

**IMPACT OF LEVEL 3 HIGHLY AUTOMATED HEAVY VEHICLES ON  
FREEWAY CAPACITY**

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A thesis submitted in partial fulfillment of

The requirements for the degree of

Master of Science

(Civil and Environmental Engineering)

At the

University of Wisconsin-Madison

2018

## **ABSTRACT**

Over the last few years, the applications of Autonomous Vehicles in the Freeway network have attracted increased attention both in practice and in the research field. However, the detection of the effect of the Autonomous Vehicles remains a challenging task due to the complex environment and heterogeneity characteristics the Freeway network has. Fortunately, the recent development of the connected vehicle technologies may provide a promising platform to observe and estimate effect of implement AV on roadway Capacity.

The efficiency of the transport network is determined by its capacity. On Freeway, the capacity is dependent on the maximum possible flow of traffic on the road sections as well as the percentage of the Heavy Vehicles, Manual Vehicles and the Autonomous Vehicles entering the Freeway. Autonomous vehicles maneuver in traffic through road networks does not requiring humans as supervisors or decision makers. Autonomous vehicles increase comfort for their passengers by removing the need for them to perform driving tasks. Autonomous Vehicle level 3 is could eliminate human reaction, and this should increase the roadway capacity since the gap acceptance would decrease.

While the capacity at traffic is determined by the amount of time required by individuals, the capacity of the Freeway may improve by implement the technics of Autonomous in the road either on the passenger cars or on the heavy vehicles.

The entry of Heavy vehicles into the traffic stream affect the number of vehicle that can be observed also they have poorer operation capacities than the passenger cars.

This project explores how the decrease of the gap acceptance will affect the roadway capacity also the different percentage of level 3 automated heavy vehicle would

investigate on the freeway capacity by using VISSIM as a microsimulation tool. Different scenarios were set up in the VISSIM freeway network to detect how different gap acceptance and different percentages of level 3 automated heavy vehicles in the traffic mix may change the freeway capacity.

This study is to demonstrate how does the Autonomous Heavy Vehicles will improve the Freeway Capacity reduction due to the heavy vehicles. The physical characteristics of heavy vehicles such as low acceleration and slow speed have less reduction effects after implement the Automated behaviors.

## **Acknowledgment**

I would first like to thank my thesis advisor professor Bin Ran of the Civil Engineering Department at University of Wisconsin Madison. The door to Prof. Ran office was always open whenever I ran into a trouble spot or had a question about my research or writing. He consistently allowed this paper to be my own work, but steered me in the right the direction whenever he thought I needed it.

My successful completion of Master's degree relies on not only the pursuer's hard work but more importantly, the directions and help given by Prof. Ran, Dr. Yang Cheng, Youngjun Han, colleagues, and also with friends. I deeply appreciate all those wonderful people that contribute to the successful completion of my degree.

I am also grateful for the supporting and encouraging from my lovely family Mother, Father and my Kids. Their advices and comments of my work are of tremendous value, not just for purse a degree but helped structured a way of finding myself and solving problems that I faced. This thesis cannot be done without the support of my special friend Huda; her unconditional love, encouragement and support on me have given me the courage and strength to battle with the stressful times I have during the research. I am thankful for all the inspirations, suggestions and comments obtained from my lab colleagues; the care given from them are truly genuine and abundant.

Last but not least, I would like to take this opportunity to give special thanks to the Wisconsin Traffic Operations and Safety (TOPS) Laboratory. TOPS Lab has supported me with all the necessary equipment and software that made this research possible.

Finally, I must express my very profound gratitude to my sisters and brothers for providing me with unfailing support and continuous encouragement throughout my years of study and through the process of researching and writing this thesis. This accomplishment would not have been possible without them. Thank you.

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## **Chapter 1 Introduction**

### **1.1 Background:**

Recently traffic congestion becomes the most transportation problem in global cities. When traffic demand exceeds the available capacity of the road network, the congestions will occur, which cause slower movement of vehicles, longer trip time and increased vehicular queueing. These negative impacts on the urban traffic not only harm the economy development but also contribute to air pollution and global warming issues in the urban area. To fulfill the increased trip demand and solve the congestion problems, transportation engineers construct new roads, bridges, and other transportation facilities, which intends to expand the capacity of the existing transportation systems. This method indeed mitigates the congestion in the short term. However, it is not a feasible solution in the long run. Besides the tremendous cost and limited land resources for adding new facilities, the new constructions attract more vehicles into the system, which keeps causing more demands and contributing to heavier congestion. Thus, researchers and engineers explore the methodology to improve the efficient usage of existing infrastructures instead of constructing new facilities.

A variety of technology technics strategies are developed to attain this goal. The underlining objective of these strategies is to achieve optimal traffic condition by improving the traffic capacity, so that drivers can efficiently utilize the existing system assets without any further construction.

Some strategies focus on solving the congestion problem in the individual links or corridors. For example, ramp metering and variable speed limits are solutions used to control the traffic flow and speed in urban roadway corridor. By control the traffic demand,

these strategies ensure the efficiency of traffic movement in the corridor and thus, prevent the traffic jam in a local area. Traffic monitoring of these strategies relies on microscopic models, which measure the traffic state variables, such as travel time, flow rate, speed and density at link or intersection. These models and indicators are successful in estimating the traffic condition in an individual section of the network. However, new techniques on vehicles tasks and performance has spatially provide solutions in delays related to human performance. Nowadays, some autonomous vehicles with Advanced Driver Assistance Systems (ADAS) features like Adaptive Cruise Control (ACC) and Lane Departure Warning (LDW) are already on the roads around the world (Bierstedt, 2014). ADAS systems can inform and warn, provide feedback on actions, warns, provide feedback on actions, increase comfort and reduce workload by actively stabilizing or maneuvering the vehicle (Zhao, 2015). Some ADAS systems working together may give the vehicle the ability to drive itself. For example, Adaptive Cruise Control (ACC) and Lane Departure Warning (LDW) working together can provide both longitudinal and lateral guidance. As these systems works based on the inputs from the physical sensors such as radar, LIDAR, ultrasonic, cameras independent of human driver input, the behavior of these vehicles could be different from vehicles operated by human drivers (Zhao, 2015).

The microscopic traffic flow of different gap acceptance should appropriately analyze and understand the vehicle performance characteristics, to identify the optimal gap acceptance and to apply the implementation strategy.

## **1.2 Research Problem Statement**

Regardless of the recent research initiatives, the bias of the Capacity estimation of the traffic with mix driver behavior is still under discussion. Notably, the deployment of

Autonomous vehicles may significantly impact the Traffic Flow. Researchers discussed how does the Automotive vehicle improve the Freeway Capacity. Also, studies point out that traffic contain different type of vehicle with various driver behaviors would probably affect the flow pattern and capacity. The effect of the autonomous vehicle on the freeway capacity is still not well-established. And it is difficult to get a well-done investigation due to difficulty of finding them in the real road. Previous studies discussed how dose eliminating human factors will improve the vehicle performance. Estimation the freeway capacity of roads contain different type and different behaviors of vehicles remains a challenging objective due to the complex environment characteristics the network has. Therefore, it is necessary to explore how does Heavy Autonomous vehicles level three will affect the Capacity and what would happen to the freeway flow if the road contain different driver behavior.

### **1.3 Research Objective**

The aim of this research is to propose the VISSIM Simulation and generating the traffic flowrate charts of the Autonomous Heavy Vehicles environment. The Result of the connection point data will be used and analyzed to figure out the Capacity rate and the flow pattern. To attain this goal, the following Five tasks are achieved:

- 1- Understanding the formation and characteristics of the traffic flow in the freeway.  
This objective helps to gain deeper knowledge on the properties of the road way Capacity and it characteristics.
- 2- Developing the VISSIM simulation network and the data estimation processing and procedures of generating Traffic flow estimation.

- 3- Establishing a combined different type of vehicles and different Scenarios in the VISSIM simulation network to investigate the effect of these combination on the Freeway Capacity.
- 4- Comparing the observed traffic flow rate under different scenarios.
- 5- Explore the impacts of the Heavy Autonomous Vehicle penetration rate to the Freeway Capacity.

By completing the above five tasks, the proposed simulation will show the feasibility of obtaining Traffic flow rate of the freeway. Two key contributions of this research are summarized as below:

- 1- This study introduces the effect of the different penetration rate of the Heavy Autonomous Vehicles on the freeway Capacity.
- 2- This study also explores the relationship and differences between the traffic flow rate of several types of Vehicles. The finding under the Autonomous vehicle environment matches the conclusions in some previous studies.

#### **1.4 Conceptual Frame work**

The conceptual framework of this thesis is presented as the following figure, the logic flow of this research starts from the review of Autonomous Vehicles theory. By reviewing and summarizing the previous work on the classification of the Autonomous Vehicles and illustrate the Benefit and drawback of driverless Cars. Following by explain the Capacity estimation process, and key characteristics of the traffic flow. Finally explain the heavy vehicles behaviors and it impact on the freeway capacity. A different Scenarios VISSIM simulation is established to figure out the effect of different penetration rate of the

Heavy Autonomous Vehicles under different combination of vehicles types. The proposed model explores the procedure of building network and Car following Model Calibration. Last and not least, use the output data from simulation to build the graphs and establish the different flow rate of different Scenarios. Finally, concludes the research and provides discussion on future research possibilities.

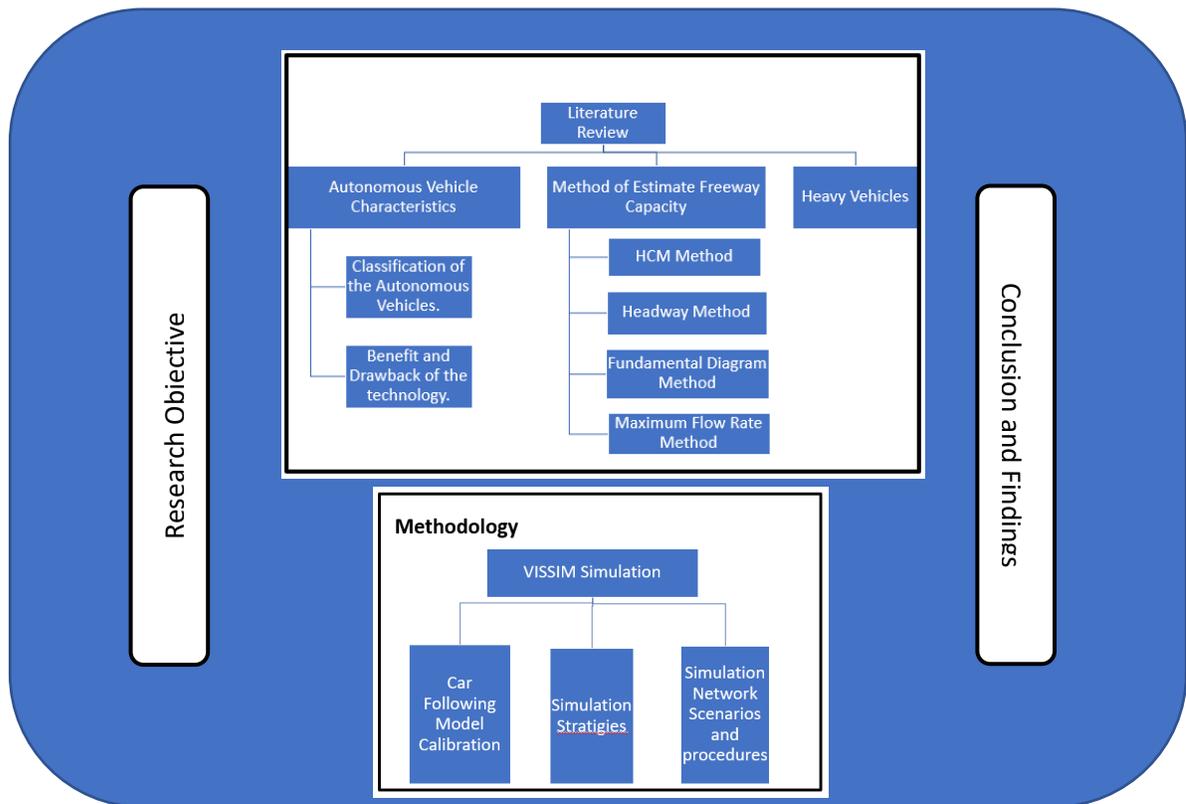


Figure 1 Thesis organization Flow Chart

## **Chapter 2 Literature Review**

### **2.1 Introduction**

Autonomous vehicles have better been understood through the performance of literature review. Published materials from a variety of industries such as electronics industry, government regulatory, civil engineering industry as well as automotive industry, have been expansively reviewed because autonomous vehicles research and development entails multidisciplinary players. The major categories of interests include SAE level 2 and 3 HAVs. Understanding these vehicles' driving behaviors and capabilities as well as the number of such vehicles that will be on the road is critical information in terms of comprehending how the expressway capacity may be affected and the strategies for expressway management. More areas including of autonomous vehicles, safety and benefits will also be covered in this chapter to ensure completeness of this research.

