0.00
37.67	0.19
42.02	0.66
49.30	0.91
60.00	1.00

Figure 15 demonstrates the contrast between observed and 3rd section simulation velocity distributions. Again, the distributions of simulation speeds conform very closely to the observed distributions of distance.

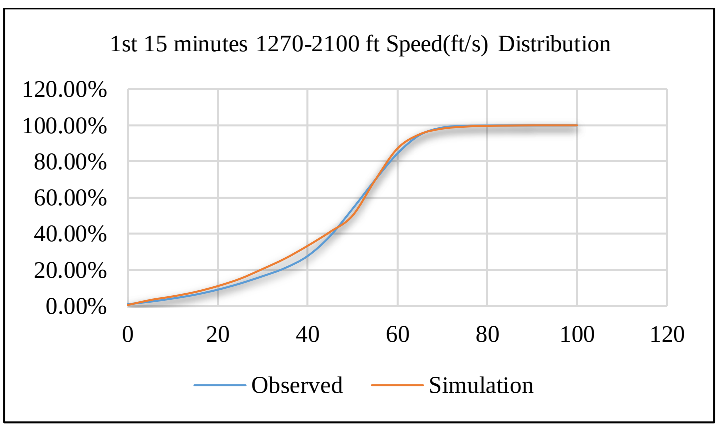


Figure 15. Third Segment Speed Distribution Matching with Selected Drivers' Choice Speed Distribution

The testing was performed using macro (comparing speed for each lane) and micro (comparing speed for every 10th of a second) levels. The space means velocity from the second segment (500-1270) was used for testing. A bottleneck formed in this segment initially during the simulation and then propagated to the first section (0-500 ft). The midpoint of the second section of lanes 1-4 from the left was chosen for effectiveness testing. Finally, the calibration performance was balanced by the space mean speed for each lane and the cumulative speed distribution for the second segment, as seen in figure 16 a and b. Both Micro and Macro velocities are satisfactorily matched to the speed distributions observed.

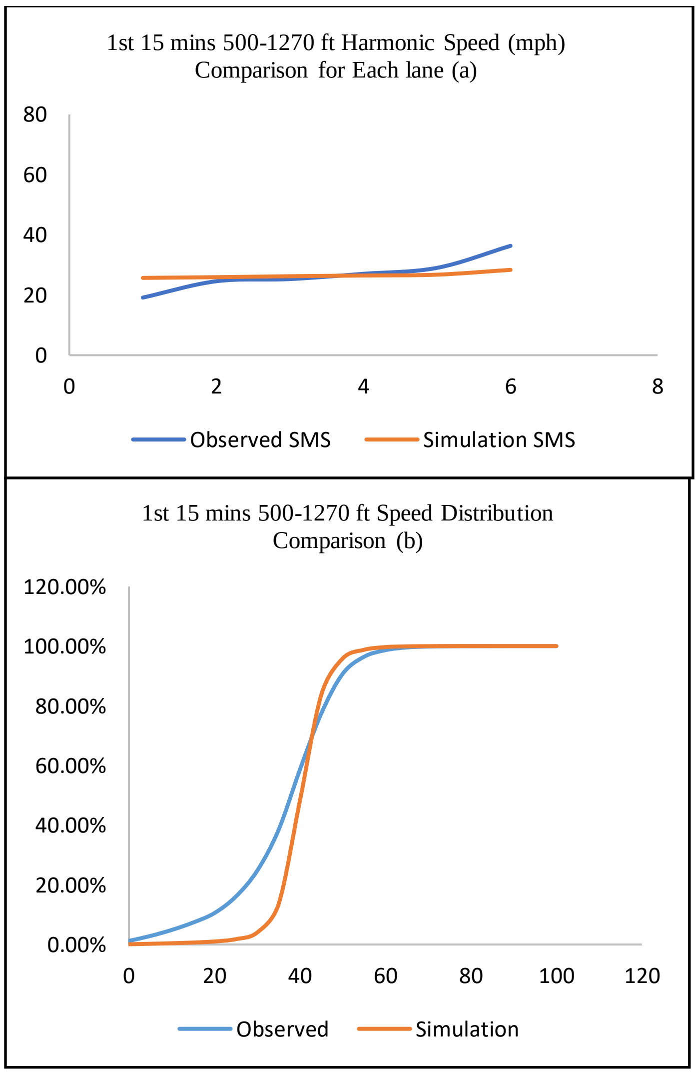


Figure 16. Speed Comparison for Calibration in Macro Level (A) and Micro Level (B)

Because the measurement section shows that the traffic is already over-saturated at the beginning of the data collection time frame, it is unacceptable to use the driver's choice of the speed range for calibration. The first segment's speed distribution was also checked for the correct speed scale since the first segment's movement influences the second segment. The distribution was kept the same as the cumulative distribution of the driver's expectations. The speed scale used was between 25 and 50 mph. The simulation output was compared in two ways. One with each lane space means speed comparison, which shows an almost good match between observed and simulation output data Figure 16(a) which is named as macro-level analysis and another with the second segment of the study section cumulative speed comparison between observed and simulated data Figure 16(b) which is named as micro-level analysis. A further paired t-test was performed comparing speed data between each lane with a 95% confidence interval where the null hypothesis was no difference between mean. P-value was found at 0.872792, which is more than 0.05, with only six observed data existing which means there's insufficient evidence in favor of the alternative hypothesis that the means differ. The excel output is given below in Table 10

Table 10. Excel Output of Space Mean Speeds T-Test for Weaving in Calibration

	Variable 1	Variable 2
Mean	26.89	26.56
Variance	32.35	0.90
Observations	6	6
Pearson Correlation	0.96	
Hypothesized Mean Difference	0	
df	5	
t Stat	0.16	
P(T<=t) one-tail	0.43	
t Critical one-tail	2.01	
P(T<=t) two-tail	0.87	
t Critical two-tail	2.57	

4.3.3. Base Model Validation for Weaving Section

This section discusses the validation of the model using a different time frame that was not used for calibration. To do this, the second 15 minutes was chosen, then space means speed

(SMS) of lanes 1-6 of the midsection (500-1270) and cumulative speed distribution of the same section were compared to the observed speeds. The 2nd 15 minutes SMS was lower than the first 15 minutes data (compared to the observed speed value 1st and 2nd 15 minutes). The velocity range (20-45 mph) was expanded to test the same distribution array as before. It is not easy to match the cumulative speed distribution curve (Figure 14b) because the data set contains the value of one-tenth of a second each. The macroscopic positioning shows improved visibility, a near straight-line SMS comparison in research (Figure 17a). A further paired t-test was performed again with a 95% confidence interval where the null hypothesis was no difference between mean. P-value was found at 0.909128, which is more than 0.05, with only six observed data existing which means there’s insufficient evidence in favor of the alternative hypothesis that the means differ. The result is given in Table 11.

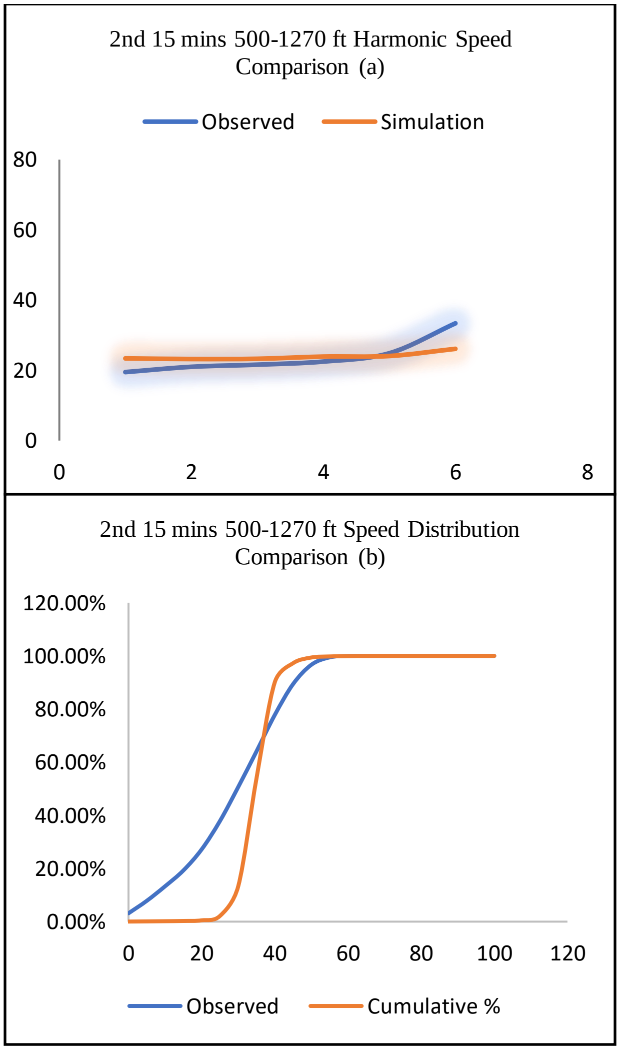


Figure 17. Speed Comparison for Validation in Macro Level (A) and Micro Level (B)

Table 11. Excel Output of Space Mean Speeds T-Test for Weaving Segment Validation

	Observed	Simulation
Mean	23.81	24.00
Variance	25.15	1.19
Observations	6	6
Pearson Correlation	0.97	
Hypothesized Mean Difference	0	
df	5	
t Stat	-0.12	
P(T<=t) one-tail	0.45	
t Critical one-tail	2.01	
P(T<=t) two-tail	0.90	

After successfully calibrating and validating the base models, the net step introduces AV/CAVs into the simulation setup. This step involves adding demand for different penetrations of AVs/CAVS and developing the CC parameters for these vehicles. Therefore, the next section discusses the implementation of CC parameters for different penetration levels of AV/CAVs.

4.4. Wiedemann Parameters for the AV Vehicles Classes / Simulations

The Coexist project proposed Wiedemann 99 CFM CC parameter values for different AV classes after numerous trials validated against naturalistic data. The data were gathered with actual automated standard traffic vehicles in the real traffic environment. With 3 test vehicles, several driving scenarios have been implemented. Various data kinds have been collected per device type: MOVE CAN interface, OXTS RTK-GPS, IBEO LiDAR, video capture (webcams). The data collected was assessed utilizing script algorithms that provide various charts. Data collection was completed from August 28th to September 1st, 2017, on the test track in Helmond, Netherlands, by TASS International. Given the lack of resources to estimate these parameters, this research uses the parameters from the Coexist project for CC values. Table 12 shows the parameter values for different AV classes used in this study to investigate mixed scenario capacity assessment from the Coexist project.

In this table, a default set of CC parameters also shows the difference between default with AV parameters. CC0 value is almost the same for each vehicle type except All-knowing. It maintains V2V communication; CC1 is lower to normal due to sensor and the weakest among four due to sensor and connectivity. According to Coexist, because of the deterministic behavior of automated vehicles and to reflect much smaller oscillation in vehicle following, CC2, CC6 can be reduced up to zero, and CC4, CC5 can be significantly reduced (Coexist2.5, 2004). CC3 value is the same for each type except cautious vehicle as it moves cautiously to the leading vehicle.

The autonomous vehicle does not change acceleration rapidly; that's why the CC7 value is lower than the default value. From stopping, when AV starts moving while stream moves forward, cautious vehicle response slower to ensure proper safety but All-knowing vehicle response quicker due to connectivity. As a result, the CC8 value is higher for All-knowing and lower for the cautious vehicle. The same logic is applicable for CC9, which is an acceleration value of more than 50 mph.

Table 12. Calibration Parameters Value for AV Classes (Coexist2.4, 2018)

Parameters	Default	AV Cautious	AV Normal	AV All-Knowing (CAV)	Unit
CC0	4.92	4.92	4.92	3.28	Ft
CC1	1.5	1.5	0.9	0.6	Second
CC2	13.12	0	0	0	Ft
CC3	-8	-10	-8	-6	Second
CC4	-0.35	-0.1	-0.1	-0.01	m/s
CC5	0.35	0.1	0.1	0.1	m/s
CC6	11.44	0	0	0	1/ (m.s)
CC7	0.82	0.33	0.33	0.33	ft/s^2
CC8	11.48	9.84	11.48	13.12	ft/s^2
CC9	4.92	3.94	4.92	6.56	ft/s^2

4.5. AV Vehicle Classes Mixed Scenario Penetration Levels Identification

It is impossible to model all the possible combinations of mixed scenarios that can happen in the future. Therefore, this research identified several penetration levels of AVs based on Figure 3 shows that less than 15% of all travel will be by AVs/CAVs by 2040. By 2045 this increases to 25%. It further increases to 50% by 2055 and 75% by 2065. This gives some context, especially to transportation planners and decision-makers. Roadways are planned to last about 30 years, and in the next, five to ten years, planners and decision-makers need to start considering the impacts of AVs/CAVs. Therefore, for this research, we use base penetration levels of AV/CAVS of 25% (approximately the year 2045), 40% (roughly the year 2050), 75% (the year 2065), and 100 % (approximately the year 2080).

4.6. Other Simulation Settings

The simulation system plays a significant role in achieving the accurate performance of the analysis. Previous studies have shown that the simulation resolution, random seed, number of runs, simulation speed could all influence the output of simulations (VDOT, 2020). Therefore, the description of those parameters has been given in Table 13 below with the value/text that has been used in this dissertation.

