EFFECTS OF AUTONOMOUS VEHICLES ON FREEWAY TRAFFIC PERFORMANCE

by

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Abstract

Autonomous vehicles (AVs) are smart transportation technologies that have drawn significant attention recently due to their rapid development and promising future. Dubai is trying to promote the use of AVs on its road network as it announced its future strategy to make 25% of its transportation automated by 2030.One of the major challenges that are expected to happen is the interaction between AVs and Regular vehicles (RVs) as the mode share, for AVs (percentage of AVs) would not be 100% in the early stages of adoption, and this interaction is not well-researched so far. The purpose of this study is to evaluate the impact of AVs on freeway traffic performance. The study considers a segment of E311 (Sheikh Mohamed Bin Zayed Road) freeway in Dubai as the test corridor for the study. A microsimulation software (VISSIM) is used to model and evaluate different scenarios. Different traffic demand to capacity ratios are evaluated by considering demand to capacity ratios. The results show that increasing AVs mode share increases the average speed and reduces average travel time and delay. Also, the impact of AVs on freeway performance is higher when the demand to capacity ratio is higher. The minimum effect is achieved when there is a 5% AVs and the demand to capacity ratio is 0.6 while the ultimate case is for 100% AVs and demand to capacity ratio of 1.2. In this case, the increase in speed is about 115%, the reduction in the average travel time is about 1.5%, and the average delay is lower by about 87%. The results obtained in this thesis represent a lower bound of what can actually be obtained, as the considered simulations assumed the lane width and capacity to remain the same. In real applications, more improvements can be achieved by designating some of the road lanes for AVs use only, at high mode shares of AVs. Such lanes have smaller width than regular lanes, which will increase the number of the lanes and road capacity.

Search term: Autonomous Vehicles, Regular Vehicles, average speed, travel time, delay, demand to capacity ratio.

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List of Abbreviations

ACC	Adaptive cruise control
AICC	Autonomous intelligent Cruise Control
AVs	Autonomous vehicles
CACC	Cooperative Adaptive Cruise Control
CO_2	Carbon Dioxide
GHG	Greenhouse gas
HCM	Highway Capacity Manual
ICC	Intelligent cruise control
LIDAR	Light Detection and Ranging
LOS	Level of Service
NHTSA	The National Highway Traffic Safety Administration
RADAR	Radio Detection and Ranging
RTA	The Roads and Transport Authority- Dubai
RVs	Regular vehicles
SAV	Shared autonomous vehicles
THW	Time headways
UVs	Unequipped vehicles
V2I	Vehicle to infrastructure
V2V	Vehicle to vehicle
VMT	Vehicle-miles traveled

Chapter 1: Introduction

Autonomous vehicles (AVs) are smart driving technology that has drawn significant attention and undergone a lot of development recently as major vehicles' manufacturers and IT companies (e.g., BMW, Google, Uber, Audi, Tesla, Mercedes) have announced their plans to develop and produce the next-generation of autonomous vehicles (AVs). Such vehicles are expected to alter the perception of transportation and lead to driverless and smart transportation systems, which are vital components of smart cities. Some automotive companies such as BMW, Bosch, Mercedes, Jaguar, and Land Rover launched driving systems that can be controlled remotely using intelligent key [1]. The driver can remotely control the vehicle from outside, using this application to control steering, accelerating, breaking and other maneuvers. The driver can remotely guide the vehicle to negotiate difficult situations like rough terrain or narrow parking spaces. The introduction of AVs is expected to affect the traffic operations and driving environment. The potential impacts of these vehicles are wide-ranging, so several studies were carried out on this topic to understand and evaluate these impacts in order to maximize their advantages and avoid any disadvantages or errors that may occur in the future to ensure that they are safe to be adopted and introduced to the public.

Dubai has announced its plans to introduce autonomous vehicles in the city. HH Sheikh Mohammed bin Rashid Al Maktoum, Vice President of the UAE and Ruler of Dubai has launched a future transportation strategy to make 25% of Dubai's transportation autonomous by 2030 [2]. The Roads and Transport Authority (RTA) in Dubai announced, on Monday 5/2/2018, that autonomous vehicles will be adopted in Dubai and that scheduled test runs have begun on Al Qudra Road starting from February 2018 [3]. Moreover, RTA also announced its plans to introduce an autonomous shuttle service within the Downtown area to transport passengers between the Dubai Mall and an underground parking garage on Sheikh Mohammed Bin Rashid Boulevard. These vehicles will be able to run along 550 meter and hold six or seven passengers [4]. Furthermore, Dubai made a deal with Tesla in February 2017 to purchase 200 vehicles of models (S) and (X) that are equipped with full self-driving hardware capabilities, with a level of safety greater than human driving; the first delivery of 50 cars was made. as a starting point in Dubai's plan of autonomous taxi [5]. Therefore, it's only a matter of time until these vehicles be on Dubai's roads. For this reason,

Studies of this new technology and its effect on Dubai traffic environment must be carried out, and the city has to prepare its infrastructure to facilitate the implantation of these vehicles.

1.1 Objectives

As mentioned before, several studies and researches on the effect of the autonomous vehicles in different regions and countries were conducted. This thesis is targeting the effect of AVs on freeway performance, considering a segment of a freeway in Dubai.

The purposes of this research are summarized as follows:

1) Evaluate the impact of AVs on freeway performance in Dubai, at different mode share values.
2) Evaluate the impact of AVs on freeway performance in Dubai, at different traffic demand to capacity ratios.

1.3 Problem Statement

One of the challenges of using AVs is the fact that these vehicles will start with a small mode share, and later the mode share for AVs will increase until it ultimately reaches 100%. Upon having any value of the mode share, the AVs have to interact with Regular vehicles, using the same freeway links. Such interaction may create positive or negative impacts on the freeway performance, based on the value of the AVs mode share. Therefore, these impacts have to be evaluated to ensure that the city of Dubai is ready for different scenarios that might be faced when allowing AVs to be on the city's road network. Therefore, this research considers different mode share values of AVs to be simulated in order to determine the effect of each rate on traffic parameters, at different demand to capacity ratios.

1.4 Scope of Work

The study will consider a section of Sheikh Mohammad Bin Zayed Road (E311). The proposed section of E311 is illustrated in Figure 1. The study area includes six junctions along E311 that represent different possible junctions' layout. Junctions 1, 3 and 4 show examples of right-in-right-out junctions, Junction 2 is a single point interchange and junctions 5 and 6 are full-cloverleaf junctions with additional ramps to provide direct access for some left turn movements. These types of junctions require different patterns of lane change and weaving maneuvers that induce traffic perturbations, which will allow for testing the freeway performance.

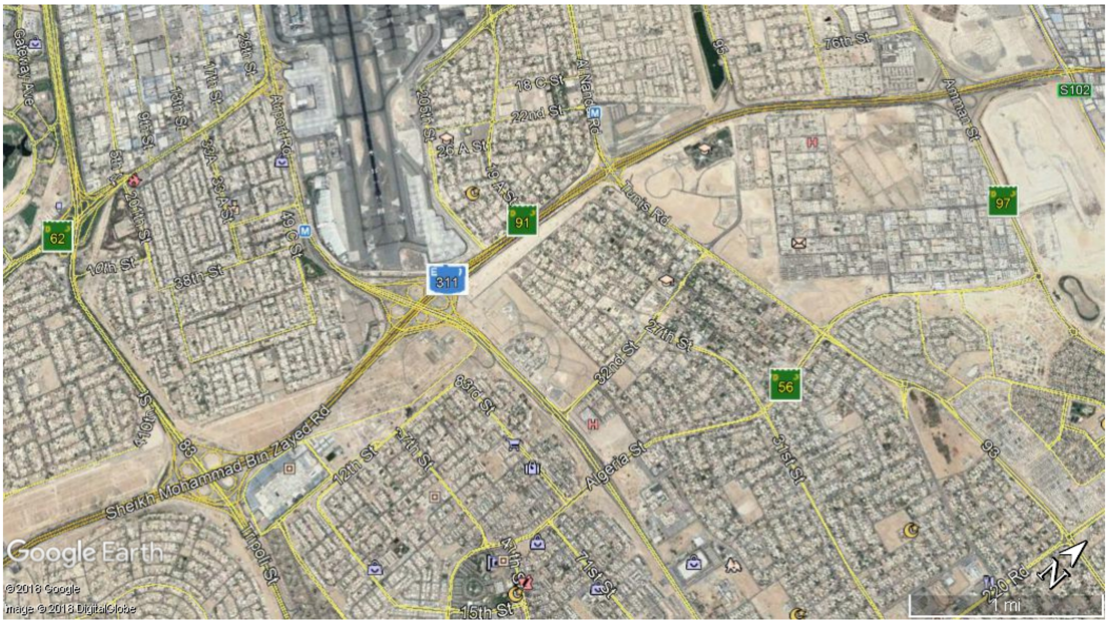


Figure 1: Study area

Chapter 2: Literature Review

This Chapter reviews the existing relevant researches on AVs regarding their potential impacts on different aspects.