### **2.2 Autonomous Vehicles**

Autonomous vehicles are viewed as vehicles that drive themselves, and therefore need no introduction to themselves (Litman, 2014). In as early as the 1920, researches on autonomous vehicles had essentially begun (Lafrance, 2016). These vehicles, however, many use magnets and radio control technologies to guide themselves. These technologies are considerably different from what the modern era autonomous vehicles are using. Current vehicles employ inputs from the physical sensors which include cameras, ultrasonic, LIDAR and radar (Zhao, 2015). Through the sensitivity sensors, the vehicle may be able to replace or help the human driver in carrying out driving responsibilities and checking the driving environment. It is necessary to understand the potentials of various autonomous vehicles from various manufacturers. This will enable the human driver to

understand the nature of tasks and the forms of driving environments that a specific autonomous vehicle can conduct under particular scenarios. Detailed information on the categorization of autonomous vehicles are provided in Section 2.4.

### 2.2.1 Classification of Autonomous Vehicles

Initially, both National Highway Traffic Safety Administration (NHTSA) and Society of Automotive Engineers (SAE) have published their “degrees” for autonomous vehicles so as to clearly define the capabilities of an autonomous vehicle. NHTSA approved the standard from SAE in October 2016 so as to promote clarity and consistency (Reese, 2016). For that reason, only the SAE’s standards for automation levels will be covered in this thesis. Only six levels of automation have been defined according to the standard. Graphical presentations of the basic of the six levels of automation are given in figure 2 below, while the subsequent six sections define them in detail.

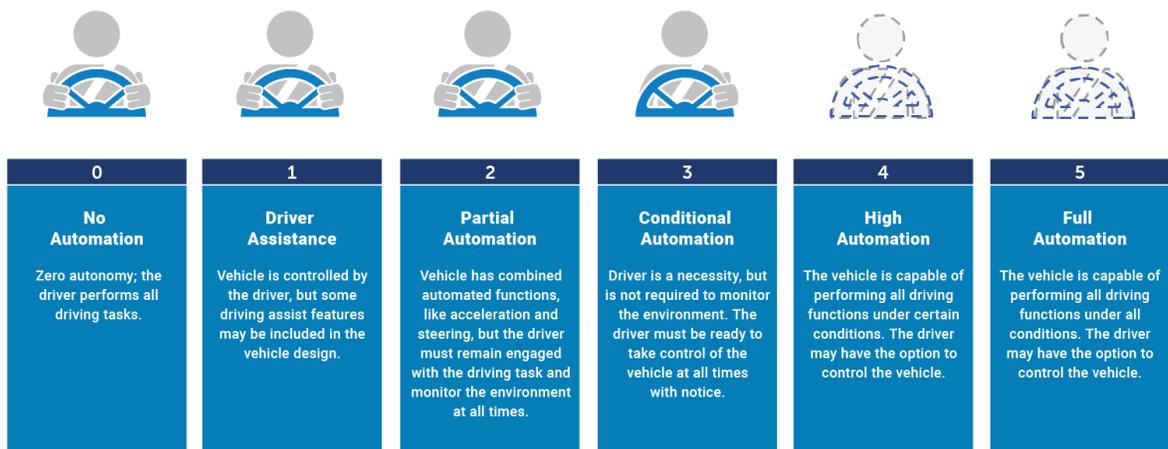


Figure 2 Classification of Autonomous Vehicles

#### 2.2.1.0 Level 0 Autonomous Vehicles

The vehicles do not have any driving automation at level 0. Even if the human driver has been notified by developed intervention or warning systems, he/she is expected

to conduct a full-time dynamic driving task (SAE, 2016). Human driver, at this level, is accountable for all of the tasks that he may encounter, from control of the vehicle to assessing the driving condition. Level 0 vehicles can no longer be seen on the US road today. Level 0 vehicles are, generally, the passenger vehicles built before 1990s.

#### *2.2.1.1 Level 1 Autonomous Vehicle*

All the vehicles having driver assistance systems fall under level 1. The driver assistance system performs the driving implementation by either deceleration/acceleration or steering using information about the driving environment and with the hope that the human driver performs all remaining forms of the dynamic driving task (SAE, 2016).

Both driver assistance systems and the human driver, at this level, carry out the task of acceleration/deceleration and steering. The responsibility of monitoring the driving environment remains in the hands of the human driver. Examples of the driver assistance systems mentioned above are Electronic Stability Control (ESC) or Anti-lock Braking System (ABS). The fact that both ESC and ABS had to be set up on all passenger vehicles by 2011 has made the majority of the vehicles on the road today in US to be level 1 (NHTSA, 2016).

#### *2.2.1.2 Level 2 Autonomous Vehicles*

The vehicles, at level 2, are partially automated. With the hope that the human driver perform all remaining parts of the driving responsibility, one or more driver assistance systems perform the driving mode-specific execution for both steering and acceleration/deceleration with the of the information about the driving environment (SAE, 2016).

Both level 1 and level 2 vehicles' human drivers are responsible for monitoring the driving condition while the system conducts the execution of steering and acceleration/deceleration. The only variation is that level 2 vehicles are able to perform both lateral and longitudinal controls of the vehicle while the system on level 1 vehicle is only able to perform either lateral or longitudinal control of the vehicle.

As of early 2017, level 2 vehicles are the state of the art. The features of Level 2 such as Lane Keeping Assist (LKA) and Adaptive Cruise Control (ACC) are going through economic of scale. Several economic models in the A and B sections are being equipped with level 2 features, and not just the first-rate models in the C and D section. It is probable that the level 2 feature will be authorized by NHTSA in the near future.

#### *2.2.1.3 Level 3 Autonomous Vehicles*

Level 3 vehicles have restricted driving automation. With the hope that human drivers will respond properly to a call to intervene, an automated driving system executes the driving mode-specific performance according to all aspects of the dynamic driving (SAE, 2016). At this point, the vehicle is capable of performing dynamic driving tasks (both lateral and longitudinal vehicle control) as well as monitoring the driving environment under particular conditions. In case particular conditions cannot be accomplished, therefore, the system will call for the intervention of the human driver. The human driver should be in a position to get control of the vehicle at all times. From a functional point of view, there is no distinction between a level 2 and level 3 vehicles. Both lateral and longitudinal control of the vehicle can be provided by both systems. The only divergence occurs in the manner in which they monitor the driving environment. While the responsibility of monitoring the driving environment is carried out by the system at level 3,

at level 2, human driver is the one responsible for monitoring the environment at all times. In essence, at level 2, the system should have an “assistant” task at all times, whereas the human driver is responsible for all other tasks related to driving. From level 3, human driver’s responsibility has shifted to an “assistant,” while the system begins to be in control. Usually, the customer or media misunderstands the dissimilarity between level 2 and level 3. There is not a single vehicle on the market today that is level 3 yet. However, level 3 vehicles are expected to appear on the market before long.

#### *2.2.1.4 Level 4 Autonomous Vehicles*

The vehicles are high driving automation at level 4. Even if a human driver does not respond in time to a request to take over, the driving mode-specific performances will controll all aspects of the dynamic driving task using an automated driving system (SAE, 2016). At level 4, human driver is totally out of the place under particular circumstances because the system is able to carry out all driving tasks, monitor the environment and will not call for human driver’s to intervention in any situation. There is no level 4 vehicle on the market that is yet at present, but a number of OEM manufacturers and level 1 suppliers are contemplating to produce level 4 vehicle by 2020 (Hanley, 2016).

#### *2.2.1.5 Level 5 Autonomous Vehicles*

For the case of level 5, the vehicles possess complete driving automation potential. The vehicle is absolutely controlled by an automated driving system on every nature of the dynamic driving duty under all environmental and roadway conditions that can be controlled by a human driver (SAE, 2016).

The vehicle, at this level, is able to do virtually all that is related to driving. Human driver will not be needed at any situation. He/she may read a book, watch a movie, take a

nap, etc. This is the most sophisticated level of automation, involving considerable innovation in motor vehicle technology. It is obvious that it will take many of years before level 5 vehicles can be developed and made available on public roads.

### 2.2.2 Highly Automated Vehicles (HAV)

Based on whether the automated system or the human driver is expected to monitor the driving environment, NHTSA has noted the difference between 0-2 levels and 3-5 levels. HAV (Highly Automated Vehicle) refers to SAE level 3-5 vehicles having automated systems that are capable of monitoring the driving environments.

### 2.2.3 Benefits of Automation

#### *2.2.3.0 Safety Benefit*

The safety benefits of automated vehicles are supreme. Automated vehicles' potential to save lives and decrease injuries is rooted in one critical and tragic fact: 94 percent of serious crashes are due to human error. Automated vehicles have the potential to eliminate human error from the crash equation, which will contribute to protect drivers and passengers, as well as bicyclists and pedestrians. When consider more than 35,092 people died in motor vehicle-related crashes in the U.S. in 2015, people begin to grasp the lifesaving benefits of driver assistance technologies. HAVs are capable of alleviating most crashes by means of technologies used by human drivers to minimize mistakes or execute the driving task. Unlike human drivers who would repeat the same mistake a million times before perfection, an HAV makes a good use of the data from HAV systems on other vehicles on the road (USDOT, 2016).

### *2.2.3.0 fuel efficiency Benefit*

Improved fuel efficiency is another anticipated benefit of autonomous vehicles. Autonomous vehicles, according to a research by Experiment done by Illinois University, researchers demonstrated experimentally that even a small percentage of such vehicles can have a significant impact on the road, eliminating waves and reducing the total fuel consumption by up to 40 percent (Leonis and Work, 2017)

On the other hand, according to a research by Carnegie Mellon, are estimated to reduce up to 10% of fuel cost in comparison with ordinary vehicles (Mersky, 2016). The improvement in fuel efficiency is made possible by the fact that the system can control the steering, brakes and throttle in a finer manner than the majority of human drivers. According to the findings of some researches, if EPA (Environment Protection Agency) will not modify the modern tests to incorporate autonomous vehicle technologies, fuel economy would possibly be degraded by 3%, depending on the program installed in autonomous vehicles by manufacturers (Mersky, 2016). It is also revealed in this research that regulators are not up-to-date with technology. These regulators should therefore come up with rules and regulations that control the implementation of autonomous vehicles. Many manufacturers, from industry observation, are aiming at integrating electric vehicles and autonomous vehicle technologies to develop smart and efficient future road worthy vehicle. Greater efficiency benefit will be brought into the society by electric-driven autonomous vehicles.

### *2.2.3.2 Efficiency and Convenience*

This thesis majorly focusses on assessing the benefits of automated vehicles on transportation operation. A characteristic road with every human driven vehicle gives an

utmost through put of close to 2,200 vehicles an hour. This, nevertheless, represents only 5% usage of highway surface (Pinjari, 2013). It is clear, from the fact that there is so much space left in between vehicles, that our roads are notably under-used. Automated vehicles are capable of sensing and foresee the lead vehicle's acceleration/deceleration decision and braking acts than human drivers (Pinjari, 2013). They are, therefore, expected to use the available space much better than an ordinary human driver. However, the amount of benefits is dependent on the proportion of the fleet mix (the number of automated vehicles against the number of ordinary vehicles), vehicle performances for instance the acceleration and deceleration rate, as well as the space between vehicles (Bierstedt, 2014). It has been proved that only ten percent of vehicles equipped with ACC (semi-automated) can free the traffic from irregular acceleration of human driven vehicles (Ioannou, 2003). It is not clear, however, if the capacity of the road can actually be influenced by the smooth of traffic. Tientrakooler al. (2011) approximated that semi-automated vehicles are able to improve the capacity of the road by about 40 percent in the event that all the vehicles are semi-automated. The idea of CACC (Corporative Adaptive Cruise Control) has lately come up in academic world. The freeway capacity is estimated to improve by up to 80%, after equipping the entire fleet of traffic with CACC. The capacity will be improved by 22 percent at 50 percent market penetration rate (Shladover, 2012).

#### 2.2.4 Weaknesses of Autonomous Vehicles

It is clear, from the previous sections, that automated vehicles are capable of bringing every sort of benefit to the people. However, automated vehicles are not without some drawbacks. There are many factors that may make automated vehicles vulnerable. These include potential job market, cyber security and vehicle system robustness etc.

#### *2.2.4.0 Vehicle System Robustness*

The robustness of vehicle system is significant for automated vehicle function. The system assists the human driver to carry out some driving tasks as illustrated in section 2.3: for a level 1 or 2 automated vehicle. However, the system is responsible for driving the vehicle and monitoring the driving environment at level 3 and above. For HAVs, it is inevitable that the system should be robust.

The system robustness of automated vehicles from different automotive companies has not yet reached the desirable level. The most recent autonomous vehicle disengagement report has it that the modern vehicles are expected to call for human driver to take control in after every 17.6 miles (Caltrans, 2017). The reports have revealed that automated vehicle technology has dramatically advanced in the last 2 years. The various causes of system disconnection include human discomfort, unexpected behavior from traffic and lane change failure. Every cause described above does not often occur in regular traffic, these problems should be resolved before HAVs can be accessible in the markets.