Table 13. Simulation Setup Parameters Description and Value

Parameters	Description (Vissim, 2020)	Value / Text	Reason to Use
Simulation Resolution	The simulation resolution impacts the behavior of vehicles, pedestrians, and the way they interact. Therefore simulations, using different simulation resolutions produce different results.	10	Higher resolution provides smoother and realistic traffic movement but also makes lowers the analysis time. So, getting an optimum value is necessary
Random Seed	The Random Seed value is used to initialize a random number generator, which generates random numbers. Using the same network file and random start number, two simulation runs will appear identical; however, if the Random Seed is changed between two simulation runs of the same network file, the stochastic functions are assigned a different value sequence, thereby altering traffic flow inside the network. In this study, the number has been used based on the Virginia DOT VISSIM user guide	42	The default value of VISSIM
Number of Runs	Several simulation runs are performed in a row. The logical value range depends on use case 5 - 20.	15	Using equation 7.1
Random Speed Increment	Difference between random seeds values when you perform multiple simulation runs	5	A constant combination of random seeds/random seed increment is recommended for both current and future-year models.
Simulation Speed	Corresponds to a time-lapse factor: Indicates simulation seconds per real-time second. Value 1.0: The simulation is run in real-time. Value 2.0: The simulation is run at double real-time speed. Maximum option: Select this option to simulate the maximum speed.	Maximum	Recommended by VDOT (2020)
Number of Cores	Several processor cores are used during simulation. The maximum number of cores used depends on your computer. Your setting remains selected when you start the next simulation run. Default: Use all cores		Use all Cores

It is therefore essential to ensure that these are used in the model. N is calculated using the equation given below (WSDOT, 2014).

$$\mathrm{N} = (* \, t_{0.025N-1})^2 \tag{4.3}$$

Here,

R = Confidence Interval for the true mean

$t_{.025,\ N-1}$= Student's t-statistic for a two-sided error of 2.5 percent (totals 5 percent) with N-1 degrees of freedom (related to a 95% Confidence Level).

S = Standard Deviation about the mean for selected MOE

N = Number of required simulations runs

For calculation purposes, t value has been considered 2.3 (for ten runs referred by (WSDOT, 2014)), S value is found 4.29 (9 runs result analysis where each run provides four values as there are four lanes in basic freeway segment), R-value is 5 (margin of error is considered +- 5). Using these values, N values show 15.56. As part of considering integer, N is counted 15 for this study.

The basic freeway capacity of the highway section depends on the free flow rate (FFS) based on HCM. It is important to establish a separate velocity distribution for different FFS. For each free-flow speed upper bound and lower bound has been chosen within a difference of 25 mph (60-35 = 25 mph; 65-40 = 25 mph; 70-45= 25 mph; 75-50= 25 mph) but in each case frequency was kept same. The proposed speed range and the corresponding distribution are given below (Table 14 as part of the speed distribution in the simulation setup.

Table 14. Speed Range and Distribution for Different FFS

55 mph		60 mph		65 mph		70 mph	
35.00	0.00	40.00	0.00	45.00	0.00	50.00	0.00
37.69	0.19	42.69	0.19	47.69	0.19	52.57	0.19
42.02	0.67	46.95	0.66	51.95	0.66	57.02	0.66
49.35	0.91	54.35	0.91	59.35	0.91	64.35	0.91
60.00	1.00	65.00	1.00	70.00	1.00	75.00	1.00

4.7. Summary

In this chapter, the step-by-step calibration and validation process for both basic freeway and weaving section were described. One of the significant findings of this section is the CC value for both parts of the freeway. Earlier drivers' choice speed distribution was measured. At the end of this chapter, simulation setup parameters were discussed, speed range, and distribution for 55, 60, 65, 70 mph.

5. RESULTS AND DISCUSSION

This chapter discussed the capacity measurement of a base model scenario for both basic freeway and weaving capacity and compared with mixed traffic cases from lower to higher penetration of autonomous and connected autonomous vehicles. The traditional vehicle is used only to measure the base model capacity for the basic freeway and weaving sections.

5.1. Base Model Capacities for Basic Freeway Segment

One of the major outputs of the simulations is the capacity calculations for each scenario. Capacity is defined as the maximum number of vehicles that can traverse a roadway over a given time (vehicles per hour for this study). The capacity resulting from the simulation is measured as the passenger car/hr/ln. Figure 18 shows the capacity (veh/hr) output from the base model simulation with only conventional cars compared to the Highway Capacity Manual values (HCM 2016) for different speeds. It shows data for a 100% passenger car scenario and a 98% passenger car/2% heavy vehicle (truck) scenario.

The capacity from the simulation scenarios is lower in comparison to the HCM capacity for both scenarios. This is because the capacity values in the model take into account the roadway conditions, whereas the HCM capacities are an ideal capacity. The differences are expected in practice and underscore the importance of estimating the capacities rather than using predefined capacities. Additionally, the 2% scenario capacities are lower since trucks by nature occupy more space and leave bigger gaps. Increasing the percentage of trucks, even more, will further reduce the capacities.

These capacities give us a starting point for comparing the impacts of AVs/CAVs to traditional vehicles. For example, suppose capacities from scenarios that have AV/CAVs are lower than the base capacities. In that case, it means the roadway will carry fewer cars, and the

AV/CAVs/Traditional vehicle scenario will potentially reduce roadway capacities compared to today for identical roadways.

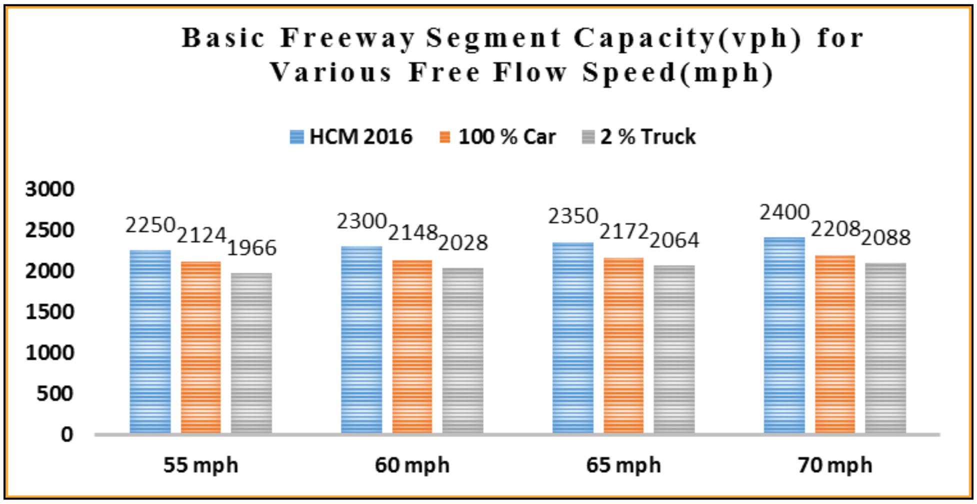


Figure 18. Base Model Simulated Capacities Compared to Base HCM

The capacity value has been determined based on the average of 15 simulation runs. Each run provides four values for basic freeways and six values for the weaving segment as there are four lanes for the basic freeway, and six lanes for the weaving segment. Each run gives analysis for five minutes flow results. Multiplying with twelve with five minutes flow data provides capacity value (veh/hr). Standard errors regarding all capacity values (base case, single class, and mixed scenarios) have been determined and shown in Appendix C for the basic freeway and weaving section.

5.2. Capacities for Single Class AVs at Different Levels of Penetrations and FFS for Basic Freeway Segment

This section discusses the results when only one AV class is used in each model for different speeds and penetration levels compared with the base case. Here, the base case means simulation output of traditional car result with 2% truck traffic. Figure 19 to Figure 22 shows the comparisons of each AV class at different speeds and penetrations with the base case model capacities.

Figures 19 to Figure 22 shows the comparison of different penetration levels for other AV/CAVs technologies concerning traditional vehicles. For AV cautious technology only, the curve is a polynomial concave upward sloping curve. The model output indicates that Capacities will reduce at all penetration levels and speeds for AV cautious. Capacities reduce as penetration levels increase to about 75% penetration levels, where capacities increase again. 75% penetration for AV-cautious is an inflection point where the impacts of AV-cautious change from decreasing to increasing, although they will still be below traditional vehicles. At 100% penetration levels of AV-cautious, the capacities are still below traditional vehicle capacities. The implication is that AV-cautious will negatively impact capacities, and roadways will carry fewer cars than traditional cars today. There will be increased congestion if AV-cautious vehicles are the only adopted technology in AVs, ceteris paribus.

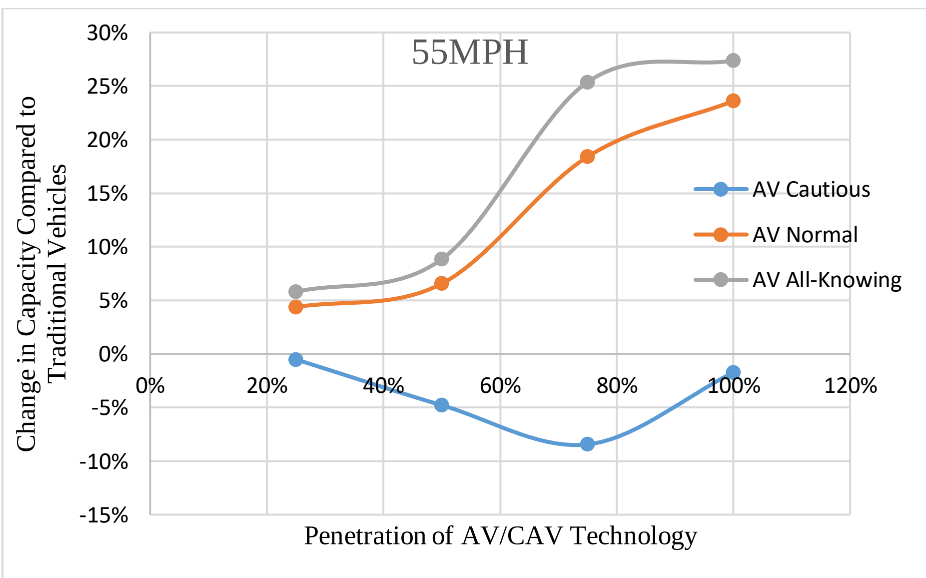


Figure 19. Capacity Impacts of Single AV Class at 55 mph and Different Penetration Levels

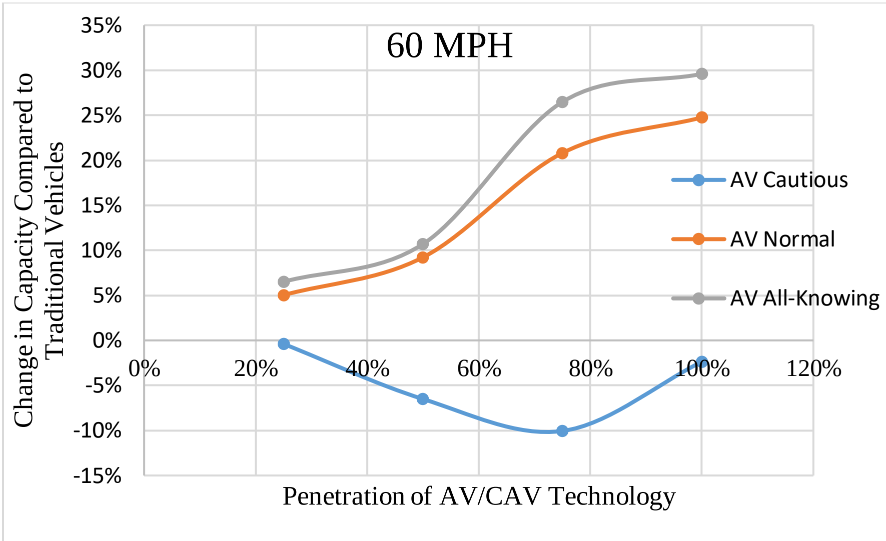


Figure 20. Capacity Impacts of Single AV Class at 60 mph and Different Penetration Levels

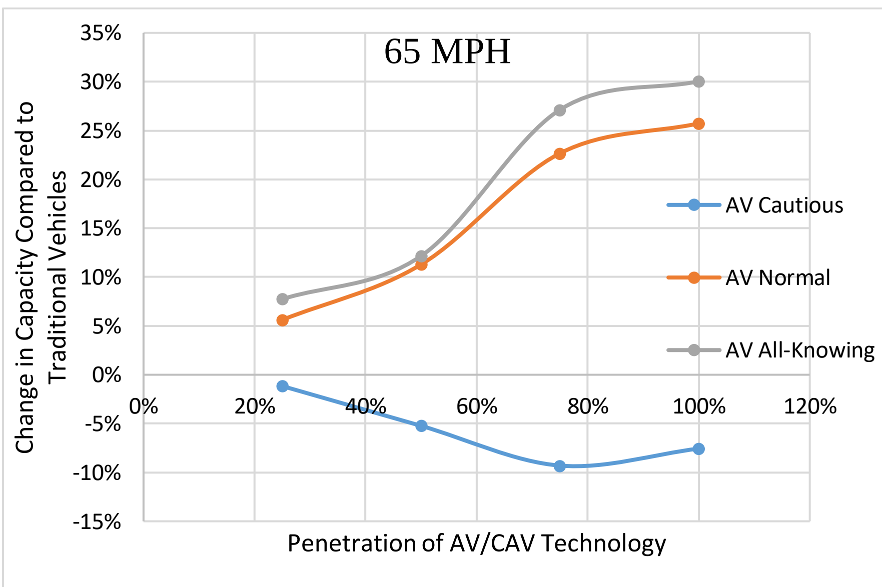


Figure 21. Capacity Impacts of Single AV Class at 65 mph and Different Penetration Levels