2.1 Definition and Levels of Autonomous Vehicles

AVs are driverless vehicles that operate without the need of a driver to control driving tasks, such as steering, braking, deceleration and acceleration, or monitor the roadway constantly. The National Highway Traffic Safety Administration (NHTSA) has classified vehicle automation into six levels; the higher the level is, the more automated the vehicle will be, as shown in the Figure 2. This research will focus on vehicles with full automation, so whenever the autonomous vehicle term is used in this research, it refers to vehicles with a full automation level (i.e., Level 5).

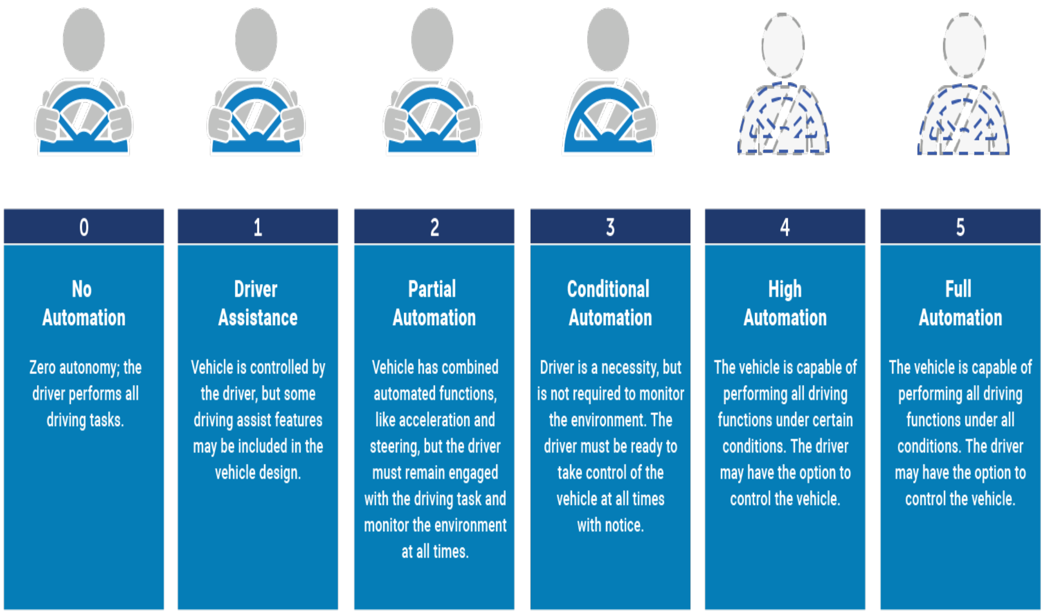


Figure 2: Automation levels [6]

2.2 Benefits of Autonomous Vehicles

AVs are expected to provide an easy, comfortable and safe mode of transportation. They are also expected to assist travelers and facilitate their travel, by making them aware of the surrounding traffic with a real-time and guidance information from the traffic management center. Such information is expected to improve the transportation system's efficiency and comfort while improving safety and mobility. In addition, they are equipped with many sensors (LIDAR and

RADAR scanning systems) that are used in collisions avoidance. According to NHTSA, 94% of accidents are due to human errors, and more than 35,000 people died in such serious accidents in U.S. in 2015, so AVs can save many lives by eliminating accidents caused by human errors [6].

The following subsections provide a summary of the expected benefits of AVs related to different measures of effectiveness.

2.2.1 Impact of AVs on safety and traffic performance. Although there are many uncertainties associated with the introduction of these vehicles and their impact, but there are many indications that help to expect such impact. Driver-assistant technologies such as Adaptive Cruise Control (ACC), Intelligent Cruise Control (ICC) and semi-autonomous vehicles are already on the roads and are currently being used. Therefore, different studies were conducted on the vehicles that are equipped with these technologies to get an initial expectation about AVs; the following is an overview of pervious research that tackled this subject.

It was found that ACC systems could have positive impacts on traffic dynamic as it can increase road capacity and reduce traffic congestion. This is mainly because vehicles that are equipped with an ACC system can track the leading vehicles and calculate distance and speed difference. Based on that, ACC automatically accelerates or decelerates the vehicle to maintain safe headway at a desired speed and prevent rear-end collisions. Such a system provides safe and smooth traffic flow by controlling longitudinal driving tasks. It was found that a small percentage of vehicles equipped with ACC system results in a drastic reduction in traffic congestion, and thus increases traffic stability and road capacity [7].

Ioannou and Chien developed an Autonomous Intelligent Cruise Control (AICC) system for automatic vehicle following [8]. The performance and effect of AICC on traffic flow were examined and compared with three models of human driver (Linear Follow-the-Leader Model, Linear Optimal Control Model and Look-Ahead-Model), using computer simulation in a single lane with no passing. The results showed that AICC system provides a safe and smooth traffic flow and increases the flow rates, compared to human driver models due to shorter inter-vehicle safety spacing, elimination of human delays and errors and lower reaction time. The transient response of AICC system is faster and better than human driver models since vehicles are able to measure the relative distance and velocity between them and the leading vehicle. Accordingly, the vehicle can adjust its own velocity and acceleration to reach the traffic flow steady state much faster than the other three models. Several emergency cases were simulated such as sudden stopping case (when the leading vehicle executes a sudden stop). The results showed that the following vehicles were able to come to full stop in a very short period (10 s) without collisions, and thus AICC may lead to safer driving. However, these simulations did not consider the interaction between AVs and Regular vehicles (RVs).

Moreover, AVs are equipped with onboard sensors and a vehicle to vehicle (V2V) communication system that can help in avoiding collisions, decreasing the safe inter-vehicle distance, and thus increasing the capacity of the road. Tientrakool, et al. compared the highway capacity when vehicles are equipped with sensors only and when they are equipped with sensors and V2V communication systems [9]. The results showed that both technologies are helpful in improving highway capacity as they decrease the average safe inter-vehicle distance and prevent collisions. According to the results, using sensors alone was found to increase the capacity 1.4 times the normal capacity when all vehicles aren't equipped with sensors and V2V communication devices. On the other hand, when using both sensors and V2V communication systems, the capacity increases 3.7 times the normal capacity. Furthermore, as the percentage of equipped vehicles on a highway increases, the capacity improves.

Another feature that is included in AVs is the Cooperative Adaptive Cruise Control (CACC), which can improve traffic performance. This technology was examined, by Arnaout and Bowling , using a traffic simulation model to evaluate how CACC systems can impact traffic performance on a freeway [10]. Using different mode share values of vehicles equipped with CACC systems, it was found that CACC improves traffic characteristics by increasing flow rate and average speed, and thus reducing the congestion problems and increasing the capacity of the highway. This improvement could be significantly large when the mode share increases and reaches about 40%.

AVs are expected to be much safer than regular vehicles as they are expected to eliminate accidents that are caused by human driver errors or their slow reaction time [11]. In addition, AVs can help in achieving a smoother traffic flow and increasing the capacity of the traffic as they can operate with a shorter time headway (THW) than the regular vehicles in a safe way.

Aria et al. investigated the effects of AVs on driver's behavior and traffic performance. A microscopic traffic simulation model, using VISSIM, was used to estimate the effect of AVs on traffic performance and road network [12]. The simulation model consists of two scenarios; the first scenario includes only Regular vehicles (RVs) while the second one includes AVs only (i.e. 100% mode share). The conducted simulation study revealed that AVs have positive effects on roads especially during peak hours as they can improve density and average travel speed and decrease traffic congestion by reducing THW.

Furthermore, they can increase traffic capacity and improve safety margins in car following. Furthermore, AVs are expected to improve traffic performance and other characteristics especially at high levels of congestion. A study was conducted by Shi and Prevedouros to assess the impacts of AVs on the traffic flow characteristics [13]. The Highway Capacity Manual (HCM) methodology was used as a standard tool for the operational analysis of highways and related facilities. HCM parameters were modified to fit AVs features that will affect HCM parameters. In this study, AVs are classified into two types: normal AVs and connected AVs with V2V and Vehicle to infrastructure (V2I) communications. Two different scenarios were conducted, using Monte Carlo simulation. The first scenario is when AVs with one certain headway are mixed in different traffic demands. The second scenario is when AVs with varied headway are mixed in the same traffic demand. The study uses different mode share to indicate the different stages of implementation because in the early stage of AVs implementation, the majority of traffic will consist of manually driven vehicles mixed with the small percentage of AVs. Therefore, it is necessary to study how traffic performance varies with different mode share of AVs. The results revealed that the capacity increases when the percentage of AVs in traffic increases.

Moreover, the Level of Service (LOS) increases with the presence of AVs in traffic since it depends on speed values, and AVs are able to maintain a higher speed at higher traffic density. Accordingly, LOS evolves when the percentage of AVs increases. The results showed that AVs provide low improvement in LOS in low density conditions and high improvement in LOS in high density conditions. Furthermore, AVs provide high improvement in LOS when AVs mode share is high and low improvement in LOS when their mode share is below 2%.