#### *2.2.4.1 Cyber Security*

Ever since, most vehicles have been physically operated by human driver only, the task and the capacity to control the vehicle was completely in the hands of a human driver (United Nations, 1968). The HAVs have enabled the automatic system systems to take up virtually all the driving responsibilities. If the system is conceding to unnecessary attacks, the results can always be very dangerous. The human driver may not be able take back the control of the vehicle, even if he/she intends to, after the system has taken a complete control of it. Recently, a team of Chinese investigators managed to control a Tesla Model S without setting a finger on it (Peterson, 2016). (Greenberg, 2015) revealed that most auto-

vehicle manufacturers have encountered the same attacks and have recalled the vehicles to resolve the cyber security issues. When researching and developing an automated vehicle, more emphasis must be put on cyber security. Any robustness obtained in the system will be compromised in proper level of cyber security is not put in place.

#### *2.2.4.2 Other Drawbacks*

Automated vehicles, besides having many advantages, may bring some unhelpful impacts to the people as well. To begin with, it is obvious automated vehicles expensive to buy, drive and sustain. The road infrastructure will possibly necessitate retrofitting for automated vehicles (Litman, 2014). It is probable that vehicle operators including but not limited to taxi drivers, bus drivers, commercial truck drivers, etc will not be required anymore vehicle automation have been adopted. Furthermore, studies from NHTSA have suggested that 94 percent of the accidents are related to human errors. With the assumption that automated vehicle can reduce all crashes are caused by human factors, traffic accidents will be significantly reduced and therefore bringing a negative impact on vehicle parts manufacturers and vehicle repair shops. Autonomous vehicles would reduce the employment opportunities (Litman, 2014).

#### 2.2.5 Market Penetration

Market penetration and the adoption rate is an important factor in vehicle automation. However, it is one of the unsure factors in automated vehicles (Pinjari, 2013). Market penetration is determined by several factors which include regulations, reliability, usability and cost. With respect to the trends of adoption from earlier technologies, studies have estimated that the market may attain 8 million in 10 years prior to the introduction of completely automated vehicles. It has also been predicted that saturation may take place in

thirty-five years after the introduction of completely automated vehicles at a market size of 75% (Lavasani, 2016). A global market share of highly automated vehicles is expected by a market research firm to attain around 15-20 percent by 2030 (Yoshida, 2013). Level 1 and level 2 automated vehicles, as described in section 2.3, are presently on the road. Level 1 automated vehicle possess 100% market penetration rate after the 2011 NHTSA approval of ABS and ESC installment. However, the authentic transformations on vehicle technologies are witnessed at level 2 or beyond. It is important to determine the market penetration rate of level 2 and level 3 vehicles to enable us to microstimulate this thesis. But the market penetration particularly for level 2 and level 3 vehicles are hard to establish. As a result, high percentage of market penetration will be tested and applied to facilitate research.

#### 2.2.6 Automated Vehicle Timeline

Researchers have made a lot of efforts to predict the accessibility and adoption rate for automated vehicles. However, the manufacturers have previously visualized that particular levels of automated vehicles will come at a planned time frame. The vehicle industry observes the estimated consensus timelines for various levels of automation of vehicles as follows:

- i. Level 0 is already in the market
- ii. Level 1 is already in the market
- iii. Level 2 is already in the market
- iv. Level 3 is expected from 2018 to 2020
- v. Level 4 is expected from 2021 to 2024
- vi. Level 5 is expected in 2025

## 2.4 Heavy Vehicles

The Heavy vehicles and their ratio in the traffic flow have increased significantly over the past decades (Hobbs 2016). This trend persists as development continues. The heavy vehicles affect the freeway Capacity due to their slow speed compared with passenger car speed (Wegman et al. 2012). Previous studies show that heavy vehicle and passenger car drivers have fundamentally different driving behavior (Moridpour S. 2010). The presence of these larger vehicles in the traffic flow affects the various parameters of traffic flow. As a result of these factors, the drivers of passenger cars are forced to drive around the large vehicles. Also, the larger vehicles' power performance may interfere with the overall traffic flow. Studies (Chitturi and Benekohal 2007; Hangfei et al. 2008) investigate the effect of HVs near work zones, which often create bottlenecks for the general traffic. Although heavy vehicles comprise a small proportion of traffic stream, they have an important effect on traffic flow and produce a disproportionate effect particularly during heavy traffic conditions (Al-kaisy AF. 2002). Typically, the proportion of heavy vehicles ranges from as low as 2% to as high as 25% of total traffic during the day (Al-kaisy AF. 2002). According to some researchers, HVs increase the risk of accidents (Gao et al. 2004; Ramírez et al. 2009). HVs produce extremely load capacity and are the backbone of the freight transportation industry. Even though, some recently manufactured HVs are equipped with more powerful engines, the majority of HVs negatively affect the general traffic because of their physical characteristics such as low acceleration and slow speed. Some researchers (Peeta et al. 2005) have concentrate on car-following models that involve HVs, in attempts to reflect the unique operating characteristics of HVs.

#### 2.4.1 The effect of Heavy Vehicles in freeway Capacity

Freeway capacity is the maximum hourly rate at which vehicles can reasonably be expected to traverse a point or a uniform section or lane of a roadway during a given time period under prevailing roadway and traffic conditions (American Association of State Highway and Transportation Officials 2004). It is expressed in passenger cars per hour per lane. The large vehicles (Heavy Vehicles HV) will produce a reduction in capacity in the traffic stream. The reduction is due to the negative effect of HV on traffic stream performance. The following HV attributes that negatively impact capacity have been addressed in past research efforts:

- 1- HV are bigger in size than Passenger Cars (PC), and thus take more space in the traffic stream.
- 2- HV have operating capabilities (acceleration/deceleration) that are slower to those of PC, thus requiring longer headways.
- 3- Passenger car drivers of nearby heavy vehicles keep longer headways.

Under steady-state flow conditions, the effect of HV on traffic flow is expected to vary with prevailing traffic level due to the interaction between HV and Passenger Cars in the traffic stream. At low volumes, when drivers have relative freedom to choose their speeds, it is reasonable to expect that larger vehicles would have only a small effect on traffic flow. As congestion level increases, the HV effect can be expected to increase due to a greater interaction between vehicles in the traffic mix and reduced opportunities for drivers to pass slower-moving vehicles. Highway Capacity Manuals (HCMs) (HCM 2010) incorporate the influences of trucks, buses and RVs through PCE values, which are based on the vehicle type, topographic properties such as road slope/length, and the ratio of the

vehicle in the traffic. Webster and Elefteriadou (1999) found that the traffic flow rate and the percentage of HVs in the traffic affect the degree of the influence of HVs on the traffic conditions. Al-Kaisy and Jung (2004) conducted a simulation-based study for the PCE factors, which were derived from a queue discharge flow. That study found that the HVs' influences differ between free-flow and congested traffic regimes. The study also concluded that during congestion, lane-use restriction and the location of bottlenecks relative to upgrades are significant factors contributing to the HVs' influences on the traffic. Van Aerde and Yagar (1984) reported that large vehicles, have a higher individual propensity to become platoon leaders, compared with passenger cars. These leader propensities were analyzed using the ratio of the percentage of leads by vehicle type to the percentage of total main-line traffic count by vehicle type. Previous studies show that passenger car drivers try to avoid being in the vicinity of heavy vehicles. They either try to provide large space gaps to the heavy vehicle ahead/follow or move into other lanes (Al-kaisy AF, Hall FL 2003).

Previous studies focused on the effect of HVs on traffic from the perspective of the car-following theories, safety, work zones, and pollution. The present study endeavors to understand the traffic flow patterns for Heavy Autonomous Vehicles HAVs and to analyze the effect of HAVs on the traffic flow on the freeway using VISSIM simulation.

#### 2.4.2 Heavy Vehicle Following behavior

Heavy vehicles physical and operational characteristics are different than passenger cars. Their different can influence the traffic stream characteristics (Daganzo and Laval, 2005). The different behaviors of heavy vehicle and passenger car drivers during lane

changing maneuvers was well-acknowledged on freeways (Moridpour et al 2010) and arterial roads (Aghabayk et al 2011). On the other hand, the different longitudinal driving behavior to a large extent determines the distributions of speeds and densities across lanes which may lead to lane changes. The lane changing maneuvers of drivers may produce several different types of instabilities in traffic flow because of their influence on the surrounding traffic (Ahn and Cassidy, 2007). The heterogeneity of traffic flow also influences instability propagation in the same lane (Hoogendoorn et al., 2007) as well as the capacity of the road (Sarvi and Kuwahara, 2007).

Sayer et al. (2000) found that passenger car drivers maintain shorter space headway behind heavy vehicles than passenger cars. Ossen and Hoogendoorn (2011) reported that heavy vehicle drivers keep longer time headway than passenger car drivers when following another vehicle. McDonald et al. (1997) figure out that the space headway in front of passenger cars is shorter when following another passenger car than a heavy vehicle. Peeta et al. (2005) investigate the interaction between heavy vehicles and passenger cars by understanding a discomfort level for passenger car drivers in vicinity of heavy vehicles. The presence of heavy vehicles in the traffic stream would cause different impacts on the behavior of the surrounding vehicles (Kostyniuk et al. 2002) than that of passenger cars.

Heavy vehicles have a lower power-to-mass ratio than passenger cars (Ramsay 1998). They also have better sight distance than passenger cars. Rakha et al. (2001) pointed to different performance of heavy vehicles from that of passenger cars in terms of maximum acceleration that can be applied by each vehicle type. Because of these reasons it is expected that heavy vehicle drivers apply lower acceleration than passenger car drivers (Aghabayk et al. 2012).

## **2.4 Freeway Capacity**

The freeway capacity refers to the highest attainable flow rate per hour at which vehicles are able to cross a point or part of a road under existing conditions (TRB, 2010). It is generally shown as vehicles number per hour for each lane. Michiel, M. & Minderhoud (1997) stated that the freeway capacity is a significant factor in relation to planning, design and function of infrastructural facilities. It is important for a traffic analyst to be in a position to know the potential of the freeway, the number of vehicles traversing a point at a particular time. Furthermore, it is desirable to clearly define and measure the capacity so as to be able to make decisions accordingly.

### 2.4.1 Methods of Estimating freeway Capacity

As a result of a series of studies on this subject, many methods of estimating the freeway capacity have been established. This section discusses three ways in which popularly used capacity estimation methods are discussed.

#### *2.4.1.0 HCM Method*

The HCM process is essentially a derivative of field observations. It is made up of equations, tables and charts that can make the problem simpler through practical experience. To be in a position to use this method, many highway features information including number of lanes and crossing point density, adjustment factor for right shoulder side clearance, adjustment factor for lane width and free flow speed are needed. The benefit of this method is that it is fairly simple to get the hypothetical capacity of the highway by the use of tables, charts and equations given in HCM after the freeway attributes are known. The drawback of this method, on the other hand, is that it is only applicable in the estimation of capacity when the traffic flow is made up of human operated vehicles only.

This thesis focusses on estimating the capacity when mix traffic (with a range of market penetration rate of automated vehicle) and this method, therefore, cannot be used.

#### 2.4.1.1 Headway Method

This method is rooted in the concept that the driver-vehicle aspects in particular traffic flow may be classified into two categories of drivers. They include the constraint drivers (followers) and the free drivers (leaders). Every driver-vehicle element is constraint whenever the capacity of the roadway is attained (Michiel M. Minderhoud, 1997).

Through this method, the capacity can be solved as follows:

$$h_m = \frac{\sum h_p}{n}$$

$$q = 3600/h_m$$

Where;

$h_p$ = Time of headway between all leading vehicles and following vehicles

$h_m$ = Mean headway between leading vehicles and following vehicles

$n$ = Total number of vehicles passing the measuring point

Michiel, M. & Minderhoud (1997) pointed out the disadvantage of the method as the fact that it can only be used in a single lane. It cannot justify the side interactions between vehicles from more than one lane, in multi-lane highways. Numerous researches related to this method have revealed that this method significantly over estimates the studied road capacity (Botma, 1996). For that reason, this is not the best method to be used in determining a dependable capacity for this research.

#### *2.4.1.2 Fundamental Diagram Method*

The fundamental diagram method founded on the correlation between three parameters: density, mean speed and traffic volume (Michiel M. Minderhoud, 1997). Any two of the three DATA listed above would be adequate to build one of the diagrams. Before constructing the diagram, one has to observe traffic at various volumes to come up with the best reliable curve fitting (Michiel M. Minderhoud, 1997). However, the collection of data from the field make it hard because the observer requires an entire and standardized road section to count the number of vehicles passing at any second.

For this research, it is easy to collect the data using microsimulation tool, VISSIM, which provides enough data as required. The need for a mathematical model suitable for the observed data constitutes the main drawback of this method (Michiel M. Minderhoud, 1997). Many different models fitting the data do exist and therefore the capacity relies on the model selected to fit the data.