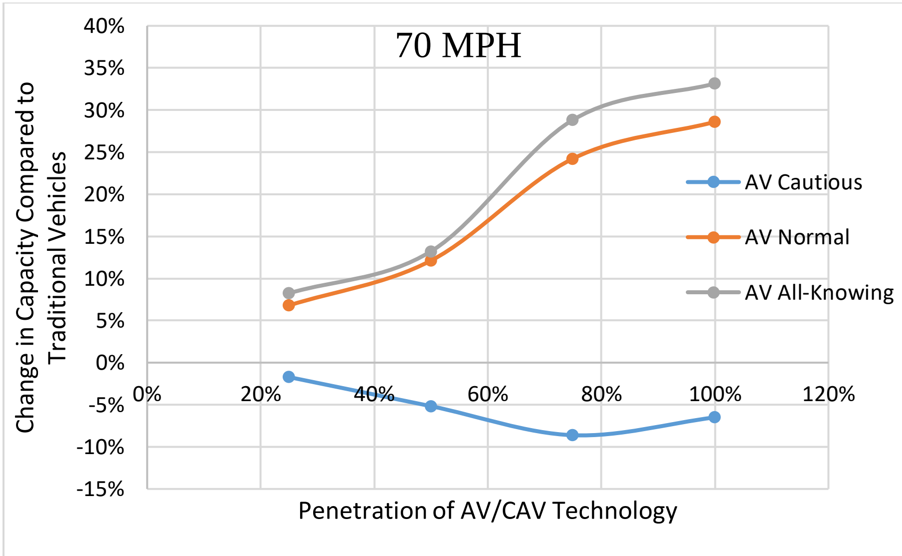


Figure 22. Capacity Impacts of Single AV Class at 70 mph and Different Penetration Levels

The CC0 value of the cautious vehicle is lower than a traditional vehicle which results in a lower negative impact in 100% penetration than 75% penetration, and the curve looks bent upper side in cautious vehicle assessment. Studies on calibrating sensitivity parameters indicate that capacity is inversely proportional to CC0 and CC1 (Lownes & Machemehl, 2006). This means lower CC0, CC1 results in higher capacity. There is no Vehicle to Vehicle (V2V) or Vehicle to Infrastructure (V2I) communications in AV-cautious. The results mean that V2V and V2I need to be incorporated into their technologies to truly capture AVs' benefits. Several cars like Tesla and Audis can perform certain AV functions under certain road conditions when writing this dissertation. The time gaps (CC1 in the Wiedemann model) that these vehicles keep for safety purposes are long enough that traditional vehicles typically cut in front of them in a travel stream. This is further exacerbated in oversaturated conditions where their bumper-to-bumper headways (CCO) are longer than what traditional vehicles typically maintain.

Technology similar to the AV-cautious cars will perhaps be the first implemented when AVs become available. It is probably due to a combination of regulations, lack of trust, and potential legal issues. The results from this study show that we might get a period in the initial phases of the introduction of AVs that we experience negative capacity gains. Transportation planners should consider this cautious vehicle penetration rate and plan for the future expansion of specific freeway sections. The plan includes how many years a significant capacity reduction will occur, necessary capacity enhancements, and a time frame for constructing a new capacity. To understand penetration rate, automobile manufacturing companies' production rate, vehicle sales rate, car registration rate, and most consumers' acceptance rate for autonomous vehicles should be considered.

Using curve fitting techniques, the best fit polynomial cuboid function for all the curves for the AV-cautious speed classes was developed. As a result, the functions all had r-square values of 1, indicating a perfect fit, shown in equation 5.1.

$$Y = \alpha + bx + cx^2 + dx^3 \tag{5.1}$$

Where,

Y = is the estimated percentage change incapacity,

α = slope of the curve

x = penetration level of AV-cautious

b, c and d are parameter estimates for the equation's first, second, and third-order derivatives.

The parameter estimates for AV-Cautious are shown in Table 15. Planners and traffic engineers can use these parameter estimates to estimate base capacity changes when forecasting the impacts of AV-cautious vehicles.

Table 15. Parameter Estimates for the Fitted Cuboid Function for Different Speed Classes and AV-Cautious Penetration Levels for a Basic Freeway Section.

	PARAMETER ESTIMATES				
SPEED	α	b	c	d	r-square
55	-0.05	0.50	-1.51	1.04	1
60	-0.03	0.23	-1.18	0.92	1
65	-0.02	0.26	-0.92	0.61	1
70	-0.03	0.27	-0.89	0.59	1

In contrast to AV- cautious, there are capacity improvements for AV Normal and AV All-knowing at all penetration levels. The curves shown in Figures 19 to Figure 22 follow a Sigmoid S-curve shape. This suggests the capacity impacts for these two technologies follow a logistic function found in natural, business, and technological domains and used to describe dynamic systems of competition. Using curve fitting techniques, the Capacity impacts increase slowly as AV penetration levels increase up to about a 60% penetration level which is the point of diminishing returns in terms of capacity improvements and maximum growth. Then the impacts increase at an increasing rate up to 75% penetration, increasing at a decreasing rate. The curves thus indicate that the critical mass penetration point for single class AV-normal or AV-cautious is about 50% penetration levels. This is where we will start seeing increasing impacts on roadway capacities for basic highways. As expected, the effects of AV All-knowing are higher than those of AV Cautious due to the aggressiveness in the AV All-knowing cars and their ability to communicate with other vehicles and the transportation infrastructure.

The AV normal and AV all-knowing classes show capacity gains for all speeds and penetration levels as shown in comparison to traditional vehicles. AV all-knowing shows higher capacity gains than AV-normal. Due to vehicle sensors and connectivity to other vehicles and the transportation system, their vehicle response time is quicker than traditional vehicles resulting in lower CC0 and CC1. These vehicles, as expected, will leave lower time and space gaps between a lead and the following vehicle, thereby increasing capacities without changing the transportation supply. These vehicles will become more available as the technology matures, and their confidence grows both the public and decision-makers.

The AV normal and AV all-knowing classes show capacity gains for all speeds and penetration levels as shown in comparison to traditional vehicles. AV all-knowing shows higher capacity gains than AV-normal. Due to vehicle sensors and connectivity to other vehicles and the transportation system, their vehicle response time is quicker than traditional vehicles resulting in lower CC0 and CC1. These vehicles, as expected, will leave lower time and space gaps between a lead and the following vehicle, thereby increasing capacities without changing the transportation supply. These vehicles will become more available as the technology matures, and their confidence grows both the public and decision-makers.

Interestingly, the model for AV Normal and AV-All knowing is different from the model for AV-cautious. However, using curve fitting techniques, the Sigmoidal 4-parameter Logistic (4-PL) curve was the best fit for all the curves. This is a significant finding and demonstrates the importance of correctly identifying the technology AVs will use to determine their impacts on the transportation system correctly.

The general sigmoidal 4-PL equation is shown in equation 5.2. The R-square ranges for all the models were between 0.97ad 0.99, offering a perfect fit between the Sigmoidal 4-PL model.

$$Y = d + \frac{a-d}{1+\left(\frac{x}{c}\right)^{b}} \tag{5.2}$$

Where,

Y = is the estimated percentage change of capacity,

a = is the minimum or theoretical capacity change at zero AV penetration

b= Slope of the curve,

c = I mid-range or inflection point, and

d =is the theoretical maximum capacity change at 100% AV penetration

Table 16 shows the parameter estimates for single class AV-Normal and AV-All Knowing for the sigmoid curve shown in equation 4.2. These values can be transferred and used in planning and traffic operations studies that measure the potential impact of AV-normal and AV-all knowing based on different penetration levels for basic freeways. The values can be used to interpolate penetration levels that are not shown in the graphs.

Table 16. Parameter Estimates for a, b, c, and d for Single Class AV-Normal/All-Knowing at Different Speeds for Basic Freeway Section

		AV-CAUTIOUS		
SPEED	a	b	c	d
55	4.35	7.18	67.03	24.68
60	4.95	6.20	62.23	24.68
65	5.50	6.07	58.63	26.52
70	6.66	7.85	61.62	29.99
		AV-All Knowing		
	α	b	c	d
55	5.79	9.942	59.98	27.50
60	6.48	8.039	62.23	29.99
65	7.72	7.85	59.87	30.43
70	8.18	6.914	61.38	33.99

The operation of AV will succeed if there is the ability to move safely in mixed situations. A reserved lane on the highway could be a better solution for separating autonomous and traditional vehicles for better operation. Reserve lane will be dedicated only for autonomous vehicle driving where conventional vehicles are not allowed to drive. This way, the reserved lane will provide better capacity than other lanes due to lower headway value. Also, lane speed could be an increase in higher traffic demand. But in lower AV penetration, a reserved lane might not be a good solution as economic or socially.

In 100% penetration, capacity gains could be 33% higher than traditional vehicles only. If all vehicles are changed into AV, CAV, each lane can handle 33% more vehicles. For example, suppose we had a three-lane highway, right now with only traditional vehicles. In that case, it would be possible to reduce the three-lane highway to a two-lane highway without affecting the efficiency of the roadway. Extra lanes can be removed or repurposed and used, such as parking shared autonomous vehicles or used as bike or bus lanes. Without removing additional lanes or lanes, it might be better to turn that lane into a dedicated lane for AV heavy vehicles, including buses and trucks. The heavy vehicle has a higher ESAL than the passenger vehicle. There is a potential economic benefit to having a dedicated HOV AV lane due to heavy vehicles; pavement deteriorates more than passenger car lanes; it will be easy to identify and do the maintenance work for a dedicated lane.

5.3. Capacities of Mixed Levels of AVs at Different Penetrations for Basic Freeway Segment

A mixed AV/CAV situation is expected throughout the immediate future, where conventional and modern AV classes will operate together in the same segment. The results for a matrix of different penetration of traditional and various AVs (year based) are shown in Table 17 to Table 22. The scenarios were selected based on Figure 3 and represent additional planning horizon years. The following subsections discuss these results in detail. This research does not consult lower levels of penetrations as they have negligible impacts on capacities.

5.3.1. 25%AV/CAVs and 75% Traditional Vehicles Circa Year 2045

AVs will be deployed within the next two decades or sooner, decreasing traditional vehicles on the road network. The capacity impacts of various AV types and their penetration levels at 25% of total travel on transportation capacity are estimated and shown in Table 17. Two scenarios were developed with different penetration levels of the different AV technologies. Scenario 1 included 10% AV- Cautious,10% AV-Normal, and 5% AV All-knowing. Scenario 2 included 5% AV- Cautious,10% AV-Normal, and 10% AV All-knowing. Whereas there were increases in capacities for both scenarios, the maximum impact was less than 4%. The impact was not significant enough in both scenarios. In the 2nd scenario, the AV All-knowing penetration is higher than AV-cautious, resulting in higher capacity change than the 1st scenario. As capacity increment is not significant in both cases, it will look the same in traffic congestion, delay, and overall traffic operation condition.

On top of that, there might be a smoother traffic condition during pick times as capacity will increase but not significantly level. Roads with 55 mph will see no impact or same as now, and roads with 70 mph will see the highest mark at 25% penetration levels for different AV classes. Thus, there could be reduced bottlenecks and lower speed oscillation in traffic streams than 100% traditional vehicle conditions.

Table 17. Capacity Change in Mixed Scenario with 75% Traditional Cars at Basic Freeway Segment

	25% AV / 75% traditional			25% AV / 75% traditional		
FFS (mph)	10% Cautious	10% Normal	5% All-Knowing	5% Cautious	10% Normal	10% All-Knowing
55		1.53			2.14	
60		2.47			2.86	
65		2.62			2.96	
70		2.97			3.93	

5.3.2. 35% AV/CAVs and 65% Traditional Circa Year 2050 with Mixed

Three decades from now, the penetration level will go up to 35% of total vehicles Table 18. In these circumstances, mixed capacity has been determined with traditional, AV, and CAV. Simulation results show that lower CAV mixed with higher AV cautious results lower capacity increment (scenario 1), whether another method is a mix of higher CAV and lowers cautious vehicles results in higher capacity increment. But both scenarios' results are noticeable but not significant like the previous case.

Table 18. Capacity Change in Mixed Scenario with 65% Traditional Cars at Basic Freeway Segment

	35% AV / 65% traditional			35% AV / 65% traditional		
FFS (mph)	10% Cautious	20% Normal	5% All-Knowing	5% Cautious	10% Normal	10% All-Knowing
55		1.93			3.50	
60		2.50			3.50	
65		3.00			4.00	
70		3.50			5.98	

5.3.3. 50% AV/CAVs and 50% Traditional Circa Year 2055 with Mixed Levels of AVs/CAVs

About three decades from now, the penetration levels of AVs will potentially increase even more and make up about 50% of total vehicle travel. It is estimated that this will happen circa early to mid-2050s. It puts us on the planning horizon of most current long-range transportation plans. Two scenarios with overall 50% penetration of AVs and different AV mixes were simulated, and the results are reported in Table 19. Scenario 1 included 20% AV-Cautious,20% AV-Normal, and 10% AV All-knowing. Scenario 2 included 10% AV-Cautious,20% AV-Normal, and 20% AV All-knowing. The capacity gains range from 2.54% to around 7.76%. The results show a slightly higher percentage of change in capacity value for the

2nd scenario where the All-knowing percentage is higher than a cautious vehicle. If the 2nd scenario case prevails, there will be a noticeable improvement in traffic congestion and bottleneck situation but not big enough to reduce road capacity impacts as the speeds increase as expected. Comparing the mix scenario at 50% to a single class AV, we see that the single class AV scenarios (Table 19), AV Normal, and AV All-knowing have higher capacity impacts than the mixed AV scenarios. For a 70mph basic freeway, the capacity impact of 13% for AV All-knowing is almost double the capacity impacts for the mix scenario with 50% of AV's best case-mixed scenario. These results show that it is important to consider the mix of AV types when evaluating the capacity impacts of AVs.