It was found that the introduction of AVs into the traffic can enhance network performance and reduce congestion as evidenced in a study conducted by Febbraro and Sacco (2016) who analyzed traffic issues associated with AVs, by evaluating gradual penetration effect of AVs among traffic of manual vehicles [14]. A simplified kinematic supply model was applied to a real-world road network in Genoa (Italy). The stochastic User Equilibrium (UE) and System Optimum (SO) states of the network were determined and compared. In addition, AVs can improve traffic stability and throughput.

Talebpour and Mahmassani investigated the influence of connected and autonomous vehicles on traffic flow stability and throughput [15]. The study developed an acceleration framework to simulate different vehicle types (Regular, connected and autonomous vehicles) for different mode share of connected and autonomous vehicles. Analytical and simulation investigations were performed to determine the impacts of connected and autonomous vehicles, with different mode shares, on string stability. The results showed that connected and autonomous vehicles improve string stability. The analytical investigation showed that autonomous and connected vehicles improve string stability of traffic flow, but autonomous vehicles are more effective in preventing the formation and propagation of the shockwaves. The simulation results revealed that the scatter in fundamental diagrams increases with the increase in the mode share of connected and autonomous vehicles, when the mode share is from 0 to 50% and decreases after this point until no scatter is observed with high mode share. Moreover, the results showed that autonomous and connected vehicles improve the throughput, but the autonomous vehicles result in higher throughput than the connected vehicles at similar mode share. It is expected that potential benefits will be evident at high mode share because at low mode shares, the potential benefits of AVs will be limited by the behavior of other vehicles, so the overall improvement will be unnoticeable. Furthermore, potential benefits will be evident in congested networks as AVs help to maintain closely spaced vehicles and reduce unnecessary acceleration and deceleration. [16].

Bose and Ioannou analyzed the traffic flow characteristics when semi-automated vehicles are mixed with manually driven vehicles [17]. Semi-automated vehicles are vehicles with an ICC option that provides automatic vehicle following capability. Pipes model was used to simulate manual driven vehicles while semi-automated vehicles were simulated using an ICC design. Three different cases, using the two models were used to analyze the transient behavior during vehicle following. In case 1, all vehicles are manually driven; in case 2, all vehicles are semi-automated; and in case 3, manual and semi-automated vehicles are mixed. The results showed that the semi-automated vehicles in mixed traffic do not contribute to the slinky-effect phenomena during smooth transients since they accurately respond to any smooth acceleration or velocity response. Moreover, they filter the response of any rough or rapid acceleration maneuver of the lead vehicle, which results in smooth traffic.

2.2.2 Efficiency, convenience and social benefits. AVs have several positive social impacts as they can help disabled or the elderly segment of the community. In addition, autonomous vehicles will save drivers' times and reduce fright prices as there is no need for truck drivers [11]. Besides, AVs can provide comfortable and luxury mode of transportation as they can be used as a mobile bedroom, lounge or office so they can reduce driver stress and tedium and increase passengers' productivity as they can achieve other tasks during travel time rather than driving tasks [18]. Table 1 shows the three operational models of AVs and their advantages and disadvantages. The AV adoption can change the consumers' lifestyle outside the vehicle. Time-use activity patterns of sub-groups of population were studied to estimate the impacts of AVs. It was found that AVs increase utility of in-vehicle time by enabling new activities to be done within the vehicle for long-traveling group. Furthermore, the time saved by AVs can be used for other activities like watching TV or sleeping. In addition, as mentioned before, AVs enable physically or legally-constrained population to travel and can affect their destinations. For example, elderly population can spend more time in shopping and socializing instead of staying at home [19]. It was found that AVs and ACC can reduce workload and situation awareness compared to the manual driver if the driver is motivated or instructed to monitor the driving environment. However, if the driver is distracted by other non-driving tasks, like reading or sleeping, he/she would not monitor and allocate attention to the road. This can deteriorate the situation awareness compared to manual driving [20].

Table 1: Autonomous vehicle operational Models [18]

	Advantages	Disadvantages	Appropriate Users
Personal autonomous vehicles - Motorists own or lease their own self-driving vehicles	High convenience. Available without delay. Items, such as equipment, tools and snacks, can be left in vehicles.	High costs. Does not allow users to choose different vehicles for different trips, such as cars for commuting or trucks for errands.	People who travel a lot, reside in sprawled areas, want a particular vehicle, or leave items in their vehicles.
Shared autonomous vehicles - Self-driving taxis transport individuals and groups to destinations.	Users can choose vehicles that best meet their needs. Door to door service.	Users must wait for vehicles. Limited service (no driver to help passengers carry luggage safely reach their door). Vehicles may be dirty.	Lower-annual-mileage users.
Shared autonomous rides - Self-driving vans (*micro-transit*) take passengers to or near destinations.	Lowest costs.	Least convenience, comfort and speed, particularly in sprawled areas.	Lower-income urban residents.

2.2.3 Environmental impacts sustainability, and fuel efficiency. AVs can impact greenhouse gas (GHG) emission either positively or negatively as they are expected to change travel behavior patterns, and thus increase or decrease overall vehicle-miles traveled (VMT). This depends on some complex factors that are listed below.

A. Driver experience: if AVs provide more comfortable driving experience, this will encourage consumers to travel more, but if they provide the same driving experience as the Regular vehicles, then this will result in limited change in travel behavior. It was found that driving in congested area can increase stress and frustration. Moreover, sitting in the driving position for long periods of time can affect drivers' health as it can cause back pain, muscle cramp and long-term spinal disc degradation. Therefore, with all these negative impacts of regular driving compared to comfortable AVs, this can encourage passengers to travel more, and thus increase the total VMT [21].

B. Safety: As AVs increase safety perception, this also can make users increase their miles-traveled.

C. Non-drivers: Added population of new travelers as AVs allows under-served, elderly and disabled people to travel independently, which can increase VMT.

D. Vehicle costs: AVs cost can decrease ownership rates, and thus reduce VMT [21].

E. Car sharing: AVs, as mentioned before, can attract new travelers, and that will generate more trips and increase VMT and the energy consumption as well. AVs and on-demand mobility (also known as car-sharing or ridesharing service in which travelers use smartphone app to reserve a vehicle for a trip) are two emerging trends that are expected to change personal transportation and replace Regular transportation by mid-century. If AVs and on-demand mobility are combined to produce shared autonomous vehicles (SAV), this will amplify adoption and positive impacts of AVs, and at the same time reduce vehicle ownership and annual distance traveled by vehicles. This will result in a decrease in energy use and GHG emissions. Moreover, it can provide an affordable and efficient mode of traveling [22]. The same idea was discussed by a research carried out by Catherine Ross et al. (2017), as they developed three different scenarios to evaluate the potential energy consumption of AVs in the U.S. the scenarios were:1) partial automation with personal vehicles dominate 2) full automation with personal vehicles dominate 3) full automation with shared vehicles dominate. It was found that the third scenario had the least energy consumption, as shown in Figure 3.

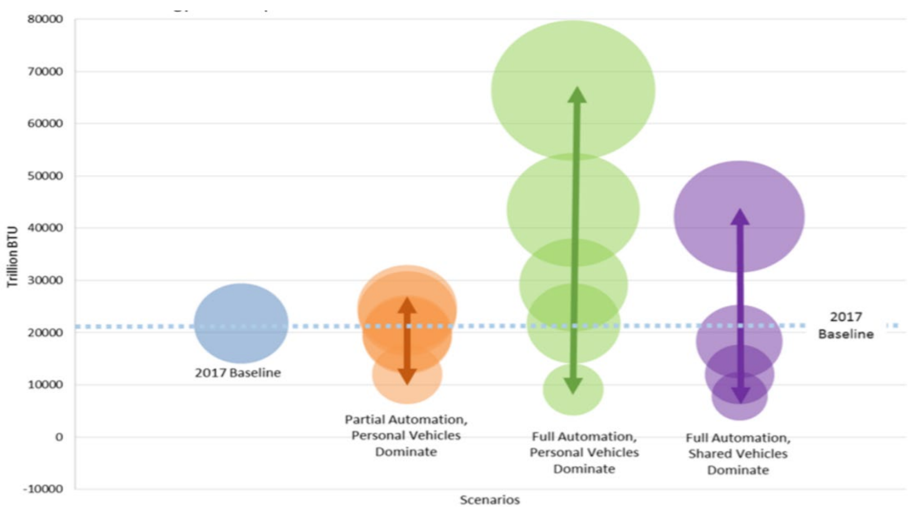


Figure 3: U.S. energy consumption estimates for AVs under the three scenarios [23].