#### *2.4.1.3 Maximum Flow Rate Method*

The maximum flow rate method calculates the capacity during the occurrence of maximum flow rate. The flow rate characteristics involve the following:

- Flow rate constantly go up before attaining the maximum flow rate
- A rapid drop in flow rate when capacity is attained, and jam occurs
- Flow rates remain relatively steady after the rapid drop

The benefit of this method is that it is rather simple if the flow rate data regarding time is obtainable. The fact that constant high frequency data collection is required makes this method disadvantageous. This method has been preferred for capacity estimation for this thesis. chapter 3 describes the details of how capacity is estimated based on the method.

## **Chapter 3 Methodology**

### **3.1 Introduction**

To build a strong ground work, this chapter starts by introducing Wiedemann car following model, how this car following model has been standardized for level 3 HAVs and the VISSIM microsimulation tool. Subsequently, this chapter will give details of how the setup of simulation network, the formulated simulation scenarios and the basis of these microsimulation scenarios. Last of all, the capacity estimation method of will be discussed in detail using the data collected from VISSIM.

### **3.2 VISSM Microsimulation Tool**

This is a microsimulation program built up by PTV. PTV Group (2015) described it as the most important microscopic simulation tool for modeling multimodal transport activities. All simulations in this research will be carried out using VISSIM.

### **3.3 Longitudinal Control**

This is the control of a vehicle which involves controlling the travel direction, such as braking and accelerating. The characteristics of longitudinal control are considered as the car following model. While the car following models available in VISSIM is discussed in the following paragraph.

#### *3.3.0 Wiedemann Car Following Model*

To correctly sample the autonomous vehicles in VISSIM, the knowledge of the car following model applied for simulation is important. Three car following models exist for microsimulation in VISSIM:

- No interaction car following model: This refers to the cars that do not recognize other vehicles (PTV Group, 2015). It is suggested that this model should be used to model pedestrian flow only.
- Wiedemann 74 car following model: This is appropriate for urban traffic where interrupted traffic flow generally takes place.
- Wiedemann 99 car following model: This possess 10 parameters and it preferable for freeway traffic modelling.

Wiedemann 99 car following model is the most preferred as the research is aimed at modelling level 3 HAVs in freeway setting. The Wiedemann 74 car following model is founded on the psycho-physical model recommended by Wiedemann and it was first presented in 1974 (Johan Janson Olstam, 2004). The Wiedemann 99 car following model somewhat resembles Wiedemann 74 car following model. It was first presented in the year 1999 to better mold the freeway car following characteristics (PTV Group, 2015). The fundamental idea of the Wiedemann car following model is that human drivers of fast moving cars start slowing down as they attain their individual perception threshold to a slow-moving car (PTV Group, 2015). The vehicles driven by human drivers are less than the speed of the leading vehicle. This is because it is not easy for a standard human driver to know the speed of the vehicle ahead. There is a insignificant and consistent deceleration and acceleration. The Wiedemann model puts into consideration several types of human driver performance through distribution functions of the distance and speed behavior (PTV Group, 2015).

The Wiedemann model assumes that the human driver is in the four driving conditions stated below (PTV Group, 2015):

- Free driving: No effects of leading cars can be witnessed in this condition. In this position, the human driver attempts to attain and maintain his preferred speed. This is called “free flow” state as described by transport engineers. The speed in free driving will really fluctuate because of flawed throttle control. It will often oscillate around the desired speed. In reality, the speed in free driving condition will vary due to imperfect throttle control. It will often swing about the ideal speed.
- Approaching: In such a condition, the human driver attempts to adjust the speed of the cars to a lower speed of the preceding car by slowing down. This is done to eliminate the difference in speed after he attains the expected safe distance.
- Following: The human driver, in this situation, follows the leading car with no conscious deceleration or acceleration. The human driver usually is determined to maintain a constant safe distance. However, the speed difference oscillates about zero owing to flawed throttle control by human driver.
- Braking: In breaking state, human driver puts moderate to high deceleration speeds in case the distance to the leading car drops below the required safety distance. This may occur when the human driver of the leading car suddenly varies his speed or the third vehicle’s driver changes lanes to get between two cars.

The four driving modes discussed above are based on the following six thresholds

(Kayvan-Aghabayk, 2013):

- AX: the ideal distance between two immobile vehicles
- BX: the least following distance which the drivers believe to be a safe distance
- CLDV: the short distance points at which the drivers see that their speeds are more than that of their lead car

- SDV: the long distance points at which drivers see differences in speed when they are catching up with slower vehicles
- OPDV: the short distances points at which drivers believe that they are driving at a lower speed than their leading cars
- SDX: The utmost following distance showing the climax of car-following act.

Figure 3 below demonstrates how the six thresholds influence the car following attributes from a reference car to the leading car:

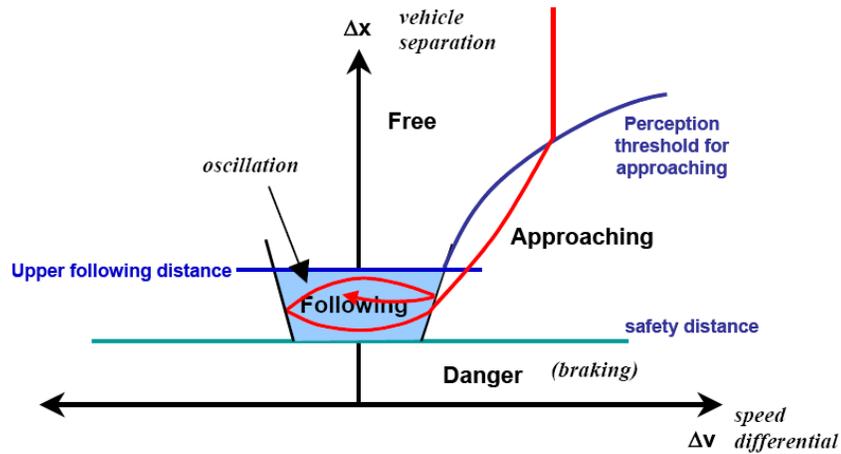


Figure 3 Wiedemann Car Following Logic

As stated in the preceding section, the Wiedemann 99 car following model possess ten variables that are defined as CC.

The ten parameters are described below: PTV Group (2015) defined CC0 as the average motionless distance between two cars. This is the distance between the reference car and the car ahead when the vehicles are not moving (such as in a traffic jam). The typical measurement of CC0 is 4.92 feet. Motor Trend's latest testing proved that a 9 ft value is generally the lowest stopping or setting off distance from a range of automobile

manufacturers (Kim, 2016). Nine feet is also the frequently applicable distance from the industry remarks. The 9 ft value will therefore be applied in our microsimulation model for both AVs and HVs since they both are HAVs.

According to PTV Group (2015), CC1 is the time development between the reference vehicle and the vehicle ahead. It is obvious that CC1 and CC0 can influence the assertiveness of the subject cars because the safety distance is described as the least distance between leading car and the subject car. This can be calculated as  $dx_{safe} = CC0 + CC1 * v \cdot 0.90$ . The default value for CC1 is 0.90 seconds. From Motor Trend's latest testing findings, semi-automated vehicles are capable of following the leading car for headway as low as 0.70 secs. The smallest headway for Heavy Autonomous Vehicle is 0.7 s (Yanakiev and Kanellakopoulos, 1995), since the VISSIM student Version does have certain values a 0.90 seconds headway is applied for the microsimulation model.

CC2 restricts longitudinal oscillation (the distance difference) or the extra distance than the required safety distance allowed by the driver before deliberately moving closer to the leading vehicle. This variable actually demonstrates the potentials of the subject vehicle to respond to the speed oscillation of the car in front. 13.12 feet is the default value for CC2. According to MotorTrend's testing, the tested vehicles had an acceleration delay of up to 0.60 seconds at standstill (Kim, 2016). Using the knowledge of car following of these vehicles, radar adaptive cruise control, the difference in distance can be calculated as 4.4 feet. A value of 4.4 ft will therefore be applied for CC2 in our microsimulation model. Since both AVs and HVs work with radar adaptive cruise control then HVs would be the same as the AVs.

The beginning of the deceleration actions is characterized CC3. It in fact reveals the manner in which approaching condition is performed from part 3.4. It influences the time needed by the car from free driving position to following position. It is not the speed of deceleration but the driver's reaction time. The default value is as low as -8.00 seconds. This fact is not verified by MotorTrend and it is complex because the value must vary according to the speed of the car. However, the sensitivity analysis of VISSIM driver actions variables on freeway capacity, CC3 poses no visible influence on the capacity (Nicholas E. Lownes, 2006). A set value of -8.00 seconds will therefore be applied for CC3 for microsimulation model.

PTV Group (2015) asserted that CC4 is the negative speed variation in the following condition. It influences the sensitivity with which the car reacts to the deceleration or acceleration of the vehicle in front. A more sensitive respond is brought about by a lower CC4 value. The set value for CC4 is -0.35 feet per sec. Since the speed of the subject car should not oscillate, for a 3 HAV, a human driver should not directly control the throttle knob. Our microsimulation model will therefore use a value of -0.10 for both AV and HVs since they both are HAVs

CC5 is a positive speed variation in the following state. The CC5 value contrasts with the CC4 value (PTV Group, 2015). Higher value of CC5, just like CC4, will lead to a less sensitive response. 0.35 feet per sec is the set value for CC5. For our microsimulation model, a value of 0.10 feet per sec will be chosen for CC5 value for both AVs and HVs, since we have used -0.10 ft/sec for CC4 value.

CC6 is the value defining the nature of subject vehicle's speed oscillation according to the distance difference between subject car and leading car. Bigger values of CC6 will

lead to higher oscillation speed when the distance between the leading car and subject car increases. When the value of CC6 is 0, the oscillation speed will not be related to the distance between subject car and leading car. 11.44 is the set value of CC6. Based on industry analysis, radar adaptive cruise control trails the leading car from a default headway time thus making the degree of oscillation to be higher. The previous researches considered the value of 20.0 for a CC6 as high oscillation degrees (Nicholas E. Lownes, 2006). Our microsimulation model therefore will use a 20.0 value for CC6 for both AVs and HVs.

All CC7, CC8 and CC9 are accelerations speeds is really based on how solely related to the mechanical potentials of the vehicle, how hard the human driver push the accelerator or how the car is programmed to work and is therefore not based on vehicle Type. Therefore, These values would be the same for both AVs and HVs since they both are HAV.

The speed oscillations during acceleration can be defined using CC7. The CC7 value is the rate of speeding up. Nicholas, E. & Lownes (2006) stated that it determines the level at which the oscillation speed reached by driver is sudden and violent or gentle and gradual. A bigger CC7 value will lead to higher oscillation in acceleration. The set value is  $0.82 \text{ ft/sec}^2$ . According to MotorTrend's testing result, the oscillation speed may be violent sometimes and typically greater than characteristic human driver (Kim, 2016). Lownes defines a value of 0.5, 1.00 and  $1.5 \text{ ft/sec}^2$  as representing small, medium and high oscillation values (Nicholas E. Lownes, 2006). The 1.25 value is therefore used for CC7 for both AVs and HVs for our microsimulation model.

CC8 describes the best acceleration speed of reference car from immobility, when reference car speed is 0 (PTV Group, 2015). The CC8's set value is  $11.48 \text{ ft/sec}^2$ . Based on MotorTrend's testing result, the acceleration speed of standstill is roughly  $6.0 \text{ ft/sec}^2$ ,

which is considerably smaller than the set value (Kim, 2016). The earlier researches revealed that a lower CC8 level negatively affect the capacity (Nicholas, E. & Lownes, 2006).  $6.0 \text{ ft/sec}^2$  will be chosen for both AVs and HVs for the CC8 value so as to maintain our microsimulation as realistic as possible.

CC9 describes the ideal speed of acceleration of reference car when the car's speed is at 50 mph (80 km/h) (PTV Group, 2015). The CC9's set value is  $4.92 \text{ ft/sec}^2$ . According to MotorTrend's testing result, the acceleration rate from 80 km/h is approximately  $4.80 \text{ ft/sec}^2$ . Our microsimulation will therefore choose the CC9 value of  $4.92 \text{ ft/sec}^2$ . As speed increased, observed accelerations dropped 3 to 4 times faster than design accelerations (Long 2000). The same value would be used for HVs.