Table 19. Capacity Change for Mixed Scenarios with 50% Traditional Cars at Basic Freeway Segment

	50% AVs / 50% traditional			50% AVs / 50% traditional		
FFS (mph)	20% Cautious	20% Normal	10% All-Knowing	10% Cautious	20% Normal	20% All-Knowing
55		2.54			5.29	
60		2.66			5.92	
65		3.68			6.10	
70		3.93			7.76	

5.3.4. 60% AV/CAVs and 40 % Traditional Vehicles Circa Year 2060 with Mixed Levels of AVs/CAVs

Four decades from now, the penetration levels of AVs are expected to increase even further and are estimated at 60% of all vehicles.

Table 20shows the alternatives modeled under this scenario. Three alternatives are modeled for different penetration levels of AV mixes. The results show that the gains in capacity increase as the AV technologies improve. The highest growth for the scenarios presented is for the 70mph basic freeway with 5% AV Cautious, 30% AV-Normal, and 25% AV All-Knowing. It is about 12 times the capacity change of the same roadway with higher levels of AV-Cautious. It will reduce other traffic congestions measures like bottlenecks, oscillations, accidents, etc. However, it is perhaps not enough to reduce the roadway capacity through lane reductions or dedicated lanes. The operations of roadways will see marked improvements, however.

Table 20. Capacity Change for Mixed Scenarios with 60% AVs and 40% Traditional Cars for Basic Freeway Segment

	60%AVs / 40% traditional			60%AVs /40% traditional			60%AVs /40% traditional		
FFS (mph)	30% Cautious	20% Normal	10% All-Knowing	20% Cautious	30% Normal	10% All-Knowing	5% Cautious	30% Normal	25% All-Knowing
55		0.71			5.60			9.87	
60		0.59			6.02			10.06	
65		0.78			6.40			10.76	
70		1.15			7.47			12.07	

5.3.5. 90% AV/CAVS and 10% Traditional with Mixed Levels of AVs/CAVS Circa Year 2070

Fifty years from now, around 90% of the vehicle will be autonomous. Three scenarios have been shown below. The 1st and 2nd scenarios have the same number of cautious vehicles, and the last scenarios have higher AV normal and CAV than the cautious vehicle. It is assumed that the number of cautious vehicles will be lower around that time. The results show (Table 21) that capacity increment shows higher values when there is a higher AV normal and CAV percentage. At 70 mph, capacity increase around 21% with 85% autonomous vehicle.

Table 21. Capacity Change for Mixed Scenarios with 90% AVs and 10% Traditional Cars for Basic Freeway Segment

	90%AVs / 10% traditional			90%AVs /10% traditional			90%AVs /10% traditional		
FFS (mph)	20% Cautious	30% Normal	40% All-Knowing	20% Cautious	40% Normal	30% All-Knowing	5% Cautious	40% Normal	45% All-Knowing
55		3.53			10.13			15.91	
60		6.26			13.18			16.96	
65		8.54			14.89			20.24	
70		10.48			17.33			21.29	

5.3.6. 100%AV/CAVS and 0% Traditional with Mixed Levels of AVs/CAVS Circa Year 2080

About 60 years from now, the literature suggests that all vehicles will be AVs/CAVs (Litman, 2021). Two alternatives for different mixes of AV classes were developed, with the results shown in Table 21. The capacity gains are much higher than the previous scenarios ranging from 16.48% to 29.31% for the scenario with 80% AV All-knowing and 20% AV Normal. The change means that if the study section gets 100% AV All-knowing without changing the road geometry, it will automatically increase the capacity by 33%. There will be an operational and economic benefit to introducing a reserved/ dedicated lane for AV/CAV or heavy vehicles in all scenarios, which will help maintain constant gaps between similar types of vehicles equivalent to platooning. Planners and engineers will be able to reduce roadway capacities through lane reductions. These could be used for parking shared AVs and CAVs or repurposed for other purposes like rapid bus transit, bike, and pedestrian facilities. Overall, the maintenance cost of these roadways will go down, accidents will probably reduce, and the overall economic and societal benefits will be positive. Compared to the 100% single class AV-All knowing alternative, the capacity gains are slightly lower but not significantly lower. The implication is that with high AV-Cautious and lower levels of AV-Normal, roadways will start seeing similar benefits to a 100% CAV situation.

Table 22. Capacity Change in Percent for Mixed Scenarios with 0% Traditional Cars at Basic Freeway Segment

	0% traditional			0% traditional		
FFS (mph)	10% Cautious	30% Normal	60% All-Knowing	0% Cautious	20% Normal	80% All-Knowing
55		16.48			21.06	
60		20.32			26.23	
65		21.12			27.42	
70		22.99			29.31	

5.4. Planning Horizon Capacity for Basic Freeway Segment

Planning horizon capacity for different free-flow speeds has been provided below as an overview of the demographics (Figure 23 to Figure 26). Underneath those, four possible outcomes have been mentioned: the best-case scenario, most probable scenario; probably scenario; and worst-case scenario. However, the best- and worst-case scenarios are different. The best- and worst-case scenarios represent capacity impacts due to single-class CAV and cautious penetration. The probable and most likely scenarios represent the mix scenario where CAV, AV normal, cautious, and traditional vehicles will co-exist in the future in some form. As it is noticeable from the graphs below, autonomous vehicles are expected to reach a certain proportion of the basic highway section in various years.

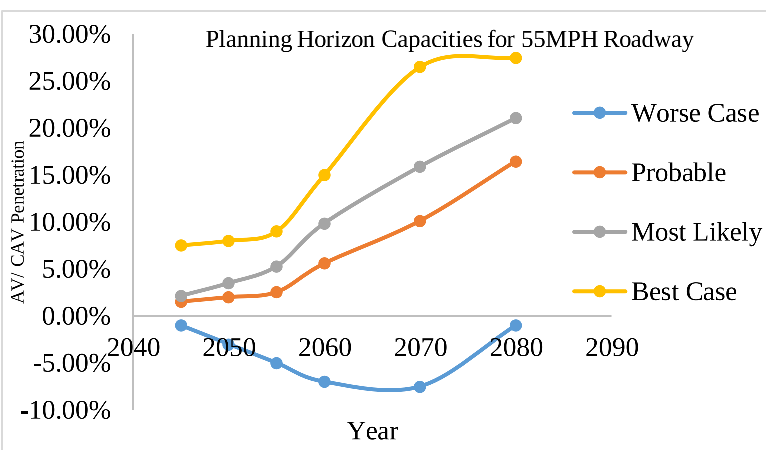


Figure 23. Planning Horizon Capacities for 55MPH Roadway

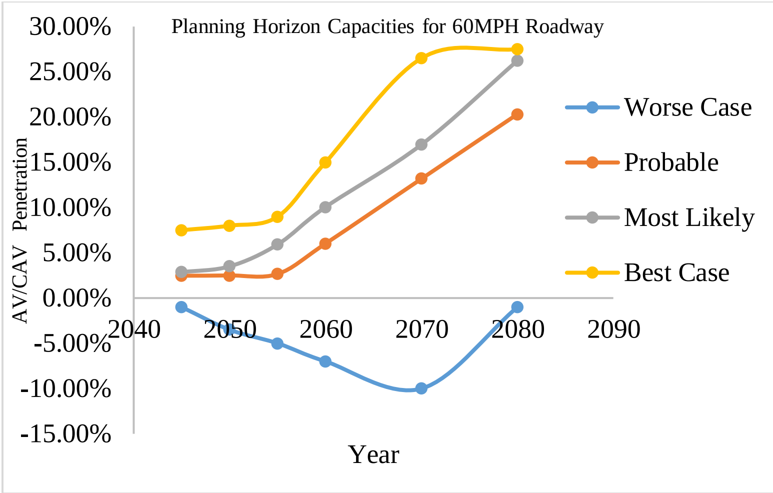


Figure 24. Planning Horizon Capacities for 60MPH Roadway

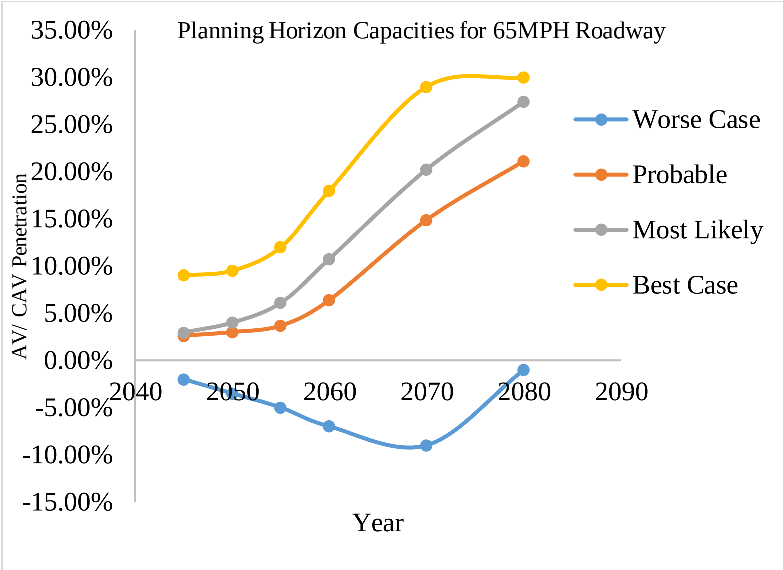


Figure 25. Planning Horizon Capacities for 65MPH Roadway

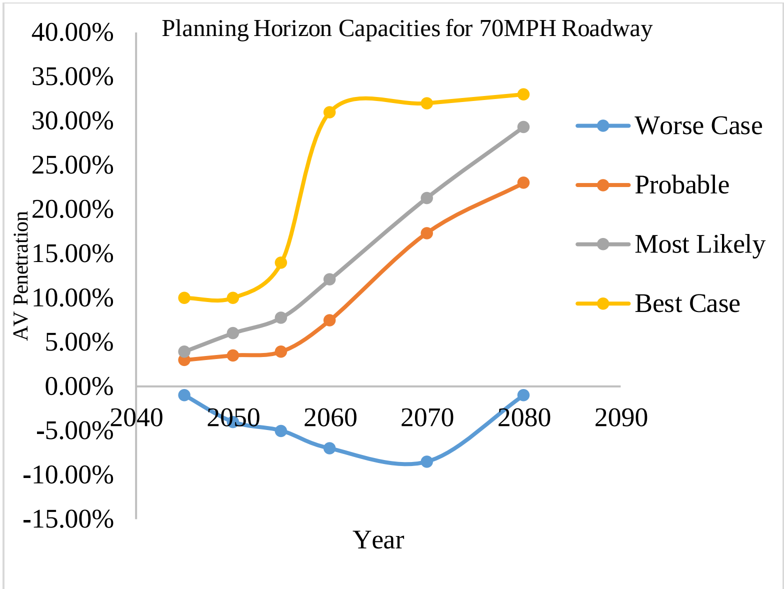


Figure 26. Planning Horizon Capacities for 70MPH Roadway

5.5. Base Model Capacities for Weaving Segment

Using a density-based equation, the capacity resulting from the observation and initial simulation run is measured as veh/hr/ln unit. This research included both cars (98% traffic) and heavy vehicles (2%). Figure 27 shows the capacity output for the basic freeway segment compared to the simulation output for the 2% heavy vehicle scenario and the density-based HCM capacity. The capacity from the simulation scenarios is lower in comparison to the HCM capacity.

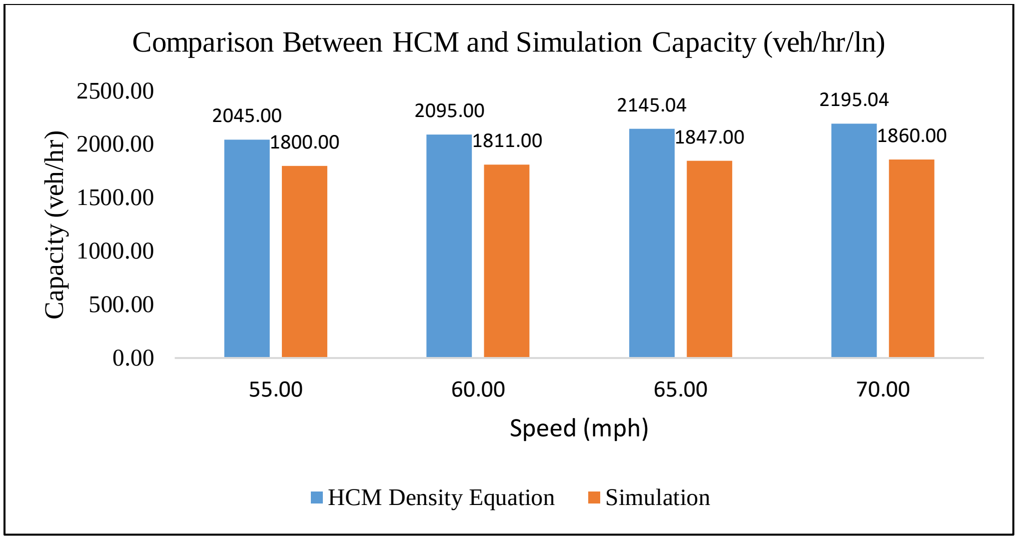


Figure 27. Capacity Value Comparison between HCM And Simulation Output for Weaving Section

5.6. Capacities for Single Class AVs at Different Levels of Penetrations and FFS for Weaving Segment

Compared to a traditional vehicle, capacity changes due to single class AVs have been shown in Figures 28 to 31. The results show capacity gains at all penetration rates relative to conventional automobiles for AV normal and All-knowing vehicles. Due to vehicle sensors and connections to other vehicles and the transportation network, resulting in lower CC0 and CC1 values (Table 12). The maximum benefit for the 55-70 mph highway at different penetration is shown (Figure 28 to 31).