Figure 3 shows energy consumption values through the position relative to the y-axis and bubbles sizes [23]. So, it can be concluded that SAV can reduce GHG emissions, and energy consumption will maintain the merits of AVs and their mobility convenience. Furthermore, fuel efficiency of AVs can be increased by using better transmission than manual transmission (4-speed transmission) that will reduce fuel consumption and Carbon Dioxide (CO_2) emissions. Moreover, AVs can reduce congestion, and thus reduce emissions [11]. In addition, optimizing AVs speed, acceleration, following distance, breaking and routing decision of the vehicle can increase the efficiency of the vehicles travel. AVs are equipped with collision avoidance, V2V and V2I technologies that will provide the drivers with a lot of information, thus the possibility of collision will be reduced, and drivers can make better decisions. This will lead to smooth traffic flow as vehicles' acceleration, declaration and following speed will be optimized which will result in a smooth vehicle platooning and congestion reduction. All these advantages can reduce energy or fuel that are consumed in congestions and traffic jams and also reduce GHG emissions [24]. AVs can increase or decrease GHG emissions. These impacts depend on AVs adoption and usage. There are major factors that will increase or decrease energy use and GHG emissions. These factors affect environmental impacts of AVs, and they are divided into two categories: 1) forces improving impacts and 2) forces worsening impact. Figure 4 illustrates these factors [25].

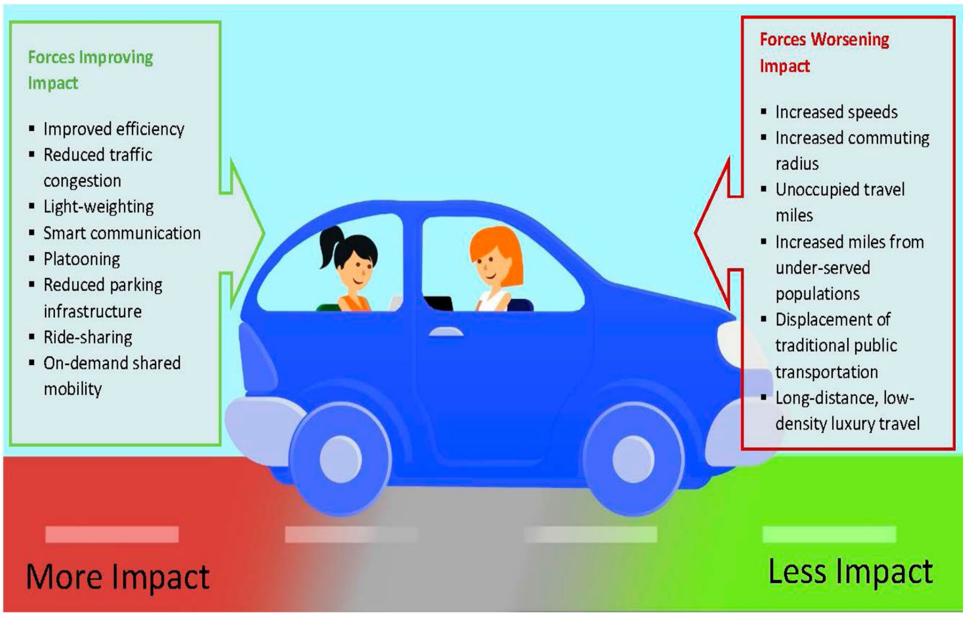


Figure 4:Major forces likely to increase or decrease energy use and GHG emissions associated with fully automated transportation [25].

2.3 Disadvantages and Risks of AVs

Although AVs have a lot of potential positive impacts and benefits such as safety, comfort, etc., but there are some negative potential impacts associated with these vehicles, such as the interaction between automation and humans and automation failures. Some researchers discussed the disadvantages of AVs which entail costs and risks associated with the introduction of these vehicles such as (offsetting behavior, rebound effects and system failures, etc.). Although autonomous vehicles are expected to be safer and reduce crashes that are caused by driver errors by about 90%, there are many technical obstacles and risks associated with them. Such obstacles must be overcome to ensure that the AVs are safe to be used by households for daily travel. There are a lot of uncertainties associated with the implementation of this technology. Testing of AVs is used to reveal any risks or errors associated with these vehicles. The U.S senate panel approved legislation that allows AVs testing, and all crashes that involve AVs regardless of severity must be reported according to California state law. Some of these tests reveal unanticipated situations and incidents. General Motors AVs were involved in 13 crashes while Alphabet Inc.'s AVs were involved in three crashes. The crashes by both companies were reported to California regulators in 2017, and most of these accidents didn't result in any injuries or serious damage. These incidents were due to other human drivers, and the AVs were not responsible [26]. California Department of Motor Vehicles collected all reported crashes involving AVs and made a report that analyzes all accidents reported by manufactures that are testing AVs in the State. The report is also used to determine the most common types of collisions, their impacts and frequencies. The most common type of collisions was found to be the rear-end collisions with AV standing in the front and hit by a Regular vehicle [27]. Figure 5 shows collisions that were reported by different manufacturers. It can be noted that Google's reports of AVs accidents are 84% of the total because Google's testing campaign, in terms of vehicles employed and miles travelled, is relatively larger than other manufacturers.

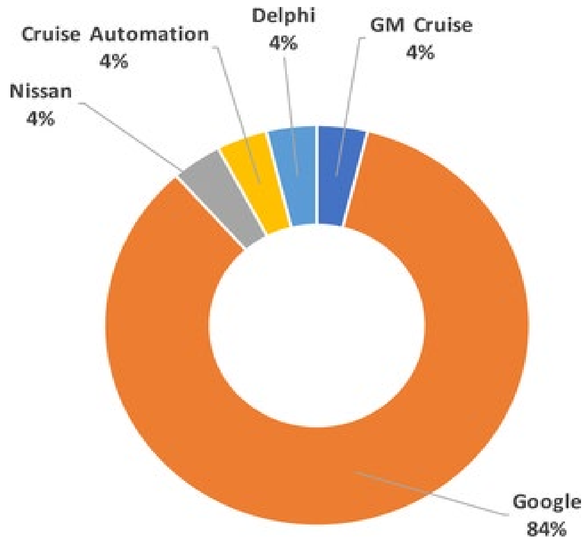


Figure 5: Breakdown of AV accident reporters [27].

Figure 6 summarizes the damage locations of the vehicles involved in the collisions.

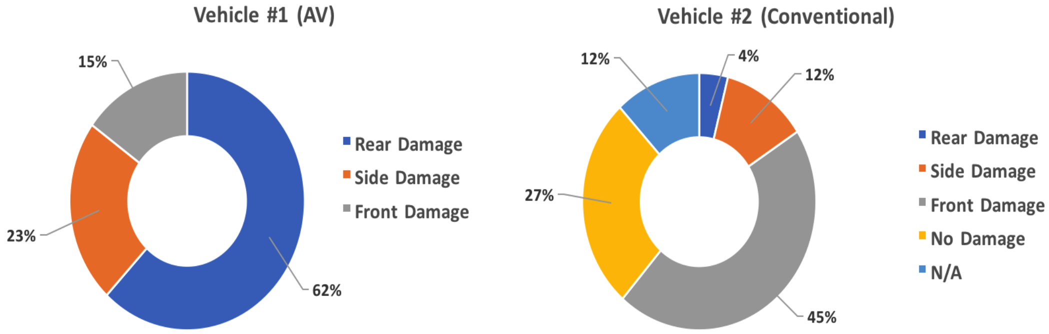


Figure 6: Damage location breakdown for vehicles involved in collisions [27].

On March 18, 2018 a woman was killed in Tempe, Arizona as one of Uber's autonomous test vehicles hit her when she was walking outside the crosswalk. Uber Technologies Inc. announced that it will pause all of AVs tests on public roads [28]. This fatal accident can be a major setback in the AVs proposed federal legislation. Furthermore, there are several uncertainties related to whether the AVs will reduce total vehicle travel and associated external costs by encouraging car sharing, and thus reduce fuel consumption and car ownership or increase them by increasing the convenience of traveling and allowing vehicle non-drivers travel. So, transportation planners have to make trade-offs between these issues [18].

Strand et al. conducted a simulation study to examine how the level of automation influences driving performance during critical situations in case of automation failures and also the influence of deceleration extent on driving performance [29]. A driving simulator was used that contains semi and highly automated vehicles under three declaration failure (moderate, severe and complete). The results indicate that the increase of automation level will degrade the driving performance in automation failures situations as it's safer in semi-automated driving than in fully automated driving. In addition, it was revealed that drivers can handle partial deceleration failure better than complete failure.

Vehicles equipped with advanced driver assistance systems are under significant progress, which allows the introduction of semi and fully automated vehicles that will lead to a mixed traffic situation between equipped and unequipped vehicles (UV). In order to determine the consequences of the interaction between equipped and unequipped vehicles Gouy et al. made a driving simulation study to examine the effect of the short THW kept in platoons of automated vehicles on driver of UV driving near this platoon [30]. Driving simulation software SCANeR studio 1.1 from Oktal was used to create three different driving scenarios, and each scenario participants were asked to follow a lead vehicle. In the first two scenarios, there was a platoon of automated vehicles in the inside lane with 0.3 s THW between the vehicles in the first scenario and 1.4 s THW in the second scenario. In the third scenario, which is the baseline, only a lead vehicle was present. The results showed that participants adapted by driving with shorter average and minimum THW when driving next to a platoon that has short THW between its vehicles. Drivers also spent more time under critical threshold of 1.0 s THW which increased the probability of collisions for UV. In addition, AVs can negatively impact driver behaviors as driving AVs during light traffic is tedious, and the driver get distracted with tasks unrelated to driving. This will take drivers' attention off the road that leads to loss of situation awareness that will intensify driver drowsiness. Moreover, overreliance on automation can degrade driving skills in absence of practice and could be dangerous in case of system failure [12].