The correlation of the initial seven variables (CC0 to CC6) may also be illustrated in the equations below (Kayvan, Aghabayk, 2013). The definition of the acronyms used in these equations explained in section 3.3.

$$AX = L + CC0$$

Where L is the length of the in front

$$BX = AX + CC1 * v$$

Where B is equivalent to the speed of subject vehicle in case it is slower than the leading vehicle, or else, it is equivalent to the speed of leading vehicle with a few arbitrary errors. The error is randomly resolved by multiplying the speed variation between the two cars by an arbitrary value between -0.5 and 0.5.

$$SDX = BX + CC2$$

$$(SDV)_i = -\frac{\Delta x - (SDX)_i}{CC3} - CC4$$

Where  $\Delta x$  is the distance headway between the two cars determined from front bumper of the subject car to front bumper of the leading car.

$$CLDV = -\frac{CC6}{17000} * (\Delta x - L)^2 - CC4$$

$$OPDV = -\frac{CC6}{17000} * (\Delta x - L)^2 - \delta * CC5$$

Where  $\delta$  is a model parameter which is equivalent to 1 when the reference car's speed is higher than CC5 and equivalent to 0 when reference car's speed is less than CC5. All CC9, CC8 and CC7 are accelerations speeds is really based on how solely related to the mechanical potentials of the vehicle, how hard the human driver push the accelerator or how the car is programmed to work and is therefore not based on the equations.

To wrap up the model calibration, table 1 below reviews the ten variables to be used in level 3 HAVs for VISSIM microsimulation:

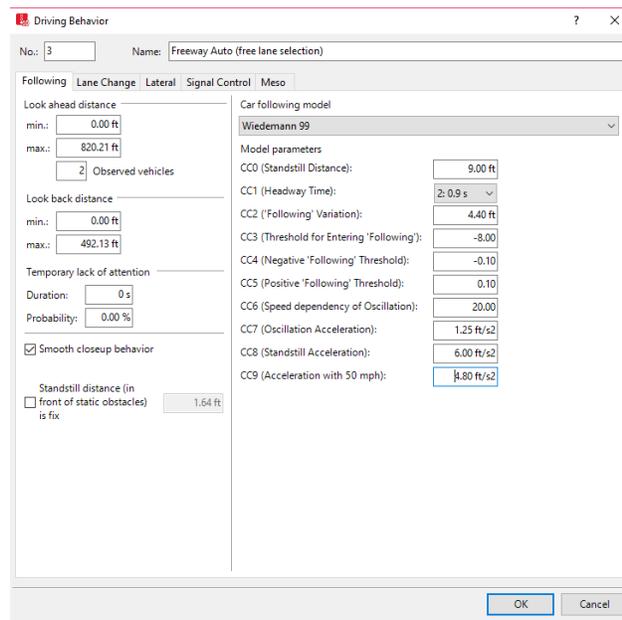


Figure 4 Calibrated Value for Level 3 HAVs

Table 1 Summary of Wiedemann 99 Car Following Model Parameters default and modified values

Parameters	Definition	Default	Modified	Source
CC0	average motionless distance between two cars	4.92 ft	9 ft	MotorTrend's latest testing,
CC1	time development between the reference vehicle and the vehicle ahead	0.9 s	0.9 s	MotorTrend's latest testing,
CC2	restricts longitudinal oscillation (the distance difference) or the extra distance than the required safety distance allowed by the driver before deliberately moving closer to the leading vehicle	13.12 ft	4.4 ft (based on 0.6sec acceleration delay)	Based on the science of car following of these vehicles – radar adaptive cruise control, the distance difference can be calculated 4.4 ft. based on MotorTrends test acceleration delay of 0.6 sec
CC3	the start of the deceleration process. It really demonstrate how the “approaching” condition performs from section 3.4. It control the time it takes for the vehicle from “free driving” condition to “following” condition. It is more of a reaction time for the driver and not the rate of deceleration	8- sec	8- sec	not tested by MotorTrend - according to a sensitivity study of VISSIM driver behavior parameters on highway capacity, CC3 has no significant impact

CC4	negative speed difference during the following condition (PTV Group, 2015). It controls how sensitive the vehicle responds to the acceleration or deceleration of leading vehicle	-0.35 ft/sec	-0.1	human driver will not be directly controlling the throttle pedal, the subject vehicle speed should not be oscillating by much
CC5	positive speed difference during the following condition; the value of CC5 should be the opposite of the value of CC4	0.35 ft/sec	0.1	
CC6	how the subject vehicle's speed may oscillate based on the difference in distance between subject vehicle and leading vehicle. Larger value of CC6 will results in greater speed oscillation when the difference between subject vehicle and leading vehicle increase	11.44	20	From industry observations, radar adaptive cruise control follows the car in front from a set headway time and therefore the degree of oscillation is quite high. From past research, the value of 20.0 for a CC6 will be considered as high level of oscillation
CC7	how the speed oscillates during acceleration. The value of CC7 is the rate of acceleration. It control the degree to which the speed oscillation produced by driver is gentle and gradual or sudden and violent (Nicholas E. Lownes, 2006). A larger value of CC7 will result in greater oscillation during acceleration	0.82 ft/sec <sup>2</sup>	take 1.25 ft/sec <sup>2</sup>	From MotorTrend's testing result, the speed oscillation can be violent at times and mostly higher than typical human driver (s:0.5,m:1,h,1.5)

CC8	desired acceleration rate of subject vehicle from standstill (when subject vehicle speed is zero)	11.48 ft/sec <sup>2</sup>	6.0 ft/sec <sup>2</sup>	MotorTrend's testing result, the standstill acceleration rate
CC9	desired acceleration rate of subject vehicle when the vehicle speed is at 80 km/h (50 mph)	4.92 ft/sec <sup>2</sup>	4.80 ft/sec <sup>2</sup>	MotorTrend's testing result,

### 3.4 Lateral Control

The perpendicular (steering) control of a car to the direction of travel is generally called lateral control. In relation to freeway capacity, the lateral control by means of changing lane can have some consequences. According to industry analysis, the actions of lane changing for level 3 HAVs are the same for human-controlled cars. Most manufacturers are contemplating to provide automatic lane change when a driver put on the turn signal indicator. Human drivers are still expected to use traffic lights, and the vehicles will change the lane by them self. Vehicles with these provisions are upcoming Mercedes E-Class and the latest Tesla Model (Reed, 2015) (McFarland, 2015). In the VISSIM microsimulation, therefore, the lane change model remains unaffected.

### 3.5 Method of Estimating Capacity

There are many ways of estimating the roadway capacity according to section 2.4. Since this thesis entails non-human-controlled car, the conventional HCM process may not be applied because the HCM process is not intended for the explanation of the occurrence of autonomous vehicle. The headway process may not be applied either since the

microsimulation freeway system has many lanes involved. As VISSIM microsimulation tool is chosen, the details of flow rate and speed in relation to time are readily available. For that reason, the greatest flow rate method is chosen in the estimation of the effects on freeway capacity alongside level 3 HAVs. For every situation, the average greatest flow rate reached from 10 simulation performed (with 10 dissimilar arbitrary seeds) is viewed as the capacity of the freeway in existing conditions.

### **3.6 Simulating Network, Scenarios and Procedures**

#### 3.6.0 Assumptions

The following are the assumptions made in our microsimulation model:

- The weather condition and road surface condition of the freeway network is normal, inclement weather and slippery road condition is not considered in this simulation
- No malfunction of vehicles (breakdown and block traffic) will happen;
- Heavy Vehicle mean all kind of vehicles of six wheels and above.
- No diverging/ merging exist in the network.
- The headway assumed to be the same for the four type of following (PC-PC, PC-HV,HV-PC,HV-HV).

#### 3.6.1 Simulation Network

The microsimulation model consists of a 5-mile-long stretch of 2-lane freeway. The lane width is set to be 12 ft, which corresponds to the AASHTO green book (AASHTO, 2011). The freeway is empty before the simulation starts. The model created in VISSIM is shown in Figure 4.

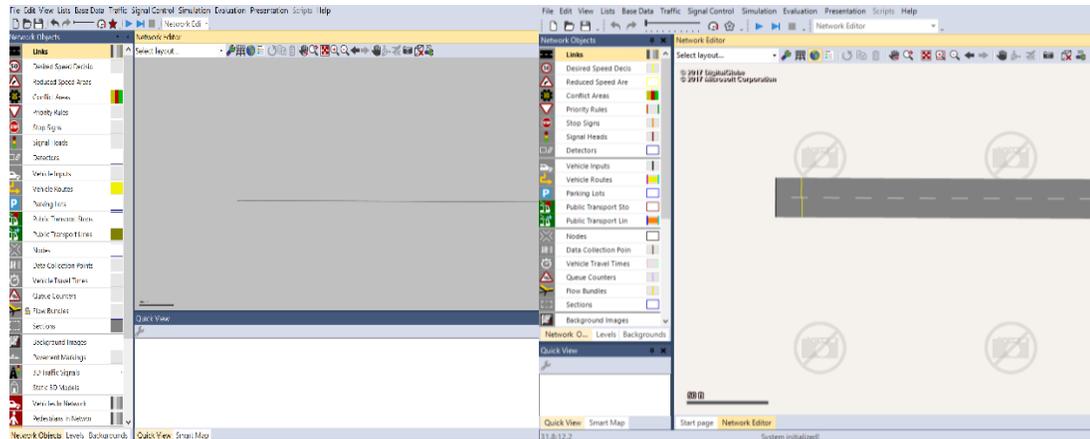


Figure 5 Two Lane Freeway in VISSIM

The speed limit (desired vehicle speed) is set to 70 mph, which corresponds to the speed limit of 70 mph for most of the freeways in the State of Wisconsin. To better investigate the capacity of the freeway, there should not be additional vehicles entering or leaving the network, other than the traffic demand generated (from vehicle input) at the start of the freeway. Therefore, no entry ramps or exit ramps are created in this microsimulation network.

### 3.6.2 Data Collection

One data collection points are placed in each lane 4 mile upstream the freeway. The simulation period is set to 65 minutes. There data from the first 5 minutes is disregarded as the first 5 minutes is seen as “warm up” time; all data are being retained for analysis as we would like to see how the flow rate changes with a decreasing traffic demand.

Data collection points collect the flow rate and speed information which are useful for capacity analysis. The frequency for data collection is set to one minute – meaning flow rate and speed information are collected every minute.

### 3.6.3 Procedures

The procedures of simulation and estimate the capacity in each scenario is the following:

1. Make simulation runs with increasing traffic demand volume with a set Heavy Autonomous Vehicle penetration rate.
2. Perform ten simulation runs with random seed of (17, 26, 35, 44, 53, 62, 71, 80, 89, and 98) for each scenario.
3. Record the speed and flow rate information from all simulation runs.
4. Take the average of the ten simulation runs with different random seeds and plot the diagrams (maximum flowrate veh/hr/lane).
5. The largest flow rate captured over the entire simulation period is deemed as the capacity.
6. Repeat step 1-5 for all of the traffic demand volumes for Manual Heavy Vehicles with the default values of the driver behavior.
7. Repeat step 1-6 for all of the traffic demand volumes in the next two scenarios.
8. Create the diagram by fitting a curve with the plots from different traffic demand volumes from step 5.

#### 3.6.4 Simulation Scenarios

Scenarios are shown in figure 6. Each scenario build with increasing traffic demands since it helps to capture how the flows vary for different input volumes. Therefore, the traffic volume varies from 600 vehicle/hr/lane to 3000 vehicle/hr/lane over the simulation period with 300 increments. The detailed breakdown of how traffic demand varies is shown in the figure 7 below, please note the volume is the aggregate of all two lanes – volume 1200 means 600 vehicles/hr/lane:

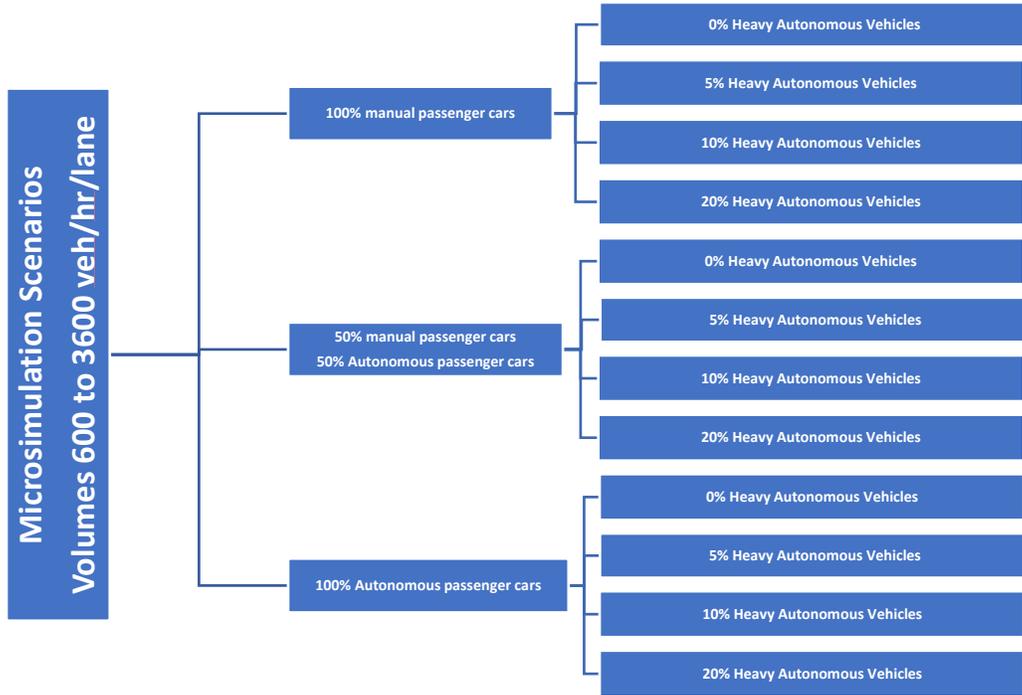


Figure 6 Scenarios

Count: 9	Cont	TimeInt	Volume	VehComp	VolType
1	<input type="checkbox"/>	0-600	1200.0	1: Scenario 1-1	Stochastic
2	<input type="checkbox"/>	600-900	1800.0	1: Scenario 1-1	Stochastic
3	<input type="checkbox"/>	900-1200	2400.0	1: Scenario 1-1	Stochastic
4	<input type="checkbox"/>	1200-1500	3000.0	1: Scenario 1-1	Stochastic
5	<input type="checkbox"/>	1500-1800	3600.0	1: Scenario 1-1	Stochastic
6	<input type="checkbox"/>	1800-2100	4200.0	1: Scenario 1-1	Stochastic
7	<input type="checkbox"/>	2100-2400	4800.0	1: Scenario 1-1	Stochastic
8	<input type="checkbox"/>	2400-2700	5400.0	1: Scenario 1-1	Stochastic
9	<input type="checkbox"/>	2700-3000	6000.0	1: Scenario 1-1	Stochastic

Figure 7 Traffic demand input

It is very hard to predict and retrieve information about market penetration for level 3 AVs. Therefore, multiple Heavy vehicle penetration rate has been selected for our microsimulation model to see how these penetration rate will affect the freeway capacity:

1. The first scenario has an input traffic of all Manual Driven Passenger Vehicles with 3 different penetration of level 3 Heavy Autonomous Vehicles (0%, 5%, 10%, 20%).