This impact is slightly different from than basic freeway segment. For each of the free-flow speeds, graphs show different movements for various autonomous vehicles. The blue color line denotes that AV cautious shows a significant capacity change after 50% market penetration. Same as BFS, 75% shows a higher impact than 100% as the CC0 value of the cautious vehicle is lower than a traditional vehicle.

AV normal and AV All-knowing denotes orange and ash color, showing a significant positive impact on weaving capacity after 40% market penetration. In addition, both CC0 and CC1 values are higher for All-knowing than for a normal vehicle. As a result, AV normal shows a comparatively lower impact than All-knowing in each case of free-flow speed. Significant capacity increments during or after 40% market penetration in all FFS cases and highest in 100% penetration.

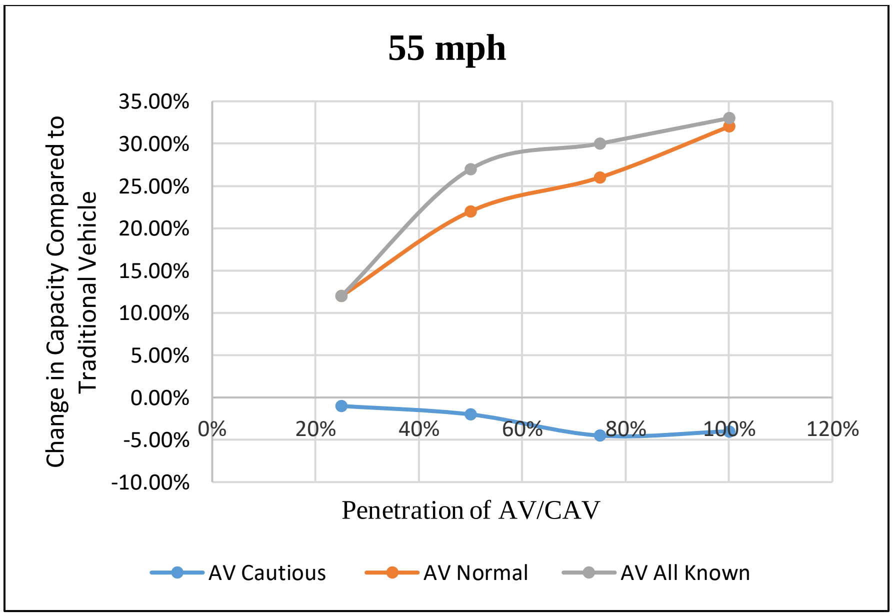


Figure 28. Capacity Changes for AV All-Knowing for 55 mph FFS and Compared to Traditional Vehicles in Weaving Section

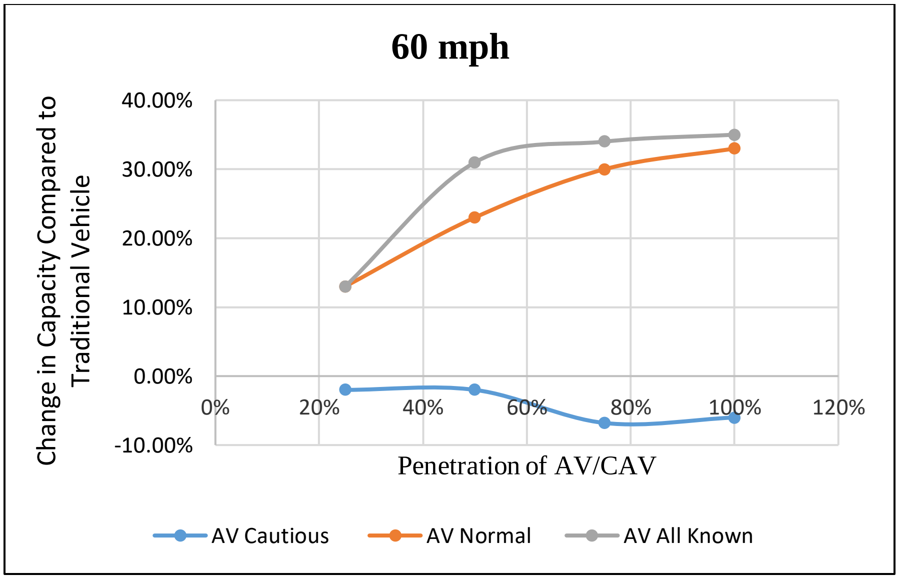


Figure 29. Capacity Changes for AV All-Knowing for 60 mph FFS and Compared to Traditional Vehicles in Weaving Section

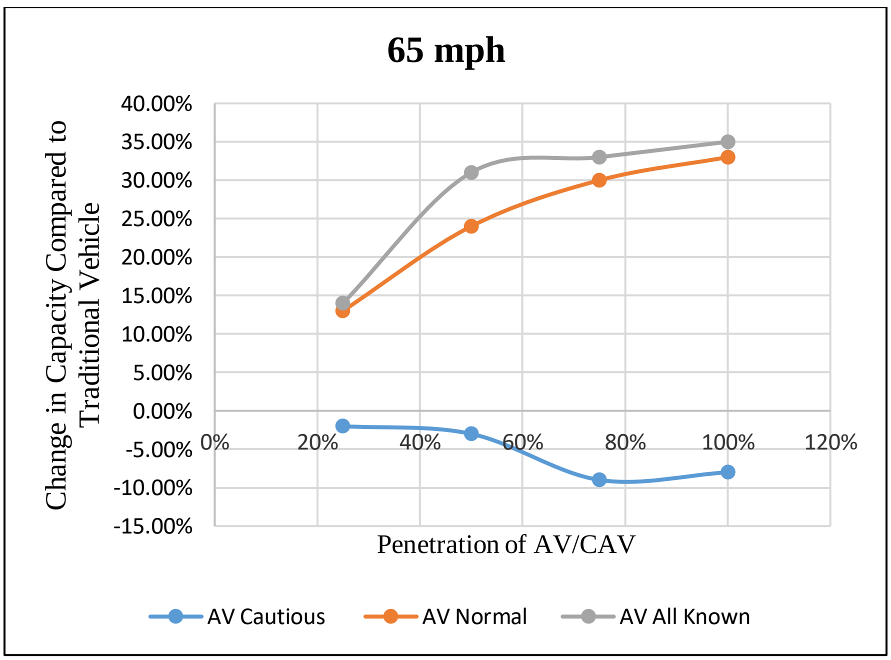


Figure 30. Capacity Changes for AV All-Knowing for 65 mph FFS and Compared to Traditional Vehicles in Weaving Section

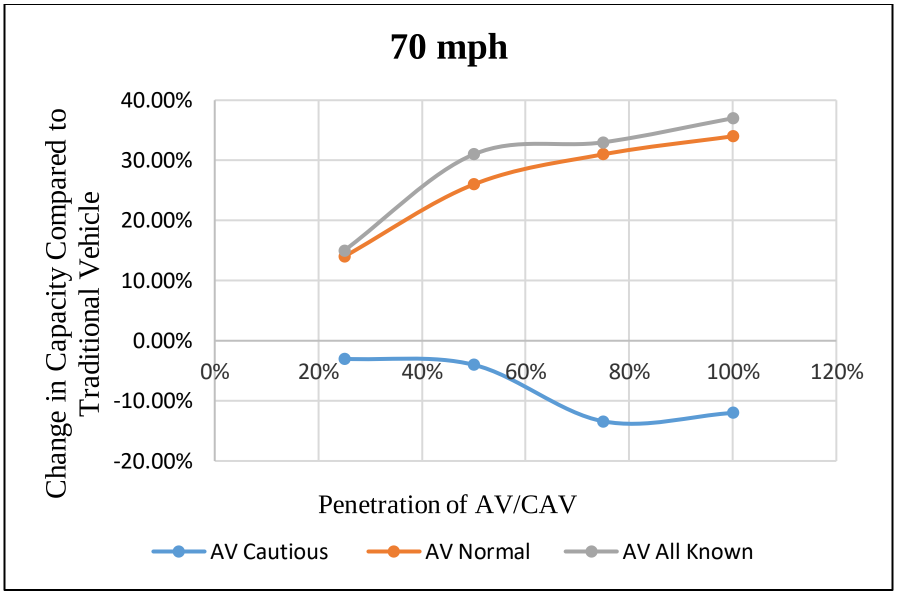


Figure 31. Capacity Changes for AV All-Knowing for 70 mph FFS and Compared to Traditional Cars in Weaving Section

Like the basic freeway segment, in 100% AV penetration, extra lanes can be used as dedicated heavy vehicle lanes that will help to avoid weaving challenges for the passenger cars. Also, the dedicated lane will prioritize pavement construction due to the higher ESAL value of the truck and bus. In a mixed case scenario where there will be a higher rate of AV than a traditional vehicle, a reserve or dedicated lane for AV might show better performance than mixed lanes by speeding up the design speed even in higher demand.

Using curve fitting techniques, the best fit polynomial cuboid function for all the curves for the AV-cautious speed classes was developed. The functions all had r-square values of 1, indicating a perfect fit, as shown in Table 23. The polynomial function follows the same equation as 4.1. Planners and traffic engineers can use these parameter estimates to estimate base capacity changes when forecasting the impacts of AV-cautious vehicles.

Table 23. Parameter Estimates for the Fitted Cuboid Function for Different Speed Classes and AV Cautious, Av Normal, AV All-knowing Penetration Levels for a Weaving Section.

	Parameter Estimates for Av Cautious				
Speed	α	b	c	d	r-square
55	-0.06	0.38	-0.84	0.48	1
60	-0.174	1.05	-2.0567	1.1134	1
65	-0.18	1.14	-2.3256	1.2842	1
70	-0.296	1.872	3.744	2.0436	1
	Parameter Estimates for Av Normal				
Speed	α	b	c	d	r-square
55	-0.12	1.35	-1.76	0.85	1
60	0.01	0.51	-0.08	-0.107	1
65	-0.05	0.8867	-0.72	0.2133	1
70	-0.1	1.2667	1.36	0.533	1
	Parameter Estimates for Av All-Knowing				
Speed	α	b	c	d	r-square
55	-0.27	2.2	-2.88	1.28	1
60	-0.33	2.5733	-3.28	1.3867	1
65	-0.33	2.68	-3.6	1.6	1
70	-0.31	2.6533	-3.68	1.7067	1

It is applicable to determine the capacity change in percentage whiles using certain penetration of AV classes using this polynomial equation.

5.7. Capacities of Mixed Levels of AVs at Different Penetrations for Weaving Segment

The freeway will soon experience a mixed traffic situation where traditional, AV cautious, normal, and All-knowing will exit together. To do that assessment, the different penetration levels of the traditional vehicle with various AVs have been assessed together, and the result has been shown from Table 24 to 29.

5.7.1. 25%AV/CAVs and 75% Traditional Vehicles Circa Year 2045

If the road has 75% traditional vehicle, two scenarios have been shown below with various percentages of cautious, normal, and All-knowing vehicles. In the 1st scenario, the cautious vehicle is higher than the 2nd scenario, resulting in a lower percentage change of capacity than the 2nd scenario, where All-knowing is higher than the cautious vehicle, resulting in a higher percentage of capacity increment. The change will occur more in 70 mph roads rather than 55 mph freeways. Though both scenarios positively impact capacity, the 2nd scenario seems noticeable in terms of operation, such as lees frequency of bottleneck, congestion, improvement in abrupt lane change in weaving area.

Table 24. Capacity Change in Percent at Mixed Scenario with 75% Traditional Cars at Weaving Segment

	75% traditional / 25% AV			75% traditional / 25% AV		
FFS	10% Cautious	10% Normal	5% All-Knowing	5% Cautious	10% Normal	10% All-Knowing
55		3.33			7.33	
60		3.42			8.67	
65		5.04			9.15	
70		5.38			9.68	

5.7.2. 35%AV/CAVs and 65% Traditional Vehicles Circa Year 2050

It is expected to be seen 35% AV penetration in the year 2050. Two scenarios have been presented below where 1st scenario consists of lower CAV with the higher cautious vehicle, and 2nd scenario is consisting of higher CAV with the lower cautious vehicle. Simulation results show a noticeable increment of capacity due to higher CAV penetration (12.70% increase at 70 mph) rather than a higher percentage of cautious vehicles (8.24% in 70 mph).

Table 25. Capacity Change in Percent at Mixed Scenario with 65% Traditional Cars at Weaving Segment

	65% traditional / 35% AV			65% traditional / 35% AV		
FFS	10% Cautious	20% Normal	5% All-Knowing	5% Cautious	10% Normal	20% All-Knowing
55		4.56			10.54	
60		6.54			11.55	
65		7.26			12.56	
70		8.24			12.70	

5.7.3. 50%AV/CAVs and 50% Traditional Vehicles Circa Year 2055

Another scenario has been introduced below where the freeway has 50% traditional vehicle. Similar scenario as the previous table, 2nd scenario has higher All-knowing than 1st scenario. The assessment result shows a noticeable percentage increment at 70 mph with 20% All-knowing AV. If 2nd scenario shows up, it will improve capacity and traffic operation in better than 75% of traditional vehicle situations in a good manner. At that moment, traffic engineers might take steps for future geometry change such as lane reduction or dedicated AV lane at the leftmost side, starting with the preliminary study.