2.4 Barriers to Implementation

2.4.1 Vehicle cost. AVs are usually equipped with a lot of sensors, communication and guidance technologies that will increase their cost in addition to costs of software, engineering and computing requirements.

This makes them unaffordable for most people, and that is an important barrier to large-scale market adoption rate. Some advocates claim that fuel, insurance and parking-cost saving will partly offset these incremental costs, and that production cost will be reduced with mass production as any other technological advances [31].

2.4.2 Licensing. AVs licensing and testing standards are among the main barriers of AVs adoption. For example, in U.S some States such as (California, Nevada Washington DC and Florida) allowed AVs licensing and enables AV testing. In some other States, legislation is still pending. Moreover, legislation significantly varies from a State to another, which leads to inconsistencies between States. Therefore, the U.S and other countries must create nationally recognized licensing and liability standards for AVs [31].

2.4.3 Security. One of the main concerns is that AVs and other intelligent transportation systems may be targeted or hacked by computer hackers or terrorists. These incidents may cause many problems such as accidents or traffic disruption or terrorism acts. Therefore, software security firms and engineers must develop a robust system that is difficult to be hacked [31].

Chapter 3: Methodology

This Chapter presents the methodology of the project. The methodology includes all the steps that will be followed in this research to achieve the research objectives.

3.1 Model Development

In order to understand and evaluate the impacts of AVs on traffic performance, VISSIM is utilized to develop a microsimulation model of mixed traffic that contains AVs and RVs. The two types of vehicles (AVs and RVs) exhibit different driving behaviors that should be modeled to accurately simulate each type of vehicles. Several functions (such as car following, lane changing and lateral behavior) govern vehicles' driving behavior in microscopic traffic simulation. Car following behavioral models govern vehicle's longitudinal speed and acceleration. It also controls the gap between the lead vehicle and the following vehicle. Lane changing model determines when it is acceptable to change lanes and how to do so. A VISSIM microscopic simulation model of the proposed network will be developed to estimate the impacts of AVs on traffic performance measures such as average speed, travel time and delay. In order to model the presence of AVs in VISSIM driver behavior, some parameters have to be adjusted.

3.2 Experimental Design

Using the VISSIM model, the following parameters will be considered:

- The traffic demand on the road network: four levels of traffic conditions will be considered in the simulation runs. These levels will consider a demand to capacity ratio of 0.6, 0.8, 1.0, and 1.2 to represent uncongested conditions, congested conditions, very congested conditions, and oversaturated conditions, respectively.
- Mode share for AVs: The percentage of AVs will be considered to be 5% to 25% with increments of 5%, which represents the early stages of using AVs. Following these mode share values, the increments will be larger, and the mode share values will be 40%, 60%, 80% and 100%. This will require simulating 9 different mode share values.

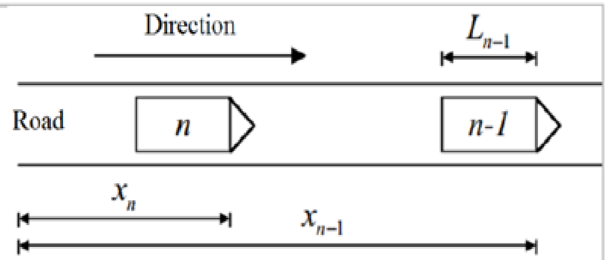
According to these parameters, the total cases considered in the experimental design will be 4 demand to capacity ratios and 9 mode share values. This will require a total of 36 scenarios to be simulated. It should be noted that each scenario will be simulated 5 times, then the trimmed average of the three middle values for each simulation will be considered the average result [12], [44].

3.3 VISSIM Overview

VISSIM is a German microsimulation modelling software developed by PTV AG. It's used for modeling and assessing multimodal transport operations by incorporating traffic demand elements together with road geometry and signal operations to reflect traffic operations. VISSIM is a time step oriented that uses time step approach to identify opportunities for each vehicle in the network. In addition, it utilizes a psycho-physical driver behavioral model developed by Wiedemann for modeling urban and rural traffic conditions.

3.3.1 Car-following models. A car-following model used to simulate how one vehicle follows another vehicle by simulating the following vehicle driver's behavior. A vehicle is considered as a following vehicle if it is determined by the front or the leading vehicle to adjust and keep a certain speed in order avoid collision. The elements and the variables of car following models are presented in Table 2.

Table 2: car following notations [32]

a_n – acceleration of the vehicle n [m/s^2] x_n – position of the vehicle n, [m] v_n – speed of the vehicle n, [m/s] Δx– distance between vehicles, [m] Δv – speed difference between vehicles, [m/s] v_n^{prop}– suggested speed for the vehicle n, [m/s]	
L_{n-1} – length of the vehicle n-1, [m] S_{n-1} – effective length of the vehicle n-1, [m] (=L_{n-1}+safety distance) T – reaction time, [s]	

3.3.1.1 Classification of the car-following models. 1. General car-following models - Gazis-Herman-Rothery class (GHR): This class of models was developed by Chandler et al. 1958. In GHR models, a stimulus-response function is used to describe the relation between the lead and following vehicles. The main assumption is that the acceleration of the following vehicle is proportional to its speed as shown in equation 1 [33].

$$a_n(t) = cv_n^m(t)\frac{\Delta v\ (t-T)}{\Delta x^l(t-T)} \qquad (1)$$

Where

a_n is the acceleration of the following vehicle at time t,

v_n is the speed of the following vehicle,

Δx and Δv, the speed and spacing differences, respectively between the lead and following vehicle, assessed at an earlier time t-T ,

T is the driver reaction time, and m, l and c are the constants to be determined.

2. Safety distance models

The original formulation of was developed by Kometani and Sasaki (1959). This class of models doesn't depend on a stimulus-response function as in GHR models, but it seeks to determine safety following distance by manipulating the basic Newtonian motion equations [33]. The main assumption is that for each 16 km/h, of the speed, the following vehicle will adopt at least one length of a vehicle as a distance from the vehicle ahead. The original formulation is as follows:

$$\Delta x\ (t-T) = \alpha v_{n-1}^2(\mathrm{t}-\mathrm{T})\ + \beta_l v_n^2(\mathrm{t})\ + \beta v_n(t) + b_0 \qquad (2)$$

The most common model for this class is Gipps models, which is considered a major development of the original formulation as it considered several factors that were neglected in the original formulation [34]. According to Gipps model, the safety headway between vehicles is the distance that allows the following vehicle to react to any action of the lead vehicle without being necessary to overtake it.

3. Psycho-physic models

The model assumes that the driver of the following vehicle reacts to the speed of the leading vehicle, and that there are stimuli that induce the driver's reaction.

The model is based on two key assumptions:

- For large distance, the driver of the following vehicle is not influenced by the magnitude of the speed difference

- For small distance, the driver of the following vehicle may not react for a specific threshold that corresponds to a specific speed or distance.

The driver of the following vehicle reacts to modifications of the speed and distance between the following and lead vehicles when certain thresholds are reached [35]. The model uses these thresholds to determine the changes in the behavior of the following vehicle's driver. After reaching the thresholds, the driver of the following vehicle will react to those modifications by modifying his/her kinetic variables [36].

3.3.2 VISSIM's car-following model. VISSIM uses a psycho-physic model developed by Wiedemann in 1974 (Wiedemann 74: which is suitable for Urban traffic) and its last improvement in 1999 (Wiedemann 99: Model mainly suitable for interurban (motorway) traffic) [37]. The model is called a psycho-physical car-following model because it's a combination of psychological aspects and restrictions of the driver's perception. Figure 8 shows the driver perception thresholds and the regimes formed by these thresholds