Example of the total 600 veh/hr/lane;

Manual Driven Passenger Vehicles (veh/hr/lane)	Level 3 Heavy Autonomous Vehicles (veh/hr/lane)
570	30
540	60
480	120

2. The second scenario has an input traffic of 50% manual driven Passenger vehicles and 50% level 3 Autonomous passengers Vehicles with 3 different penetration of level 3 Heavy Autonomous Vehicles (0%, 5%, 10%, 20%).

Example of the total 600 veh/hr/lane;

Manual Driven Passenger Vehicles (veh/hr/lane)	level 3 Autonomous Passengers Vehicle (veh/hr/lane)	Level 3 Heavy Autonomous Vehicles (veh/hr/lane)
285	285	30
270	270	60
240	240	120

3. The third scenario has an input traffic of 100% level 3 Autonomous passengers Vehicles with 3 different penetration of level 3 Heavy Autonomous Vehicles (5%, 10%, 20%).

Example of the total 600 veh/hr/lane;

Manual driven passenger vehicles (veh/hr/lane)	Level 3 Heavy Autonomous Vehicles (veh/hr/lane)
570	30
540	60
480	120

## Chapter 4 Findings

### 4.1 Result:

Based on simulation runs, the flow rate for the three different scenarios which mentioned in 3.6.4 was captured. A Sample set of data collected from the simulation runs can be found in the appendix. The results related to these scenarios are shown in this section.

#### 4.1.1 Scenario 1

##### 4.1.1.0 Scenario 1 with heavy Autonomous vehicles

This Scenario Contains Manual Passenger Cars and Autonomous Heavy Vehicles only:

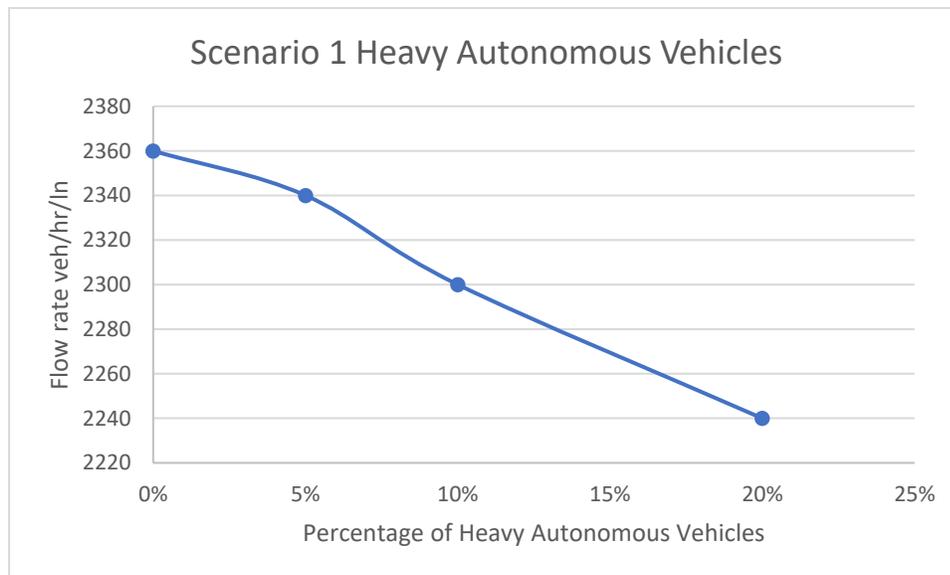


Figure 6 Scenario 1 flowrate versus penetration rate of heavy Autonomous vehicles

The graph shows the maximum flow rate per lane over the different penetration rates of Autonomous Heavy Vehicles. The maximum flow rate was in the case we don't have Heavy Vehicles which was almost 2240 veh/hr/ln. Then it decreases when The

Autonomous Heavy Vehicle penetration rates increase to reach to the minimum flow at 20% HAV of 2670 veh/hr/ln.

#### 4.1.1.1 Scenario 1 with heavy manual vehicles

The same Scenario was done with non-Autonomous Heavy Vehicles in the following graph:

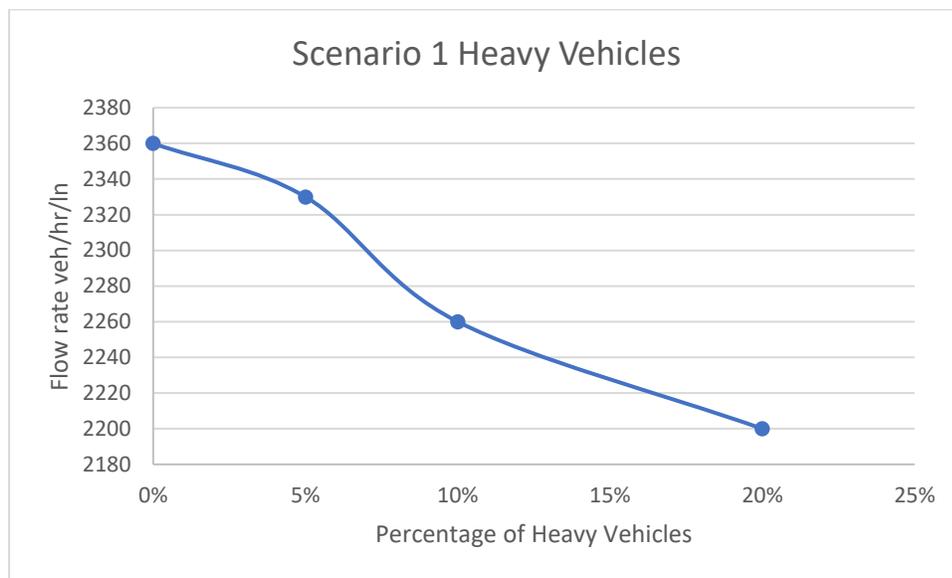


Figure 7 Scenario 1 flowrate versus penetration rate of heavy vehicles

The graph shows the maximum flow rate per lane over the different penetration rates of non-Autonomous Heavy Vehicles. The maximum flow rate was in the case we don't have Heavy Vehicles which was almost 2360 veh/hr/ln. Then it decreases when the heavy vehicles penetration rate increases to reach to the minimum flow at 20% HAV of 2220 veh/hr/ln.

#### 4.1.2 Scenario 2

##### 4.1.2.0 Scenario 2 with heavy Autonomous vehicles

This Scenario is a combination of Manual and Autonomous Passenger Cars and Autonomous Heavy Vehicles.

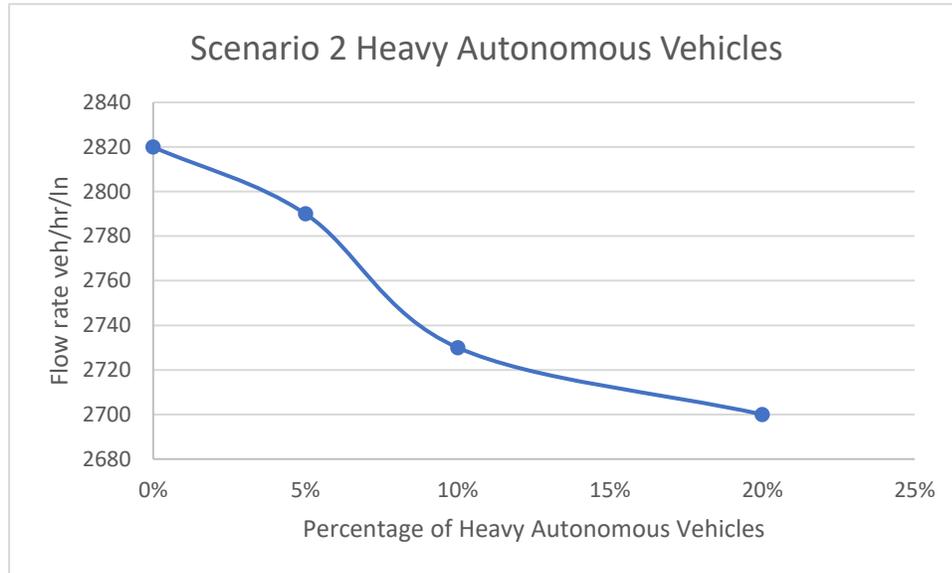


Figure 8 Scenario 2 flowrate versus penetration rate of heavy Autonomous vehicles

The graph shows the maximum flow rate per lane over the different penetration rates of Autonomous Heavy Vehicles. The maximum flow rate was in the case we don't have Heavy Vehicles which was almost 2820 veh/hr/ln. Then it decreases when the heavy vehicles penetration rate increases to reach to the minimum flow at 20% HAV of 2700 veh/hr/ln.

#### 4.1.2.1 Scenario 2 with heavy vehicles

The same Scenario was done with non-Autonomous Heavy Vehicles in the following graph:

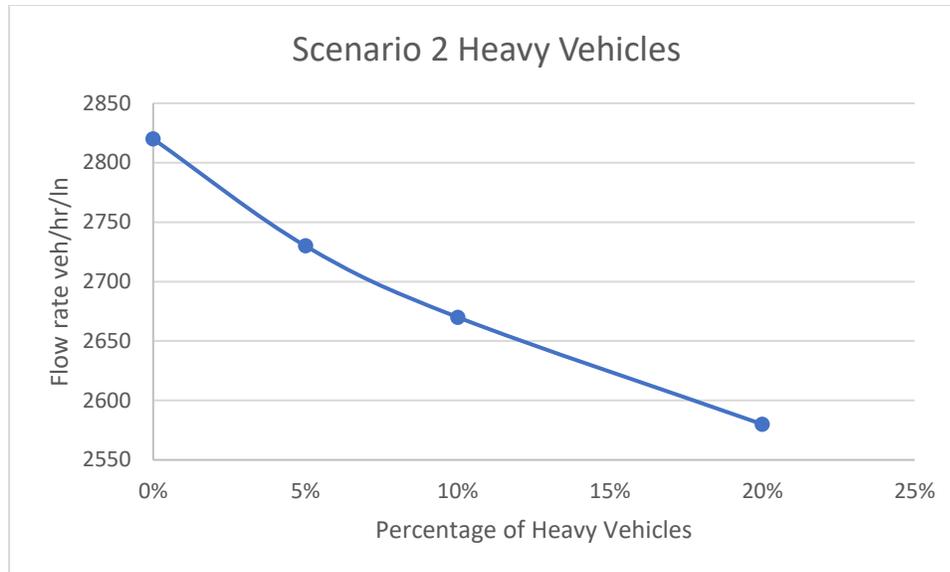


Figure 9 Scenario 2 flowrate versus penetration rate of heavy vehicles

The graph shows the maximum flow rate per lane over the different penetration rates of the non-Autonomous Heavy Vehicles. The maximum flow rate was in the case we don't have Heavy Vehicles which was almost 2810 veh/hr/ln. Then it decreases when the heavy vehicles penetration rates increase to reach to the minimum flow at 20% HAV of 2580 veh/hr/ln.

#### 4.1.3 Scenario 3

##### *4.1.3.0 Scenario 3 with heavy Autonomous vehicles*

This Scenarios is mainly built of full Automated Vehicles, Passenger and Heavy Autonomous Vehicles.