Table 26. Capacity Change in Percent at Mixed Scenario with 50% Traditional Cars at Weaving Segment

	50% traditional / 50% AV			50% traditional / 50% AV		
FFS	20% Cautious	20% Normal	10% All-Knowing	10% Cautious	20% Normal	20% All-Knowing
55		8.89			12.78	
60		9.39			13.97	
65		9.91			14.78	
70		10.22			15.59	

5.7.4. 60% AV/CAVs and 40% Traditional Vehicles Circa Year 2060

At 40% penetration of traditional vehicles, three scenarios have been shown in Table 22; 3rd scenario has higher AV normal and AV All-knowing penetration than the 1st and 2nd scenarios. The results indicate a significant increment of capacity for all free-flow speeds. Suppose 1st or 2nd case of scenario happens. In that case, the same types of actions might be taken: a preliminary study of changing geometry or assessing the benefit of a dedicated AV lane. However, if 3rd scenario happens, a reserved or dedicated lane will be beneficial in all senses.

Table 27. Capacity Change in Percent at Mixed Scenario with 40% Traditional Cars at Weaving Segment

	40% traditional / 60% AV			40% traditional / 60% AV			40% traditional / 60% AV		
FFS	30% Cautious	20% Normal	10% All-Knowing	20% Cautious	30% Normal	10% All-Knowing	5% Cautious	30% Normal	25% All-Knowing
55		13.33			18.00			26.67	
60		14.63			19.27			27.33	
65		15.32			19.44			27.34	
70		16.13			19.35			28.39	

5.7.5. 90% AV/CAVs and 10% Traditional Vehicles Circa Year 2070

Based on Litman's prediction, around 90% of the total vehicles on the road will be autonomous vehicles. Three probable scenarios have been simulated and resulted below, where all three scenarios are showing significant improvement. The difference between the three scenarios varies in terms of cautious penetration and CAV. The 1st scenario consists of the higher cautious vehicle, and the 3rd scenario consists of a lower cautious vehicle. As expected, the 3rd scenario shows more than a 30% increase in capacity due to higher AV normal and CAV vehicles.

Table 28. Capacity Change in Percent at Mixed Scenario with 10% Traditional Cars at Weaving Segment.

	10% traditional / 90% AV			10% traditional / 90% AV			10% traditional / 90% AV		
FFS	30% Cautious	40% Normal	20% All-Knowing	20% Cautious	40% Normal	30% All-Knowing	5% Cautious	45% Normal	40% All-Knowing
55		14.52			24.69			29.12	
60		16.27			25.63			30.15	
65		17.23			26.18			31.56	
70		18.84			27.45			32.85	

5.7.6. 100% AV/CAVs and 0% Traditional Vehicles Circa Year 2080

A mixed scenario has been shown in Table 23, with no traditional vehicle but a significant increment of All-knowing vehicles among the three scenarios. The result shows that when there is no traditional vehicle and cautious vehicle, lower headway and lower space headway have accelerated the significant increment of capacity, ranging from 30% to 36%. All three scenarios show higher capacity gain in the weaving area, which will provide less turbulence of traffic during weaving maneuver due to speed reduction and smooth operation during peak hours. Also, bottleneck frequency will be no or lower if traffic demand does not change.

Table 29. Capacity Change in Percent at Mixed Scenario with 0% Traditional Cars at Weaving Segment

	0% traditional			0% traditional		
FFS	10% Cautious	30% Normal	60% All-Knowing	0% Cautious	20% Normal	80% All-Knowing
55		30.00			32.22	
60		32.52			33.90	
65		33.19			34.27	
70		35.48			36.56	

5.8. Planning Horizon Capacity of Weaving Section

Overview of demographic planning horizon capacity at various free-flow speeds (Figure 32 to 35). There are four potential outcomes same as basic freeway segment: best case, most likely; probable; and worst-case scenario. Best- and worst-case situations are taken from the single-class CAV and cautious penetration analysis. A mix of CAV, AV normal, cautious, and traditional cars impact have been analyzed before, and probable, and most likely cases have been taken from there. AV's penetrations are anticipated to achieve a specific percentage of basic highway sections in various years, as shown on the graphs.

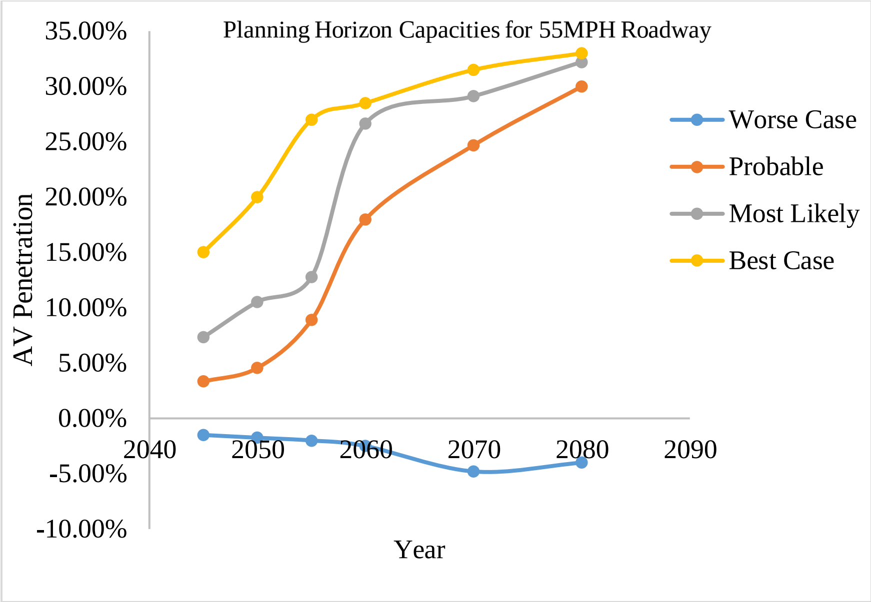


Figure 32. Planning Horizon Capacities for 55MPH Roadway

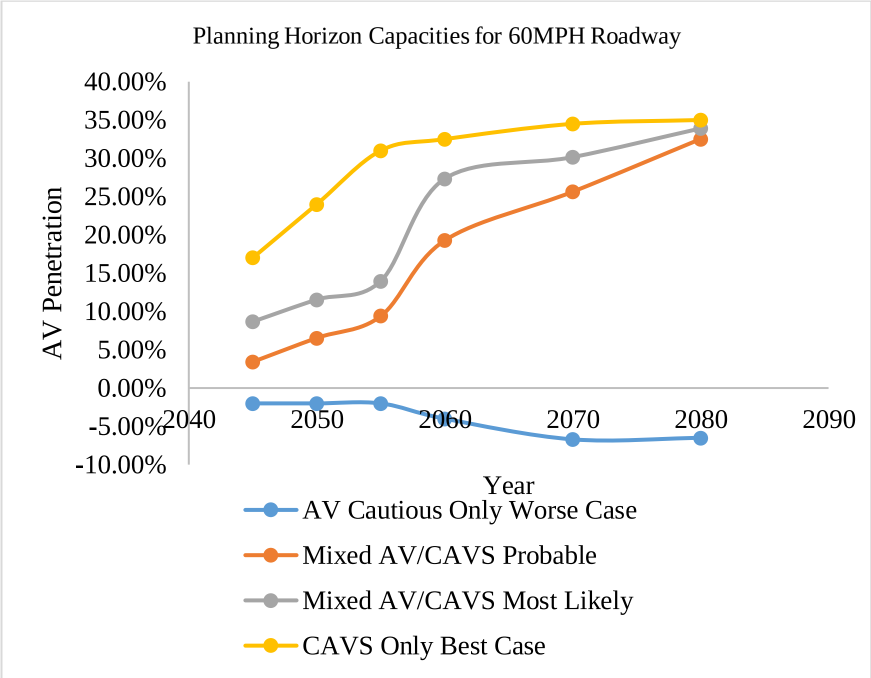


Figure 33. Planning Horizon Capacities for 60MPH Roadway

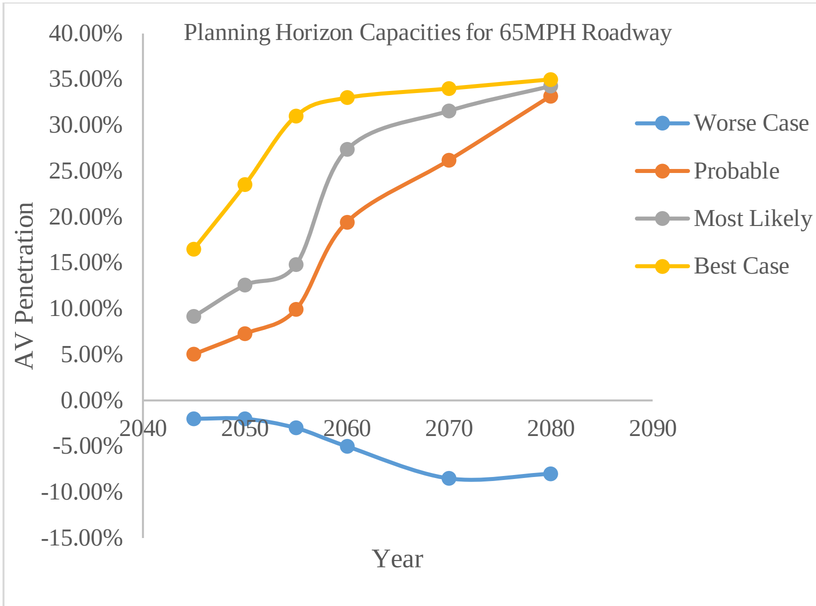


Figure 34. Planning Horizon Capacities for 65MPH Roadway

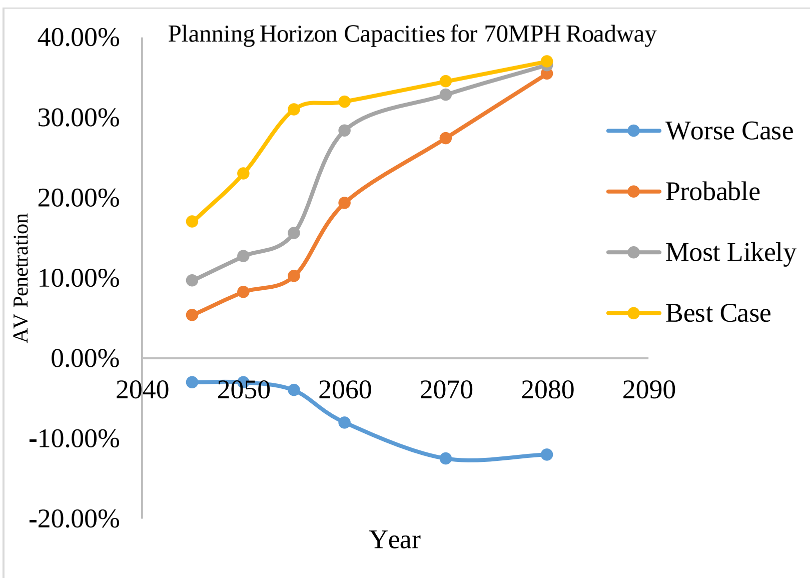


Figure 35. Planning Horizon Capacities for 70MPH Roadway

6. CONCLUSIONS AND RECOMMENDATIONS

6.1. Conclusions

In this study, a simulation-based method has been built that calibrates and validates a base model using trajectory data to achieve freeway capacity. A real-world data from the European-funded Co-exist project that mimics three levels of autonomous vehicles was merged with the base model and further set up a simulation model for AVs and CAVS. Then the output capacities for different penetration levels for all three vehicles classes to the base case were compared. This study attempted to capture the mixed scenario, which is one of the primary contributions. Moreover, this research contributed to a step-by-step microsimulation process that includes calibration and validation using oversaturated traffic data with proper driver's choice speed distribution.

The Study results indicate that the level of autonomy of vehicles will impact capacities compared to traditional vehicles. In this study, two types of mixed situations have been discussed. The first type was the capacity assessment of the traditional vehicle and single class AV, where a change of freeway capacity has been shown graphically. Results indicate that penetration of AV caution will negatively impact capacity. As these vehicles get introduced, their technologies will be very cautious, leading to lower capacities than traditional vehicles. It is because they will leave wider vehicle to vehicle gaps than most traditional vehicles today.

On the other hand, AV normal and All-knowing penetration showed a positive and significant impact after a certain penetration level. The second type was a reduction of traditional vehicle penetration and increasing different types of AV penetration. Various types of mixed situations have been tried to assess in this study. A preliminary study of dedicated AV lane introduction has been suggested for the planners when there is a noticeable increment. If there is a moderate or significant increment, a dedicated AV lane has been suggested. When there is 0% penetration of traditional, dedicated AV truck lane has been suggested. The importance of this result, especially to planners and engineers, is that they need to develop tools and traffic demand management policies that will help manage the lower or higher capacity. The lower capacities could lead to significant public outcry that could impact the introduction of these vehicles and retard their potential positive impacts. As it has been seen right now, out of the thousands of accidents that happen on our roadway, every Tesla accident that involved self-driving is highly scrutinized with significant negative public attention.

This dissertation evaluated the output from the AV scenarios and compared them to the traditional vehicle-only scenarios as it exists today. The major findings from these results are as follows:

1. The use of trajectory data to estimate base capacities in microsimulation environments. They provide the models with improved input parameters that truly represent how vehicles move in traffic streams. The base capacity calculations in this dissertation are lower than what the Highway capacity suggests. The implication is that starting with the HCM capacities would have resulted in lower capacities than capacities developed from the trajectory data. The implication is that the capacity gains are slightly higher than what would have been obtained using the HCM capacities. It means that modelers need to pay attention to local conditions when making assumptions about the capacity impacts of AVs/CAVs.
2. The technology in AVs will play a big part in how they impact capacities. Technologies that leave bigger gaps represented in AV-cautious cars will reduce capacities with additional negative impacts to the transportation system, such as congestion and

environmental impacts. Capacities could be reduced up to 9%. Therefore, it is plausible that in the nearest future, when AVs get introduced over the next 10-20 years, we will perhaps see a decline in capacities.