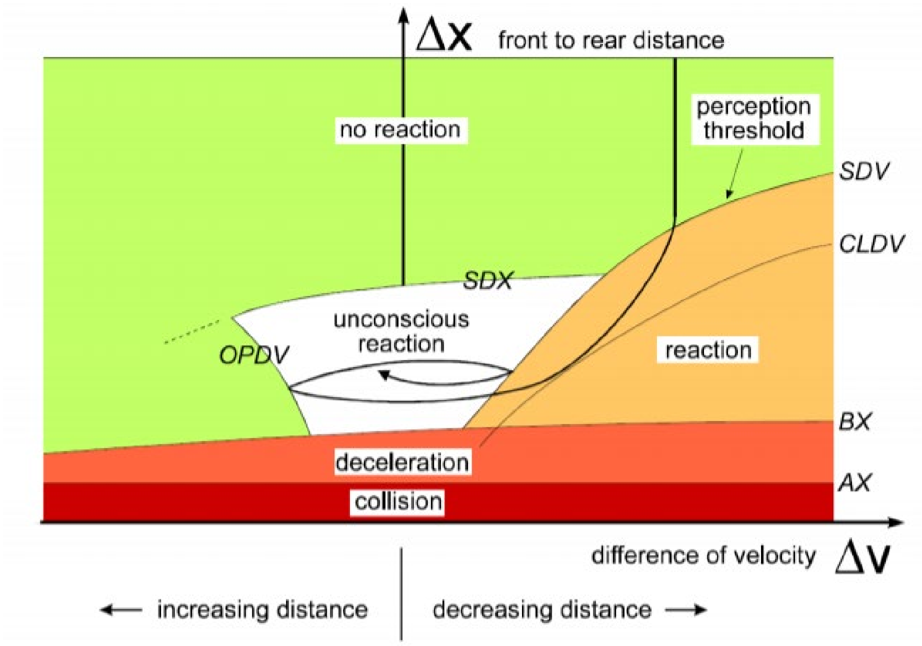


Figure 7: A typical car-following behavior of a vehicle [37]

Where:

- AX: the desired distance between two stationary vehicles

- BX: the minimum following distance which is considered as a safe distance by drivers
- CLDV: the points at short distances where drivers perceive that their speeds are higher than their lead vehicle speeds
- SDV: the points at long distances where drivers perceive speed differences when they are approaching slower vehicles
- OPDV: the points at short distances where drivers perceive that they are travelling at a lower speed than their leader
- SDX: The maximum following distance indicating the upper limit of car-following process

As observed in Figure 6, the basic idea of this model that the driver can be in one of four regimes namely:

1) Free driving regime: when no preceding vehicles are observed, and the driver travels freely without preceding vehicles influence. The driver tries to reach and maintain his/her desired speed. Due to imperfect throttle control, the driver's speed will oscillate around the desired speed.
2) Approaching regime: when the driver approaches a slower preceding vehicle. The driver will decelerate until the difference in speed is zero in order to reach to a desired safety distance
3) Deceleration following regime: when the driver follows the preceding vehicle without conscious acceleration or deceleration to maintain the safety distance, but again due to imperfect throttle control, the difference in speed will oscillate around zero
4) braking regime: when the distance falls below the desired safety distance in case that the preceding vehicle changed its speed suddenly or a third vehicle changed its lane in front of the vehicle, so the driver has to apply medium to high deceleration rates to get back to the safety distance. Drivers switch between driving regimes when they reach certain thresholds that are a combination between speed difference and distance. Vehicle's acceleration is a function of its speed, speed difference, distance to the preceding vehicle and the characteristics of individual driver because each driver has his/her own precipitation of safety distance, desired speed and speed difference. Table 3 shows the equations of each threshold.

Table 3: Threshold of the VISSIM model [32]

Threshold X_s	desired distance between stationary vehicles	$X_s = L_{n-1} + a_1 + S_{1n}a_2$ (3)
Threshold X_{min}	desired minimum following distance	$X_{min} = X_s + b, \quad b = (b_1 + S_{1n}b_2)\sqrt{v}$ (4)
Threshold X_{max}	maximum following distance	$X_{max} = X_s + e\,b$ (5) $e = e_1 + e_2(R - S_{2n})$ (6)
Threshold A	Describes the point from which the driver of the follower is getting closer to a slower vehicle	$A = (\frac{\Delta x - L_{n-1} - X_s}{c})^2$ (7) $c = (c_1 + (S_{1n} + S_{2n})c_2)c_{const}$ (8)

Where:

a_1, a_2, b_2,c_1, c_2, e_1, e_2 are calibration parameters;

S_{1n}, S_{2n}- are randomized parameters that simulate the behavior of the driver of the following vehicle n.

R is a random number generated based on a normal distribution;

The driver can switch from one mode to another by reaching to these thresholds.

In order to obtain a realistic simulation of different types of vehicles, the model parameters have to be adjusted. VISSIM has several calibration parameters to calibrate the reaction time of the drivers. VISSIM Car-Following model simulates how drivers examine traffic situations during driving by defining look-ahead and look-back distances, and each distance has a minimum and a maximum value as shown in Table 4.

Table 4: Forward and backward-looking distance [38].

Car-Following Parameters	**Definitions**	**Notes**
Max. Look Ahead Distance	Max. distance a driver can see forward in order to react.	
Min. Look Ahead Distance	Min. distance a driver can see forward, important for lateral vehicle behavior.	When this value is zero, only the number of observed preceding vehicles is applicable.
Max. Look Back Distance	Max. distance a driver can see backward in order to react.	
Min. Look Back Distance	Min. distance a driver can see backward in order to react.	Relevant when accounting for lateral behavior of vehicles

Parameters for Wiedemann Models:

As mentioned before, VISSIM uses two algorithms to represent driver behaviors described in the Wiedemann car-following model. The first algorithm is Wiedemann 74 (W74) which is suitable for urban and arterials roads and Wiedemann 99 (W99) which is suitable for freeways. Wiedemann 74 model has three parameters to control distance between consecutive vehicles. The safety distance d is calculated by the following equation

$$d = ax + bx \quad (9)$$

$$bx = (bx_{add} + bx_{mult} * z) * \sqrt{v} \quad (10)$$

where:

ax = Standstill Distance.

v = Vehicle speed.

z = A value of range [0,1], normally distributed around 0.5 with a standard deviation of 0.15. Table 5 summarizes Wiedemann 74 parameters.

Table 5: Wiedemann 74 model parameters [38].

Parameters	Definitions
Average Standstill Distance (ax)	Average Desired Standstill Distance between two cars. The range is [−1, 1] and the value is normally distributed around 0 m with a standard deviation of 0.3 m.
Additive Part of Safety Distance (bx_{add})	Value used for computation of the desired safety distance.
Multiplicative Part of Safety Distance (bx_{mult})	Value used for computation of the desired safety distance.

Wiedemann 99 Model has nine parameters as summarized in Table 6.

Table 6 : Wiedemann 99 parameters [39].

Parameters	Unit	Description
CC0	m	Standstill distance: The desired standstill distance between two vehicles. It has no variation. You can define the behavior upstream of static obstacles via the attribute **Standstill distance for static obstacles** (see "Editing the driving behavior parameter Following behavior" on page 273).
CC1	s	Time distribution of speed-dependent part of desired safety distance Shows number and name of time distribution Each time distribution may be empirical or normal. Each vehicle has an individual, random **safety** variable. Vissim uses this random variable as a fractile for the selected time distribution **CC1**. Based on the time distribution, the following distance for a vehicle is calculated. This is the distance in seconds which a driver wants to maintain at a certain speed. The higher the value, the more cautious the driver is. The safety distance is defined in the car following model as the minimum distance a driver will maintain while following another vehicle. In case of high volumes this distance becomes the value which has a determining influence on capacity.
CC2	m	It restricts the distance difference (longitudinal oscillation) or how much more distance than the desired safety distance a driver allows before he intentionally moves closer to the car in front. If this value is set to e.g. 10 m, the following behavior results in distances between dx_{safe} and $dx_{safe} + 10m$. The default value is 4.0m which results in a quite stable following behavior.
CC3	s	It controls the start of the deceleration process, i.e. the number of seconds before reaching the safety distance. At this stage the driver recognizes a preceding slower vehicle.
CC4	m/s	defines negative speed difference during the following process. Low values result in a more sensitive driver reaction to the acceleration or deceleration of the preceding vehicle.
CC5	m/s	defines positive speed difference during the following process. Enter a positive value for **CC5** which corresponds to the negative value of **CC4**. Low values result in a more sensitive driver reaction to the acceleration or deceleration of the preceding vehicle.
CC6	1/(m • s)	Influence of distance on speed oscillation while in following process: ➤ Value 0: The speed oscillation is independent of the distance ➤ Larger values: Lead to a greater speed oscillation with increasing distance
CC7	m/s^2	Oscillation during acceleration
CC8	m/s^2	Desired acceleration when starting from standstill (limited by maximum acceleration defined within the acceleration curves).
CC9	m/s^2	Desired acceleration at 80 km/h (limited by maximum acceleration defined within the acceleration curves).

The relation between Wiedemann 99 parameters and thresholds are defined by equations (11) to (16).

$$AX = L + CC0 \tag{11}$$

Where L is the length of the lead vehicle

$$BX = AX + CC1 \times v \tag{12}$$

Where v is equal to the subject than the lead vehicle; otherwise, it is equal to lead vehicle speed with some random errors. The error is determined randomly by multiplying the speed difference between the two vehicles by a random number between -0.5 and 0.5.

SDX= BX +CC2 (13)

$$(SDV)_i = -\frac{\Delta X-(SDX)_i}{CC3} - CC4 \qquad (14)$$

Where Δx is the distance headway between two successive vehicles.

$$CLDV = \frac{CC6}{17000} \times (\Delta x - L)^2\_CC4 \qquad (15)$$

$$OPDV = - \frac{CC6}{17000} \times (\Delta x - L)^2\_\delta.CC4 \qquad (16)$$

Where δ is a dummy variable equal to 1 when the subject vehicle speed is greater than CC5 and 0 else.