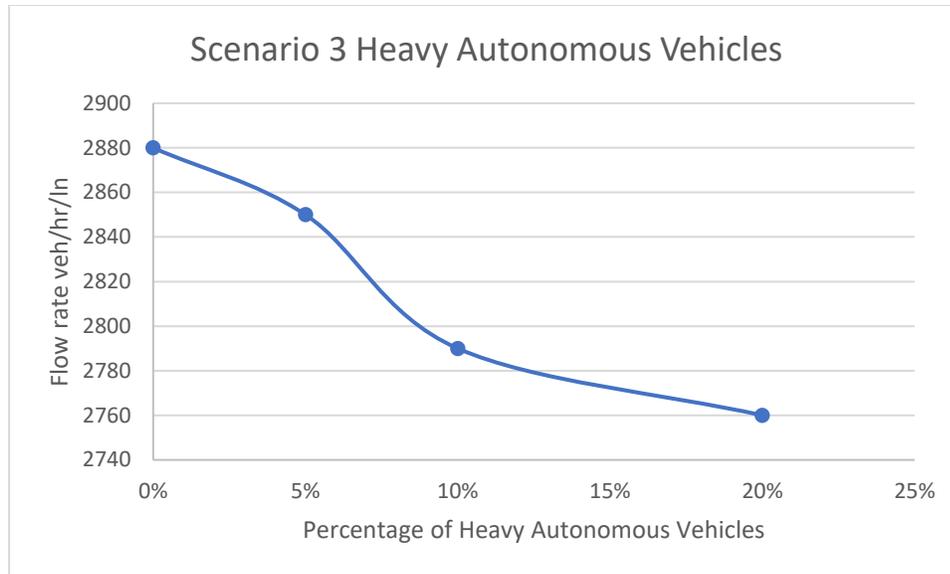


Figure 10 Scenario 3 flowrate versus penetration rate of heavy Autonomous vehicles

The chart captures the maximum flow rate per lane over the different penetration rates of Autonomous Heavy Vehicles. The maximum flow rate was found when we do not have Heavy Vehicles which was 2880 veh/hr/ln. Then the flow decreases when the Heavy Autonomous Vehicles increase to reach a value of 2760 veh/hr/ln.

#### 4.1.3.1 Scenario 3 with heavy vehicles

The same Scenario was done with non-Autonomous Heavy Vehicles in the following graph:

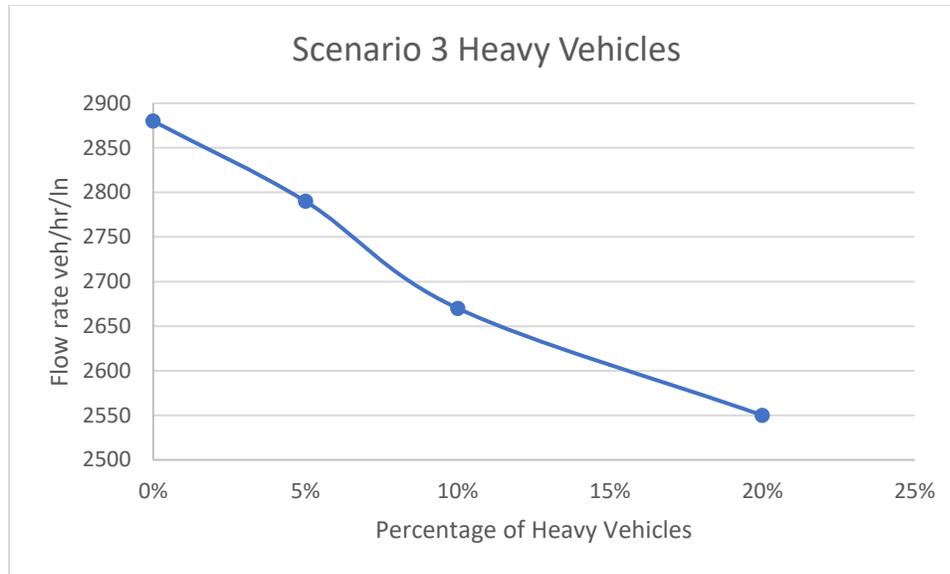


Figure 11 Scenario 3 flowrate versus penetration rate of heavy vehicles

The chart captures the maximum flow rate per lane over the different penetration rates of non-Autonomous Heavy Vehicles. The maximum flow rate was found when we do not have Heavy Vehicles which was 2875 veh/hr/ln. Then the flow decreases when the heavy vehicles increase to reach a value of 2550 veh/hr/ln.

## 4.2 Analysis:

### 4.2.1 Comparing effect of different Combination of Vehicles in flow rate under fixed penetration rate of heavy autonomous vehicles

The first research objective is to see how the different Heavy Autonomous Vehicles penetration rates will affect the throughput of traffic flow on the different compensations of the vehicles types. The first one only contained manual passenger cars, this was applied to figure out the first step of the traffic flow and how it will increase when Autonomous Vehicles on the freeway increase.

The figures below explain the maximum flow rate for the different Scenarios. When passenger Autonomous Vehicles as well as the Heavy Autonomous Vehicles increase, this

would help to explain the effect of overall Autonomous Vehicles increases on freeway capacity.

For fixed penetration rates of heavy Vehicles, the comparison over the different Scenarios were defined in the following bar chart:

#### 4.2.1.0 Scenarios without heavy vehicles

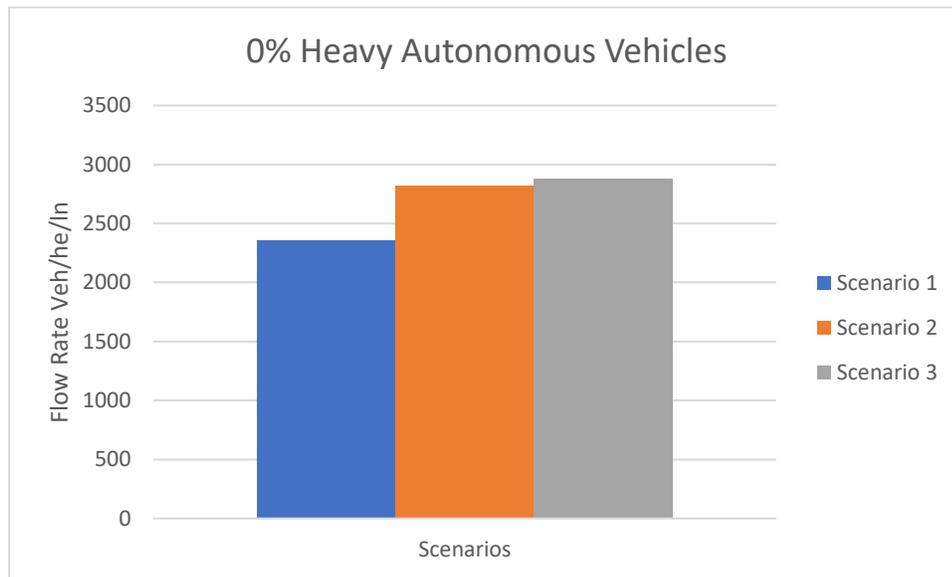


Figure 12 flow rate of Scenario 1,2 and 3 for 0% heavy autonomous vehicles

This bar chart shows the flow rate increases when Automotive Vehicles increase. This chart explains how the flow rate increases when the penetration rate of Autonomous Vehicles increases without the effect of the heavy vehicles. When the road is full of manual car the maximum flow rate was almost 2360 veh/hr/ln. When we have 50% Autonomous vehicles the flowrate increases to almost 2820. Finally, in scenario three when the road is full of Autonomous Vehicles the flow rate reaches the maximum point of 2880 veh/hr/ln.

The effect of Heavy Autonomous Vehicles will be explained in the following chart. The flow rate of the 5%, 10%, and 20% of Heavy Autonomous Vehicles over these

different scenarios was used to measure how HAV's affect the roadway capacity on the different penetration rates of autonomous scenarios.

#### 4.2.1.1 Scenarios with 5% heavy vehicles

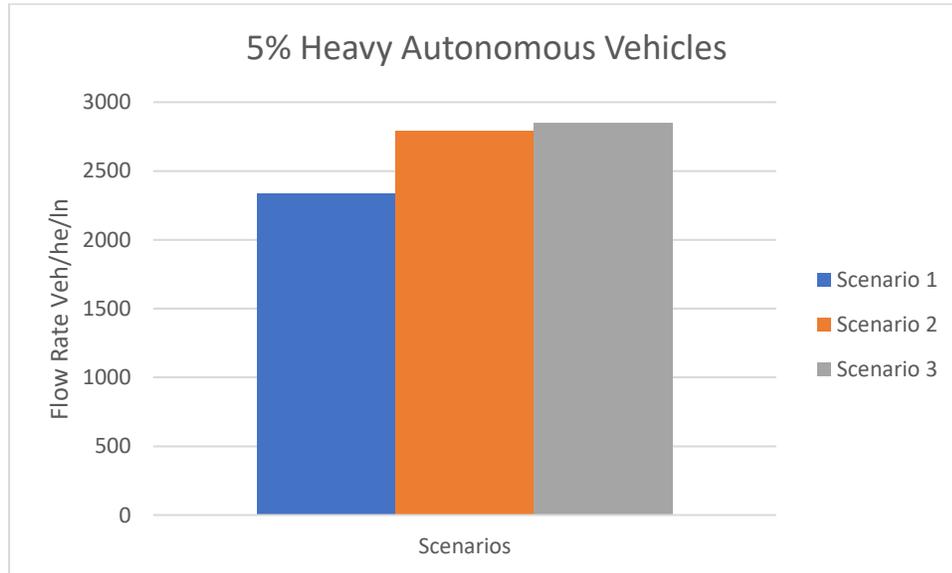


Figure 13 flow rate of Scenario 1,2 and 3 for 5% heavy autonomous vehicles

The bar chart explains how the flow rate increases when the penetration rates of the Autonomous Vehicles increase with a fixed percentage of Heavy Autonomous Vehicles.

#### 4.2.1.2 Scenarios with 10% heavy vehicles

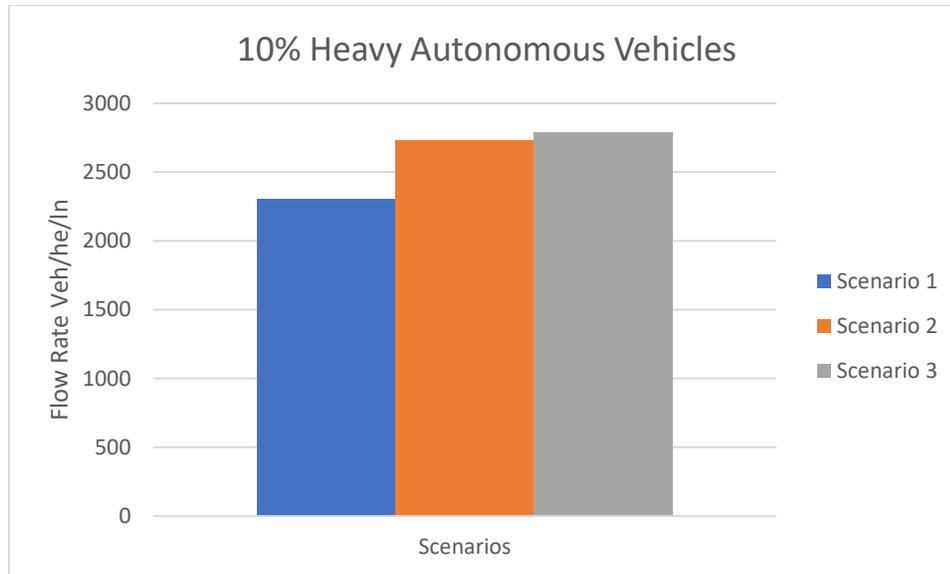


Figure 14 flow rate of Scenario 1,2 and 3 for 10% heavy autonomous vehicles

The bar chart shows the flow rate of 10% Heavy Autonomous Vehicles. The difference in increase between Scenario 1 and Scenario 2. At first glance, we can see that there is jump in the increases between Scenario 2 and 3 and this happened because of overall Autonomous Vehicle increases in the passenger car and Heavy Vehicle categories.