3. When technologies become more aggressive, capacities will be improved up to 37% for CAVs in weaving sections. Thus, to get the optimal impacts of AVs on our transportation systems, the technologies in the cars have to be CAVs.
4. Looking at the timeline for the adoption of AVs, we will not witness any significant capacity improvements over the next 30 years. Therefore, the most plausible scenario is that different mixes and penetrations of AVs/Traditional vehicles will differ over this period. The higher the mix of CAVs, the higher the capacity impacts.
5. The functional forms of the mathematical relationships between roadway capacity changes and AV classes/mixes are different for different roadway and AV types. For example, for AV-Normal and AV-All-knowing, capacity changes follow a sigmoidal-curve function for the basic freeway segment. In contrast, they follow a polynomial function for the weaving section. Additionally, the functional form for AV-cautious is different for This should be taken into account by transportation analysts and modelers who estimate the impacts of AVs and CAVs.
6. For basic freeways, capacity gains start to increase exponentially at about the 40% penetration level for single class AV-Normal and CAVs. The inflection point occurs at about the 75% percent penetration levels where the capacity gains but decreases. The implication is that the critical mass point for basic highways to start seeing capacity gains is at about 40% penetration levels of AVs. Below that, the gains are due to AVs being minimal.

6.2. Recommendations to Potential Policy Changes

Before the implementation of any certain plan, a preliminary study is necessary. The study above found that AV penetration rate plays a vital role in changing capacity. As a result, there should be a mutual understanding between planners, operation engineers, decision-makers. Based on market sales, consumer adaptation rate, and cost-effectiveness, the planner should incorporate a certain penetration rate of AVs during future road network planning, lane expansion, or reduction issues. For example, if capacity increment causes excess lanes for a particular location, introducing a dedicated AV might provide benefit to the mixed traffic situations. A dedicated AV truck lane might provide better results in 100% AV / CAV penetration. Besides, traffic operation engineers should predict freeway bottleneck situations, traffic merging point handling, and travel time improvement issues based on AV penetration. A proper simulation-based assessment might help to take the necessary steps. Finally, a decision-maker should consider spending money on the appropriate place, such as building new technology-based infrastructure for better V2V, V2I connections in ramp junction, intersection, automated parking, accident alert system. An affordable autonomous vehicle cost to the middle-class people should be the primary challenge, and huge investment is necessary for cheaper and safe technology.

6.3. Major Shortcomings and Future Studies

One of the major shortcomings of this study is that even though the Co-exist project simulated different AV car-following algorithms; this may not be the final algorithm that these cars will have as they are not yet in circulation. However, this study provides insight to transportation planners, engineers, and decision-makers on what to expect when these vehicles get introduced.

Additionally, the percentage of heavy vehicles was low compared to typical highways in the U.S. Thus, the capacity impacts shown in this study might be lower when more trucks are introduced into the traffic stream. Additionally, the study considered only autonomous cars and not autonomous trucks. As the coexist project only discussed the passenger vehicle, the calibrated components are missing for the AV trucks. Future studies should focus on AV truck CC parameters finding from filed data useful for research purposes.

There is a wide scope of research on AV, such as how infrastructure will be developed for connectivity, the architectural design for V2V or V2I connection, and the protocol for AVs in response to adverse weather. These all are in the broader scene. As part of traffic operation, future research should assess the freeway's capacity in a more complex situation for higher heavy vehicle percentage, managed lane, dedicated lane service. The work can be further expanded to analyze capacities of ramp influence areas as well as urban, signalized intersection, and arterials. Autonomous trucks should also be incorporated into the mix in addition to autonomous cars.

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APPENDIX A. DETAILS ABOUT NGSIM DATA

A detailed data analysis of NGSIM data for the 1st and 2nd 15 minutes has been provided below in figures and tables. All figures and tables have been collected from a report created by Cambridge Systematic (Systematic, 2005).

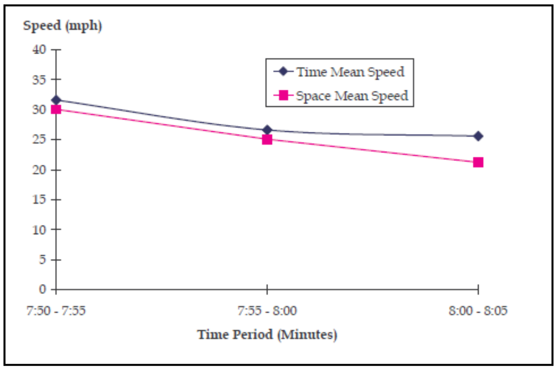

Figure A.1. Time Mean Speed and Space Mean Speed by Travel Period (1st 15minutes)

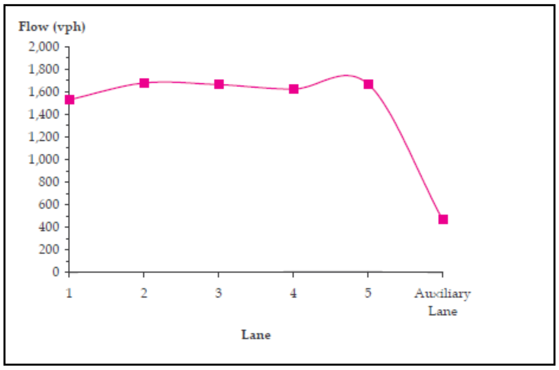

Figure A.2. Flow by Lane at Study Location (1st 15minutes)

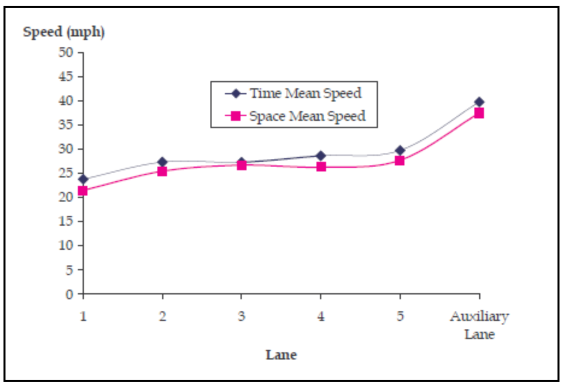

Figure A.3. Speed by Lane at Study Area (1st 15minutes)

Table A.1. Aggregate Results Summary for the Entire Section (1st 15minutes)

Period	Flow	Time means speed	Space Mean Speed
		mph	mph
7.50 am - 7.55 am	9156	31.6	30.03
7.55 am - 8.00 am	8820	26.6	25.06
8.00 am- 8.05 am	7860	25.59	21.22
Average	8612	28.06	25.66

Table A.2. Aggregate Flow and Speed for Each Lane (1st 15minutes)

Lane	Flow	Time Mean Speed (mph)	Space Mean Speed (mph)
1	1528	23.76	21.45
2	1676	27.33	25.45
3	1660	27.27	26.68
4	1620	28.62	26.27
5	1664	29.73	27.7
Auxiliary Lane	464	39.76	37.45
Average	8612	28.06	26.21

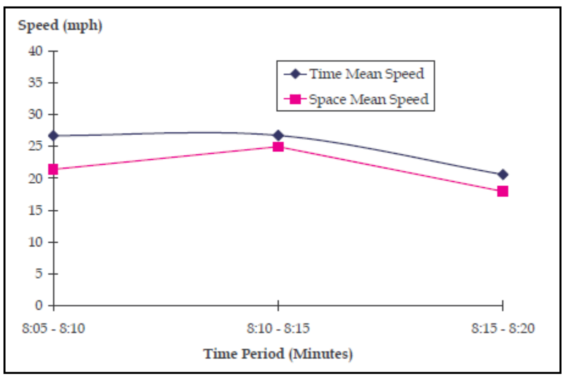

Figure A.4. Time Means Speed and Space Mean Speed by Period (2nd 15 minutes)

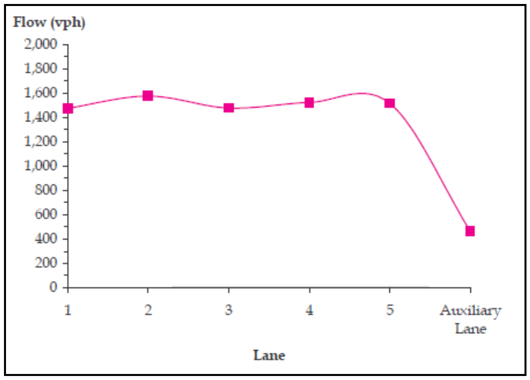

Figure A.5. Flow by Lane of the Study Section (2nd 15 minutes)

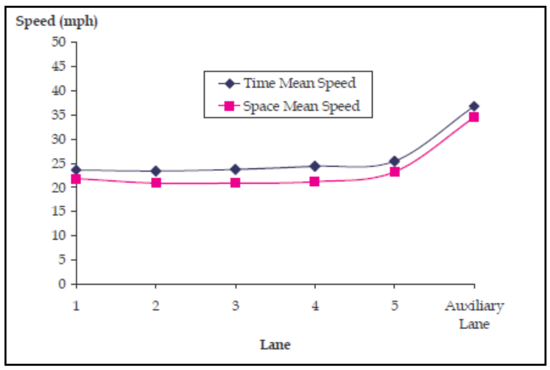

Figure A.6. Speed by Lane at Study Section (2nd 15 minutes)

Table A.3. Aggregate Results Summary for the Entire Section (2nd 15 minutes)

Period	Flow	Time mean speed (mph)	Space Mean Speed (mph)
8.05 am -8.10 am	8136	26.7	21.41
8.10 am -8.15 am	8484	26.73	24.97
8.15 am - 8.20 am	7428	20.6	17.94
Average	8016	24.83	21.59

Table A.4. Aggregate Flow and Speed for Each Lane (2nd 15 minutes)

Lane	Flow	Time Mean Speed (mph)	Space Mean Speed (mph)
1	1474	23.61	21.84
2	1574	23.39	20.88
3	1474	23.73	20.9
4	1518	24.38	21.19
5	1512	25.43	23.22
Auxiliary Lane	464	36.82	34.51
Average	8016	24.85	22.35

Vehicle_	Frame_ID	Total_Fram	Global_Tim	Local_X	Local_Y	Global_X	Global_Y	v_Length	v_Width	v_Class	v_Vel	v_Acc	Lane_ID	Preceeding	Following	Space_Hdw	Time_Hdwy	Pre-Veh_Vel	PreVeh_Class
726	1823	359	1.119E+12	56.378	517.25	6451454.2	1872975	20.5	6.9	2	34.98	0	5	709	735	51.42	1.47	41.39	2
726	1824	359	1.119E+12	56.505	520.75	6451456.7	1872972	20.5	6.9	2	34.98	0	5	709	735	52.06	1.49	41.32	2
726	1825	359	1.119E+12	56.633	524.25	6451459.2	1872970	20.5	6.9	2	34.98	0	5	709	735	52.69	1.51	41.21	2
726	1826	359	1.119E+12	56.76	527.74	6451461.7	1872968	20.5	6.9	2	34.98	0	5	709	735	53.31	1.52	41.07	2
726	1827	359	1.119E+12	56.886	531.24	6451464.3	1872965	20.5	6.9	2	34.98	0	5	709	735	53.93	1.54	40.81	2
726	1828	359	1.119E+12	57.014	534.74	6451466.8	1872963	20.5	6.9	2	34.98	0	5	709	735	54.5	1.56	40.47	2
726	1829	359	1.119E+12	57.141	538.24	6451469.3	1872960	20.5	6.9	2	34.98	0	5	709	735	55.02	1.57	40.17	2
726	1830	359	1.119E+12	57.268	541.73	6451471.8	1872958	20.5	6.9	2	34.98	0	5	709	735	55.51	1.59	40	2
726	1831	359	1.119E+12	57.396	545.23	6451474.4	1872955	20.5	6.9	2	34.98	0	5	709	735	56	1.6	39.97	2
726	1832	359	1.119E+12	57.523	548.73	6451476.9	1872953	20.5	6.9	2	34.97	-0.07	5	709	735	56.5	1.62	39.99	2
726	1833	359	1.119E+12	57.65	552.23	6451479.4	1872951	20.5	6.9	2	34.97	-0.03	5	709	735	57.01	1.63	40.01	2
726	1834	359	1.119E+12	57.778	555.72	6451481.9	1872948	20.5	6.9	2	35.02	0.91	5	709	735	57.52	1.64	40.02	2
726	1835	359	1.119E+12	57.914	559.22	6451484.4	1872946	20.5	6.9	2	35.19	2.27	5	709	735	58.04	1.65	39.9	2
726	1836	359	1.119E+12	58.03	562.75	6451487	1872943	20.5	6.9	2	35.38	2.16	5	709	735	58.51	1.65	39.46	2
726	1837	359	1.119E+12	58.119	566.3	6451489.6	1872941	20.5	6.9	2	35.49	0.31	7	714	710	38.53	1.09	34.32	2
726	1838	359	1.119E+12	58.109	569.87	6451492.3	1872938	20.5	6.9	2	35.46	-1.33	7	714	710	38.38	1.08	34.08	2

Figure A.7. Snapshot of NGSIM Data Table from 7.55 am to 8.05 am

APPENDIX B. BASIC FREEWAY & WEAVING SEGMENT ANALYSIS

This section has detailed information about the weaving segment, such as flow per lane, including weaving and non-weaving lanes. The calculation is given below.

Lane #	Volume	Veh/ hr.	VR
1			
2			
3	1936	7744	0.08
4			
5			
5 to 6	105	420	
6 to 5	72	288	
6	15	60	

Calculation for Weaving capacity

Ls = 698 ft

N_{wL}= 2

$C_{IWL} = C_{IFL} - [438.2\ (1+VR)1.6] + [0.0765\ L_s] + [119.8\ N_{wl}] = 2045.04$ veh/hr/ln

$C_w = C_{IWL} * N* f_{HV} * f_p = 12270.24$ veh/hr.