Since the purpose of this research is to evaluate impacts of AVs on freeways, Wiedemann 99 parameters will only be adjusted since Wiedemann 74 is used to model urban traffic.

3.3.3 VISSIM lane changing model. Lane change is generally divided into two categories:

- Mandatory lane change (MLC): lane changing that is required to keep the drivers in their routes.
- Discretionary lane change (DLC): it happens when drivers change their lane to bypass slower vehicles to target lane that has better traffic condition.

DLC is probabilistic, depending on the driver's patience and perception of speed difference, that is when the driver feels that the speed of the preceding vehicle is lower than his/her speed.

The most common lane changing model is gap acceptance model which is used to model the drivers' decision of lane changing [38].

3.3.3.1 ***Lane changing Model Parameters.*** Necessary lane change has three main parameters for the vehicle and trailing vehicle on the new lane.

- **Maximum deceleration:** defines the maximum deceleration of the two involved vehicles.
- **Accepted deceleration:** defines the minimum accepted deceleration of the two involved vehicles.
- **1 m/s2 per distance (the change of deceleration parameter):** controls the maximum deceleration at different distances to the emergency stop position. The closer the vehicle is to the emergency stop position, the higher its maximum deceleration and Vice Versa. When the vehicle gets farther from the emergency stop position, its maximum deceleration will be reduced to the accepted deceleration as shown in Figure 8. [38].

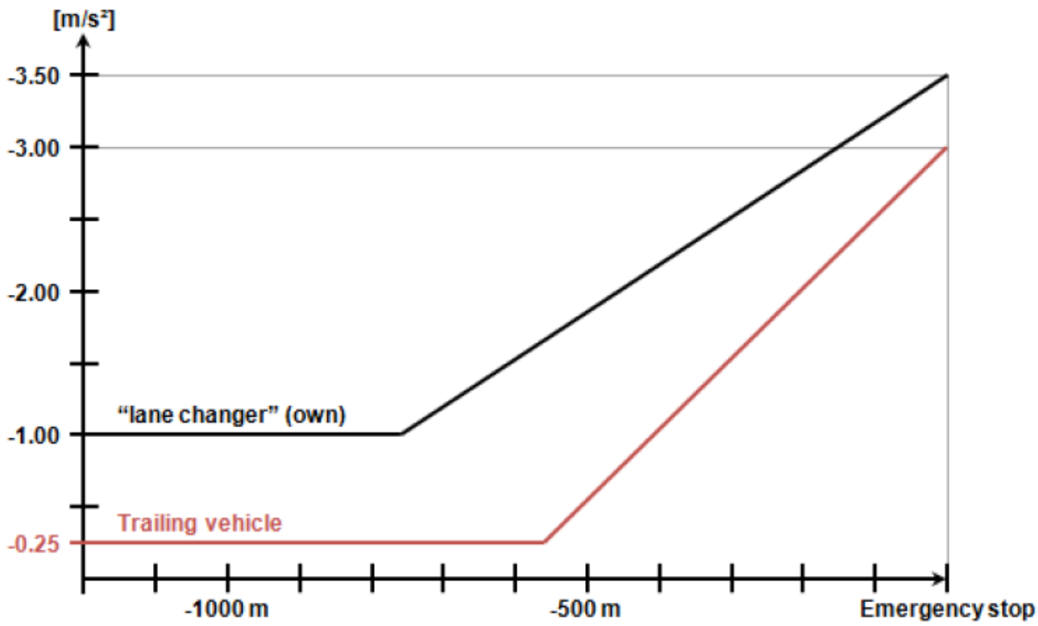


Figure 8: Change of deceleration diagram [38].

Both MLC and DLC types have the following parameters [38]:

- **Waiting time before diffusion:** defines how much time a vehicle will wait at the emergency stop position for a gap for lane changing to stay on its route. If this time is reached, the vehicle will be taken out of the network
- **Min. Headway (front/rear):** Before the vehicle changes its lane, VISSIM will check if the minimum front and rear headway of the vehicle will be available after lane changing. Otherwise, lane changing won't take place.

- **Safety distance reduction factor:** During lane changing VISSIM will reduce the safety distance of lane changer vehicle to the leading vehicle and of the trailing vehicle in the new lane by multiplying safety distance factor. After lane changing, the original safety distance is regarded again.
- **Maximum deceleration for cooperative braking:** defines how the trailing vehicle in the new lane brake, cooperatively brakes to let the adjacent vehicle change its lane. If the trailing vehicle finds that it has to brake harder than this value, it will not let the lane changing happen.
- **Overtake reduced speed areas:** if this option is off, vehicles will ignore reduced speed areas in the target lane and won't start free lane change directly upstream a reduced speed area. If this option is checked, the user can model lane-dependent speed limits, which are considered for lane changing
- **Advanced merging:** if this option is checked, vehicles are allowed to start their necessary lane changing earlier, so it will reduce the probability of vehicles to wait at emergency stop position
- Cooperative lane change: means that the trailing vehicle in the target lane observes the lane changer vehicle; it will then move to the next lane to let the vehicle change its lane.

3.4 Modeling AVs

AVs have different capabilities and performance than other Regular vehicles. AVs can be modeled in VISSIM through internal model interface and external interfaces as shown in Figure 9. The regular driving behavior parameters used by VISSIM should be adjusted in order to model the presence of AVs. VISSIM enables users to customize driving behaviors parameters such as (car following, lane changing, lateral behavior and reaction to signal controls). However, the modeled traffic network is a freeway segment, which means that there are no signals in the network, so there is no need to modify signal control parameters in the driving behavior. In addition, the freeway lanes are wide enough for one vehicle, and overtaking is not allowed. Therefore, there is no need to modify later behavior parameters as they define the interaction between vehicles in the same lane if the lane is wide enough, and overtaking is allowed.

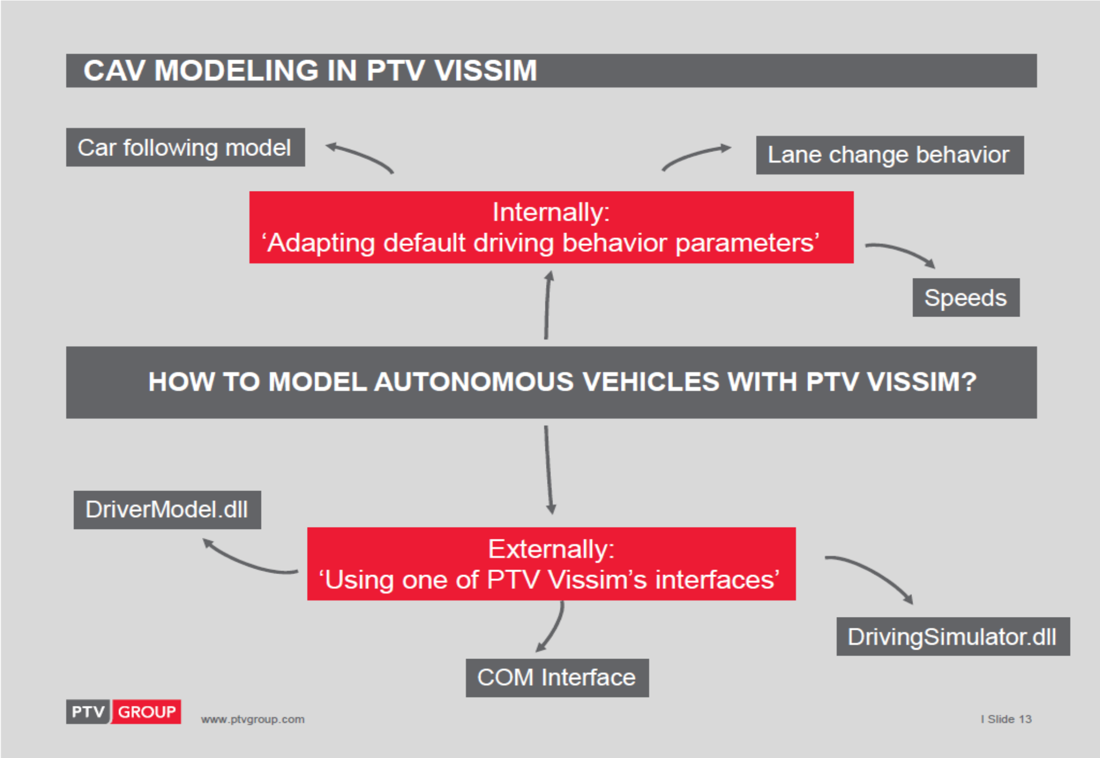


Figure 9: AVs modeling in PTV VISSIM [40].

Although AVs driving behavior is under development, and there is no standard driving behavior model of AVs, in this research, AVs driving behavior model parameters are adjusted based on literature review.

Based on the general understanding of the driving behavior of AVs, it can be described as follow:

- AVs keep smaller standstill distance;
- AVs keep smaller headway.
- AVs keep the desired speed strictly (without a distribution).
- AVs accelerate & decelerate equally (without a distribution).