#### 4.2.1.3 Scenarios with 20% heavy vehicles

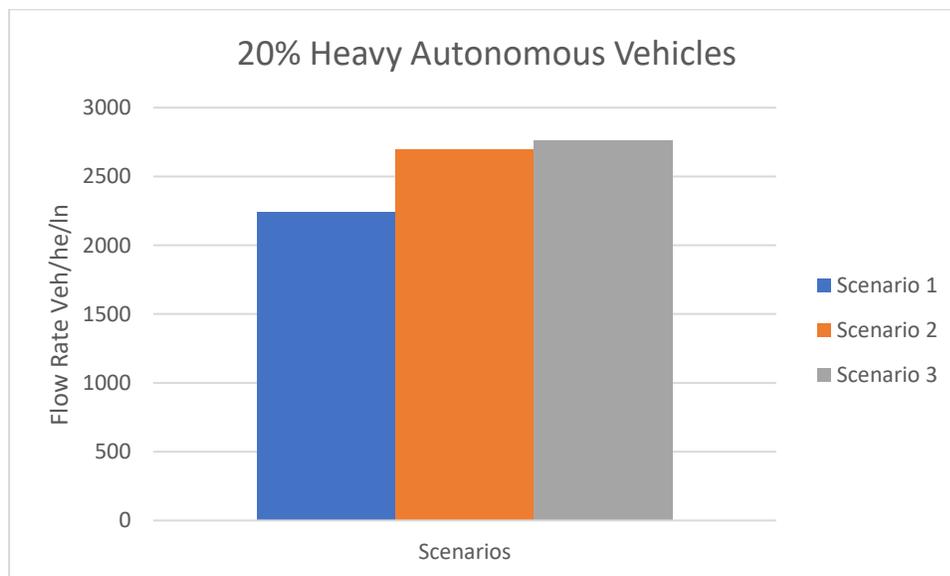


Figure 15 flow rate of Scenario 1,2 and 3 for 20% heavy autonomous vehicles

Finally, for the Capacity of the 20% of Heavy Autonomous Vehicles captured, we see the same difference in the increase of the flow rate between Scenario 2 and Scenario 3. Again, this is happened because the Autonomous Vehicles on the freeway increased.

#### 4.2.2 Comparing the effect of manual and autonomous heavy vehicles on freeway capacity

##### *4.2.2.0 Scenario 1*

The second research objective is to see how the different Heavy Autonomous Vehicles penetration rates will affect the traffic flow on the different compensations of vehicles types and show the effects of these Heavy Autonomous Vehicles and how Autonomous Vehicles will improve freeway capacity whether they are passenger cars or Heavy Vehicles. The following charts illustrate the improvement of using Heavy Autonomous Vehicles.

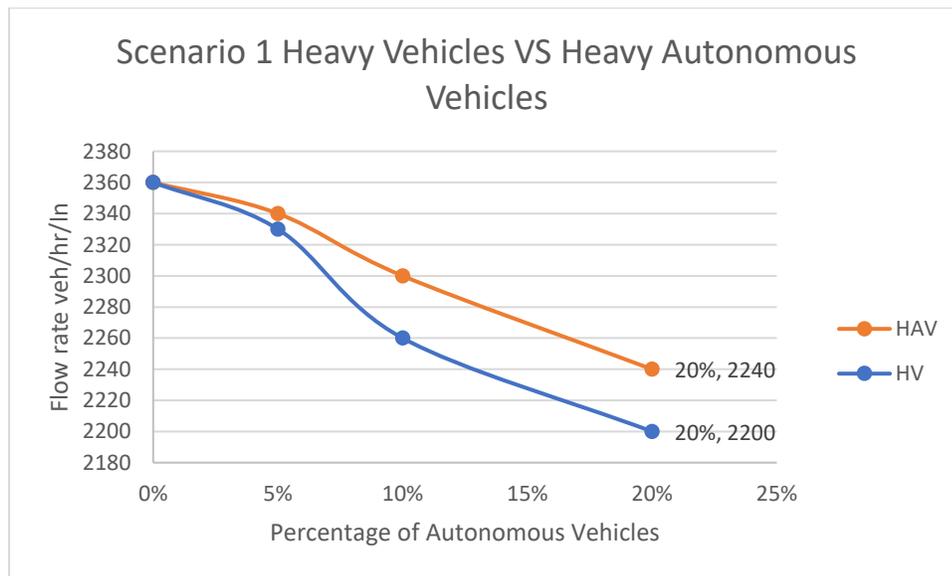


Figure 16 Scenario 1 flowrate versus penetration rate of manual and autonomous heavy vehicles

The flowchart explains the decrease in the freeway capacity when Heavy Vehicles increase. The decrease of the flowrate was less when these Heavy Vehicles were

Autonomous. The difference in the flow rate between automated and manual Heavy vehicles increases when the percentage of Heavy Vehicles increases. There is a slight improvement in freeway capacity when the heavy vehicles are 5%. The improvement increases dramatically at 20% heavy vehicles.

#### 4.2.2.1 Scenario 2

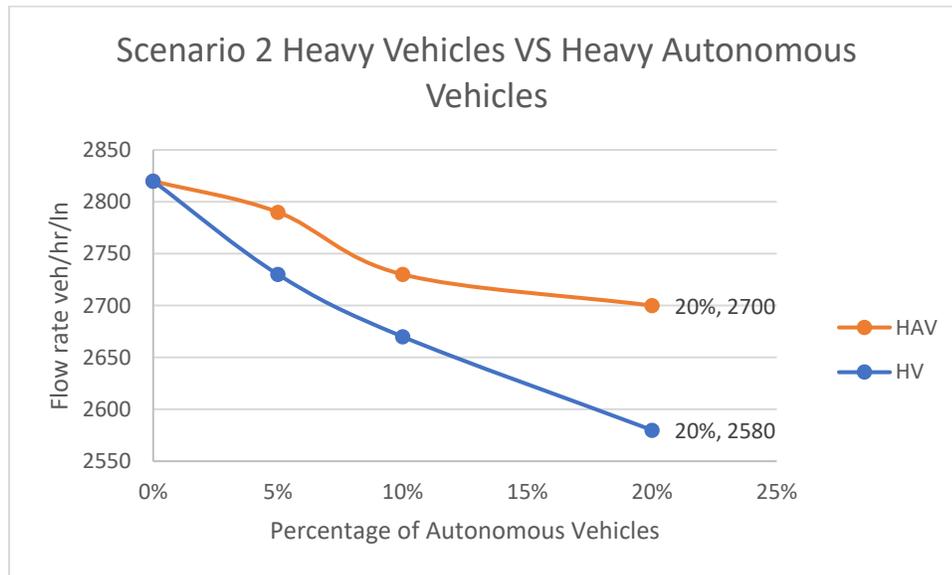


Figure 17 Scenario 2 flowrate versus penetration rate of manual and autonomous heavy vehicles

The flowchart explains the decrease in freeway capacity when the Heavy Vehicles increase in compensation vehicles. The decrease of the flowrate was less noticeable because as the Autonomous vehicles increase, there is still improvement in the capacity when using Heavy Autonomous Vehicles.

#### 4.2.2.2 Scenario 3

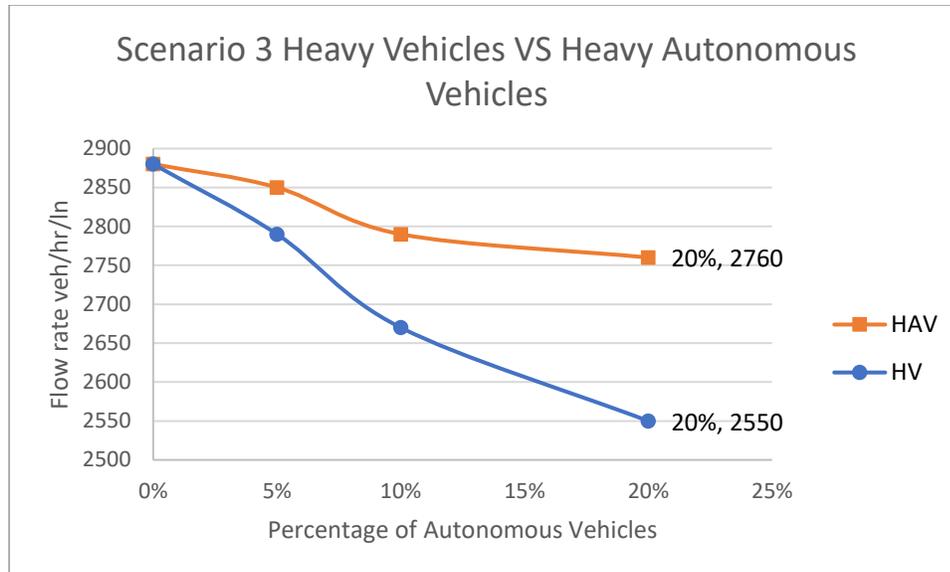


Figure 18 Scenario 3 flowrate versus penetration rate of manual and autonomous heavy vehicles

The flowchart explains the decrease of freeway capacity when the Heavy Vehicles increase in the presence of only Autonomous passenger cars. The decrease in the flowrate was more noticeable than in Scenario 2, because as the Autonomous vehicles increase versus the manual Heavy vehicles increase.

There is a noticeable improvement in freeway capacity when using Autonomous Heavy Vehicles rather than manual Heavy vehicles. However, if the vehicles are able to communicate with each other (V2V), this change will be much more dramatic. According to a research from the University of California at Berkeley and Nissan, the capacity can be improved by as much as 97% (Steven E. Shladover, 2012).

## **Chapter 5 Conclusions and Future work**

### **5.1 Conclusions**

The research investigates the benefit of using Autonomous Heavy Vehicles on the Freeway to estimate the improvement the Microsimulation by VISSIM was with different penetration rate of Heavy Autonomous Vehicles and different compensation of passenger cars. The major contribution of this study is to demonstrate how does the Autonomous Heavy Vehicles is more effective than the manual heavy vehicles. The simulation is based on various assumptions outlined in section 3.6 to simplify the modelling a bit, but in general, it is believed that this simulation still shows the fundamental relationship between freeway capacity, level 3 highly automated heavy vehicles market penetration. Although level 3 highly automated heavy vehicles have shown better car following capability comparing to the manual Heavy Vehicles, this improvement was noticeable when the penetration rate of heavy vehicles increase. The Capacity decrease when both manual and automated heavy vehicles increase. But the decrease in capacity of the heavy autonomous vehicles is smaller than the decrease in the manual autonomous vehicles.

In addition, this study further explores the impact of the heavy autonomous vehicles in different under the different penetration rate of heavy vehicles. It shows that the improvement in the freeway Capacity is more noticeable when the freeway was full of autonomous vehicles.

Finally, this research discusses the process to produce the driving behaviors and explain the different between the manual behaviors and the autonomous behaviors and the

physical characteristics of heavy vehicles such as low Capacity and slow speed have less reduction effects Capacity after implement the Automated behaviors.

## **5.2 Future Work**

Several limitations exist in the proposed model. First of all, this research is based on some assumptions and therefore cannot fully represent the real world operating conditions for heavy autonomous vehicles. The car following parameter of Wiedemann were based in assumption and previous test there is no expert in driving behaviors of heavy autonomous vehicles. In the future, if appropriate tools are available, it is better to run more realistic models to simulate the impact on freeway throughput from level 3 heavy autonomous vehicles. For example, bringing real test to detect the different in driver behaviors between the autonomous passenger car and autonomous heavy vehicles. From section 4.2.2.1 it shows that the difference in capacity improvement between autonomous and manual heavy vehicles was less noticeable when the road has manual and autonomous passenger cars. It is worth investigating why this phenomenon happens. This experiment uses two lane freeway more study should be done to estimate the improvement in the weaving area.

Finally, the research and development in automated vehicles is happening at lightning speed. It is also believed that level 4 and 5 automated vehicles will be eventually be out on the road. At such elevated levels, the driver behavior will be completely out of the loop; it is possible that the vehicle operating characteristics and behaviors will be very different from human operated vehicles or even level 3 vehicles. It is really interesting to investigate how the level 4 and 5 automated vehicles affect the capacity of the freeway.

## Appendix

Table 2 below shows the raw data retrieved from data collection points that are placed in each lane. This data has been further processed to make the figures available from chapter 4.

Table 2 Sample Data

<b>TIMEINT</b>	<b>DATA COLLECTION MEASUREMENT</b>	<b>Flow Rate veh/hr/ln</b>
0-60	4	0
60-120	4	0
120-180	4	24
180-240	4	192
240-300	4	204
300-360	4	252
360-420	4	276
420-480	4	276
480-540	4	348
540-600	4	192
600-660	4	336
660-720	4	228
720-780	4	276
780-840	4	324
840-900	4	312
900-960	4	336
960-1020	4	348
1020-1080	4	408
1080-1140	4	528
1140-1200	4	540
1200-1260	4	420
1260-1320	4	408
1320-1380	4	456
1380-1440	4	420
1440-1500	4	780
1500-1560	4	720
1560-1620	4	600

1620-1680	4	648
1680-1740	4	288
1740-1800	4	828
1800-1860	4	912
1860-1920	4	636
1920-1980	4	540
1980-2040	4	816
2040-2100	4	1116
2100-2160	4	720
2160-2220	4	864
2220-2280	4	864
2280-2340	4	684
2340-2400	4	1080
2400-2460	4	900
2460-2520	4	804
2520-2580	4	1032
2580-2640	4	1068
2640-2700	4	792
2700-2760	4	1044
2760-2820	4	1032
2820-2880	4	984
2880-2940	4	1116
2940-3000	4	900
3000-3060	4	996
3060-3120	4	984
3120-3180	4	1020
3180-3240	4	1116

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