Table B.1. CC Parameters with Range for Basic Freeway Segment

Parameter	Car	Truck	Range
CC0	8	18	0.07 to 113.44
CC1	1	2	0.01 to 24.53
CC2	11	25	4 to 75
CC3	-3	-3	-0.3 to -3.6
CC4	-1.12	-1.8	3.7 to 15
CC5	1.5	1.8	3.7 to 16
CC6	11.44	11.44	11.44
CC7	0.47	1.7	-11.2 to 11.2
CC8	5.8	6	-11.2 to 11.3
CC9	0.51	1.25	-11.2 to 11.4

Table B.2. CC Parameters with Range for Weaving Segment

Parameter	Car	Truck	Range
CC0	8	18	0.07 to 301
CC1	1	2	0.13 to 21.5
CC2	11	25	1 to 48
CC3	-3	-3	-0.19 to -8.0
CC4	-1.12	-1.8	-1 to -11
CC5	1.5	1.8	-5 to 11
CC6	11.44	11.44	11.44
CC7	0.47	1.7	-11.2 to 11.2
CC8	5.8	6	-11.2 to 11.3
CC9	0.51	1.25	-11.2 to 11.4

APPENDIX C. RESULTS AND DISCUSSION

Table C.1. Capacity and Standard Error of Basic Freeway Segment in the Base Case

Speed (mph)	HCM	100 % Car	SE	2% Truck	SE
55	2250	2124	0.708786	1966	0.700966
60	2300	2148	0.419003	2028	0.646183
65	2350	2172	0.502465	2064	0.751742
70	2400	2208	0.65879	2088	0.840949

Table C.2. Capacity and Standard Error for Single Class AV (Cautious) at Basic Freeway Segment

Follower	Leader	55 mph	60 mph	65 mph	70 mph
AV Cautious	Traditional	55 mph	60 mph	65 mph	70 mph
0%	100	1966 (0.7009)	2028 (0.6461)	2064 (0.7517)	2088 (0.8409)
25%	75	1956 (0.7164)	2028 (0.7938)	2040 (0.0.7516)	2052 (0.6928)
50%	50	1872 (0.8064)	1896 (0.8006)	1956 (0.6559)	1980 (0.7003)
75%	25	1800 (0.6826)	1824 (0.7553)	1872 (0.7543)	1956 (0.7193)
100%	0	1932 (0.7531)	1980 (0.7461)	1908 (0.7916)	1836 (0.6982)

Table C.3. Capacity and Standard Error for Single Class AV (Normal) at Basic Freeway Segment

Follower AV Normal	Leader Traditional	55 mph	60 mph	65 mph	70 mph
0	100	1966 (0.7009)	2028 (0.6461)	2064 (0.7517)	2088 (0.8409)
25	75	2052 (0.8156)	2125 (0.8246)	2188 (0.6913)	2148 (0.7994)
50	50	2220 (0.7692)	2345 (0.8006)	2256 (0.7664)	2292 (0.0.7439)
75	25	2328 (0.8044)	2340 (0.7729)	2400 (0.7394)	2460 (0.6845)
100	0	2604 (0.7938)	2616 (0.7394)	2640 (0.7813)	2652 (0.8077)

Table C.4. Capacity and Standard Error for Single Class AV (Aggressive) at Basic Freeway Segment

Follower AV Aggressive	Leader Traditional	55 mph	60 mph	65 mph	70 mph
0	100	1966 (0.7009)	2028 (0.6461)	2064 (0.7517)	2088 (0.8409)
25	75	2080 (0.7698)	2160 (0.6993)	2052 (0.7434)	2064 (0.7364)
50	50	2290 (0.7134)	2390 (0.8052)	2268 (0.7848)	2340 (0.7881)
75	25	2508 (0.7593)	2520 (0.8133)	2544 (0.8070)	2580 (0.8244)
100	0	2616 (0.7116)	2628 (0.7688)	2652 (0.7299)	2688 (0.6528)

Table C.5. Capacity Value and Standard Error of Mixed Traffic Scenario with 25% AV at Basic Freeway Segment

	25% AV / 75% traditional			25% AV / 75% traditional		
FFS (mph)	10% Cautious	10% Normal	5% All-Knowing	5% Cautious	10% Normal	10% All-Knowing
55	1996 (0.7511)			2008 (0.6284)		
60	2078 (0.6852)			2086 (0.7112)		
65	2118 (0.8064)			2125 (0.7266)		
70	2150 (0.7241)			2170 (0.7355)		

Table C.6. Capacity Value and Standard Error of Mixed Traffic Scenario with 65% Av at Basic Freeway Segment

	35% AV / 65% traditional			35% AV / 65% traditional		
FFS (mph)	10% Cautious	20% Normal	5% All-Knowing	5% Cautious	10% Normal	10% All-Knowing
55	2003 (0.6351)			2035 (0.8155)		
60	2079 (0.7244)			2099 (0.6742)		
65	2126 (0.7328)			2147 (0.7593)		
70	2182 (0.8041)			2213 (0.6893)		

Table C.7. Capacity Value and Standard Error of Mixed Traffic Scenario with 50% AV at Basic Freeway Segment

	50% traditional / 50 % AV			50% traditional/ 50 % AV		
FFS (mph)	20% Cautious	20% Normal	10% All-Knowing	10% Cautious	20% Normal	20% All-Knowing
55	2016 (0.7844)			2070 (0.7122)		
60	2082(0.7266)			2148 (0.7622)		
65	2140 (0.6933)			2190 (0.7436)		
70	2170 (0.7266)			2250 (0.7438)		

Table C.8. Capacity Value and Standard Error of Mixed Traffic Scenario with 60% AV at Basic Freeway Segment

	40% traditional / 60% AV			40% traditional / 60% AV			40% traditional / 60% AV		
FFS (mph)	30% Cautious	20% Normal	10% All-Knowing	20% Cautious	30% Normal	10% All-Knowing	5% Cautious	30% Normal	25% All-Knowing
55	1980 (0.6925)			2076 (0.6588)			2160 (0.7264)		
60	2040 (0.7522)			2150 (0.7433)			2232 (0.7812)		
65	2080 (0.7392)			2196 (0.6554)			2286 (0.7344)		
70	2112 (0.7816)			2244 (0.7136)			2340 (0.7482)		

Table C.9. Capacity Value and Standard Error of Mixed Traffic Scenario with 90% AV at Basic Freeway Segment

	10% traditional / 90% AV			10% traditional / 90% AV			10% traditional / 90% AV		
FFS	30% Cautious	40% Normal	20% All-Knowing	20% Cautious	40% Normal	30% All-Knowing	5% Cautious	45% Normal	40% All-Knowing
55	2251 (0.8254)			2451 (0.8055)			2538 (0.7938)		
60	2358 (0.7961)			2548 (0.7921)			2640 (0.7168)		
65	2420 (0.7893)			2625 (0.7822)			2715 (0.8391)		
70	2481 (0.7269)			2661 (0.7644)			2774 (0.8164)		

Table C.10. Capacity Value and Standard Error of Mixed Traffic Scenario with 100% AV at Basic Freeway Segment

	0% traditional			0% traditional			0% traditional		
FFS (mph)	10% Cautious	30% Normal	60% All-Knowing	0% Cautious	20% Normal	80% All-Knowing	0% Cautious	0% Normal	100% All-Knowing
55	2290 (0.7276)			2380 (0.7806)			2460 (0.6833)		
60	2440 (0.6982)			2560 (0.7156)			2640 (0.7394)		
65	2500 (0.8045)			2630 (0.7088)			2710 (0.7411)		
70	2568 (0.7588)			2700 (0.7943)			2780 (0.7167)		

Table C.11. Base Case Weaving Capacity Value with Standard Error at Weaving Segment

Speed (mph)	HCM	Simulation value	SE
55	2045	1800	0.7264
60	2095	1811	0.7622
65	2145	1847	0.7269
70	2195	1860	0.7638

Table C.12. Capacity Value and Standard Error of Single Class AV (Cautious) at Weaving Segment

AV Cautious	0.00%	25.00%	50.00%	75.00%	100.00%
55 mph	1800 (0.7264)	1787 (0.7812)	1800 (0.7634)	1763 (0.7133)	1727 (0.7205)
60 mph	1811 (0.7622)	1860 (0.7234)	1847 (0.7491)	1823 (0.7584)	1775 (0.7439)
65 mph	1847 (0.7269)	1883 (0.6985)	1860 (0.7822)	1847 (0.7694)	1715 (0.7367)
70 mph	1860 (0.7638)	1860 (0.7164)	1871 (0.7648)	1800 (0.7260)	1643 (0.7438)

Table C.13. Capacity Value and Standard Error of Single Class AV (Normal) at Weaving Segment

AV Normal	0.00%	25.00%	50.00%	75.00%	100.00%
55 mph	1800 (0.7264)	2015 (0.7155)	2195 (0.7861)	2375 (0.7648)	2580 (0.7168)
60 mph	1811 (0.7622)	2051 (0.8014)	2255 (0.7943)	2447 (0.7294)	2615 (0.7468)
65 mph	1847 (0.7269)	2063 (0.8066)	2267 (0.7162)	2495 (0.7361)	2640 (0.7269)
70 mph	1860 (0.7638)	2087 (0.7843)	2279 (0.8237)	2507 (0.7943)	2675 (0.7146)

Table C.14. Capacity Value and Standard Error of Single Class AV (All-Knowing) at Weaving Segment

AV All-Knowing	0.00%	25.00%	50.00%	75.00%	100.00%
55 mph	1800 (0.7264)	2003 (0.7646)	2291 (0.7468)	2435 (0.7436)	2555 (0.7349)
60 mph	1811 (0.7622)	2039 (0.8064)	2375 (0.7364)	2471 (0.7439)	2579 (0.7106)
65 mph	1847 (0.7269)	2075 (0.7619)	2411 (0.7496)	2591 (0.7135)	2615 (0.7439)
70 mph	1860 (0.7638)	2100 (0.7941)	2435 (0.7951)	2495 (0.7391)	2651 (0.7165)

Table C.15. Capacity Value and Standard Error of Mixed Traffic Scenario with 25% AV at Weaving Segment

	25% AV / 75% traditional			25% AV / 75% traditional		
FFS	10% Cautious	10% Normal	5% All-Knowing	5% Cautious	10% Normal	10% All-Knowing
55	1860 (0.7055)			1932 (0.7198)		
60	1873 (0.7814)			1968 (0.6689)		
65	1940 (0.6545)			2016 (0.8034)		
70	1960 (0.6982)			2040 (0.7598)		

Table C.16. Capacity Value and Standard Error of Mixed Traffic Scenario with 35% AV at Weaving Segment

	65% traditional / 35% AV			65% traditional / 35% AV		
FFS	10% Cautious	20% Normal	5% All-Knowing	5% Cautious	10% Normal	20% All-Knowing
55	2055 (0.6922)			2173 (0.8251)		
60	2160 (0.8259)			2262 (0.8326)		
65	2213 (0.7361)			2323 (0.7629)		
70	2260 (0.7629)			2353 (0.7166)		

Table C.17. Capacity Value and Standard Error of Mixed Traffic Scenario with 50% AV at Weaving Segment

	50% traditional / 50% AV			50% traditional / 50% AV		
FFS	20% Cautious	20% Normal	10% All-Knowing	10% Cautious	20% Normal	20% All-Knowing
55	1960 (0.6792)			2030 (0.6492)		
60	1981 (0.7345)			2064 (0.7291)		
65	2030 (0.7962)			2120 (0.7923)		
70	2050 (0.7491)			2150 (0.7518)		

Table C.18. Capacity Value and Standard Error of Mixed Traffic Scenario with 60% AV at Weaving Segment

	40% traditional			40% traditional			40% traditional		
FFS	30% Cautious	20% Normal	10% All-Knowing	20% Cautious	30% Normal	10% All-Knowing	5% Cautious	30% Normal	25% All-Knowing
55	2040 (0.7461)			2124 (0.7034)			2280 (0.8024)		
60	2076 (0.7926)			2160 (0.7146)			2306 (0.7634)		
65	2130 (0.6991)			2206 (0.7824)			2352 (0.7842)		
70	2160 (0.6828)			2220 (0.7514)			2388 (0.6559)		

Table C.19. Capacity Value and Standard Error of Mixed Traffic Scenario with 90% AV at Weaving Segment

	10% traditional / 90% AV			10% traditional / 90% AV			10% traditional / 90% AV		
FFS	30% Cautious	40% Normal	20% All-Knowing	20% Cautious	40% Normal	30% All-Knowing	5% Cautious	45% Normal	40% All-Knowing
55	2061 (0.7293)			2244 (0.7096)			2324 (0.7033)		
60	2105 (0.7618)			2275 (0.7391)			2357 (0.7816)		
65	2165 (0.8045)			2330 (0.7358)			2430 (0.6952)		
70	2210 (0.7614)			2371 (0.8122)			2471 (0.7361)		

Table C.20. Capacity Value and Standard Error of Mixed Traffic Scenario with 100% AV at Weaving Segment

	0% traditional			0% traditional			0% traditional		
FFS	10% Cautious	30% Normal	60% All-Knowing	0% Cautious	20% Normal	80% All-Knowing	0% Cautio us	0% Normal	100% All-Knowing
55	2340 (0.8154)			2380 (0.6943)			2400 (0.7615)		
60	2400 (0.8078)			2425 (0.7182)			2440 (0.7169)		
65	2460 (0.7694)			2480 (0.7918)			2495 (0.6926)		
70	2520 (0.7491)			2540 (0.7691)			2544 (0.7066)		