The adjusted driving behavior parameters are described in this section. PTV Group has provided guidance recommendations on how to model AVs in VISSIM as shown in Table 7 [41]. Some of the recommended adjustments can be done through the internal model interface. (Refer to Equations 9,10 and Table 6).

Table 7: Recommendations for modeling connected and autonomous vehicles in VISSIM [41].

No.	Connected and Autonomous Vehicle Behavior	**Recommended Model Adjustment**
1	Keep smaller standstill distances	W74: change W74ax parameter, W99: change CC0 parameter
2	Keep smaller distances at non-zero speed	W74: change W74ax, W74bxAdd, and W74bxMult parameters; W99: change CC0, CC1, and CC2 parameters
3	Accelerate faster and smoothly from standstill	W74: change acceleration functions, W99: change acceleration functions and CC8, CC9 parameters
4	Keep constant speed with no or smaller oscillation at free flow	COM Interface or External Driver Model/Driving Simulator Interface
5	Follow other vehicles with smaller distance oscillation	W74: reduce W74bxMult or set it to 0, W99: change CC2 parameter
6	Form platoons of vehicles	COM Interface or External Driver Model/Driving Simulator Interface
7	Following vehicles react on green signal at the same time as the first vehicle in the queue	COM Interface or External Driver Model/Driving Simulator Interface
8	Communicate with other AVs, i.e. avoid broken-down vehicles	COM Interface or External Driver Model/Driving Simulator Interface
9	Communicate with the infrastructure, i.e. vehicles adjusting speed profile to reach a green light at signals	COM Interface or External Driver Model/Driving Simulator Interface
10	Perform more co-operative lane change as lane changes could occur at a higher speed co-operatively	Switch to cooperative lane change, change maximum speed difference, and change maximum collision time
11	Smaller lateral distances to vehicles or objects in the same lane or on adjacent lanes	Same lane – change default behavior when overtaking on the same lane and define exceptions for vehicle classes
12	Exclusive AV lanes, with and without platoons	Define blocked vehicle classes for lanes, or define vehicle routes for vehicle classes, use COM for platooning
13	Drive as CAV on selected routes (or areas) and as Regular human-controlled vehicles on other routes; i.e. Volvo DriveMe project	Use different link behavior types and driver behavior for vehicle classes; and/or (depending on complexity of CAV behavior) COM Interface
14	Divert vehicles already in the network onto new routes and destinations; i.e. come from a parking place or position in the network to pick up a rideshare app passenger on demand	COM Interface, Dynamic Assignment required (allows access to paths found by dynamic assignment, vehicles can be assigned a new path either when waiting in parking lot or already in the network, if path starts from vehicles current location)

The following are the adjusted car-following parameters:

- ‘Standstill distance (CC0) is reduced from 1.5 m to 0.75 m to reduce gaps between stopped vehicles since AVs can keep smaller gaps [39].
- AVs can operate with a shorter THW than Regular vehicleswithout affecting the safety of the traffic. Therefore, the parameter ‘Headway time (CC1) is set to 0.3 s [31].
- AVs keep smaller distance at non-zero speed ‘Car-following distance/following variation parameter’; (CC2) is reduced by 25% from 4 m to 3 m to reduce gaps between moving vehicles and make AVs follow other vehicles with smaller oscillation distance [41].
- Negative and positive threshold values are reduced from 0.35 to 0.1 to increase the sensitivity of following vehicles to leading vehicles acceleration or deceleration [42].
- Since AVs keep the desired speed strictly without distribution and oscillation, the ‘Speed Dependency of Oscillation parameter’ (CC6) is set to 0 to make the speed oscillation independent of the distance to the preceding vehicle.
- CC8 (standstill acceleration) and CC9 (Acceleration at 80 km/h) are increased from 3.5 m/s^2 and 1.5 m/s^2 to 4 m/s^2 and 2 m/s^2 respectively, to make AVs accelerate faster and more smoothly from standstill [42].
- AVs are equipped with ultrasonic sensors and radars that increase the area scanned by the vehicle to allow the vehicle to observe more activities on the road than the human driven vehicles, and thus the look ahead and look back distances are increased to be twice the values of the human-driven vehicles, and the number of observed vehicles is increased from 2 to 10 vehicles [42].
- ‘Temporary lack of attention parameter’ is set to 0 since AVs have no temporary lack of attention.

The list of default and modified Car-Following parameters values of Wiedemann 99 Car-Following model are summarized in Table 8.

Table 8: Car Following Parameters – Wiedemann 99 Model

Parameter	Default Value	Used Value for AVs
CC0 - Standstill distance (m)	1.5	0.75
CC1 - Headway time (gap between vehicles) (seconds)	0.9	0.3
CC2 - Car-following distance/following variation (m)	4.00	3.00
CC3 - Threshold for entering following (seconds)	-8	-12
CC4 - Negative following threshold (m/s)	-0.35	-0.1
CC5 - Positive following threshold (m/s)	0.35	0.1
CC6 - Speed dependency of oscillation (1/(m.s))	11.44	0
CC7 - Oscillation during acceleration (m/s^2)	0.25	0.25
CC8 - Standstill acceleration (m/s^2)	3.5	4
CC9 - Acceleration at 50 miles per hour (m/s^2)	1.5	2
Look ahead distance	0 to 250 m	0 to 500 m
Look back distance	0 to 150m	0 to 300m
Observed vehicles	2	10
Smooth close-up behavior	Checked	Checked

Adjusted lane change parameters:

- 'Advanced merging' option should be activated since AVs will make their routing decision in advance. Therefore, by activating this option, they will change their lanes to the next connector along their routes earlier.
- AVs communicate with each over through V2V communication system, to announce their movement decisions, so they will perform more cooperative lane change

maneuvers than RVs, and thus lane changing parameters should be changed to facilitate lane changing between AVs as follow:

- As mentioned before, AVs can operate with shorter time headway safely, so the 'Min. headway' parameter will be reduced from 0.50 m to 0.4 m, which reduces the acceptable distance between two vehicles after lane changing thus facilitate lane changing between AVs [41].
- 'Safety distance reduction factor' will be reduced by 25% to allow smaller gap between the lane changing vehicle and the trailing vehicle during lane changing maneuver [41].
- 'Maximum declaration for cooperative braking' parameter will be increased from -3 to -4 m/s2 to make the trailing vehicle brakes more cooperatively [41].
- 'Cooperative Lane change' should be activated with 'Maximum speed difference' set to 10.80 km/h and 'Maximum collision time' set to 10 s [43].
- The complete list of the modifications of lane changing parameters of AVs is shown in Table 9.

Table 9: Lane change parameters

Parameter	**Default Value**	**Used Value for AVs**
General behavior	Free lane selection	Free lane selection
Maximum deceleration - own vehicle (m/s^2)	-4.00	-4.00
Maximum deceleration - trailing vehicle (m/s^2)	-3.00	-3.00
-1 m/s^2 per distance - own vehicle and trailing vehicle (m)	100	100
Accepted deceleration - own vehicle (m/s^2)	-1.00	-1.00
Accepted deceleration - trailing vehicle (m/s^2)	-1.00	-1.00
Minimum headway - front/rear (m)	0.5	0.4
Safety distance reduction factor	0.6	0.45
Maximum deceleration for cooperative braking (m/s^2)	-3.00	-4.00
Cooperative lane change	Not checked	Checked
Maximum speed difference (km/h)	10.80	10.8
Maximum collision time (seconds)	10	10

3.5 Scenario Description

Each scenario will be simulated for 5 runs, with different random seed number and the trimmed average of the three middle values, for each simulation, will be considered the average result [12], [44]. Each run lasts for 5400 seconds (1.5 hours). The results were collected from time span 900-4500 seconds (1 hour), and half an hour warm up period (15 min. at the start and 15 min. at the end) is used to saturate the system and eliminate the start-up period that begins with an empty system.

Chapter 4: Results and Discussion

As mentioned before, the impact of each mode share value of AVs (0%, 5%, 10%, 15%, 20%, 25%, 40%, 60%, 80%, and 100 %) on freeway traffic performance is evaluated at different demand to capacity ratios (0.6, 0.8, 1.0 and 1.2). Some statistical analyses are carried out to understand the impact of AVs on freeway traffic performance at different mode share values and demand to capacity ratios. This will require calculating some descriptive statistics, such as trimmed average and standard deviation for each scenario and conduct some tests of hypotheses to examine the significance of the difference between the scenarios.

4.1 Results Relative to Different Mode Shares of AVs

In this section, the performance of both AVs and RVs (in terms of average speed, travel time and delay) for each demand to capacity ratio is evaluated at each AVs mode share scenario. The numerical values, reported in this section, are the percent improvements or reductions for each demand to capacity ratio at different mode share scenarios, compared to the baseline scenario, which is 0% AVs.

4.1.1Average speed. The average speeds for AVs and RVs were obtained for different demand to capacity ratios. The values shown in this section are the percentage of improvement in average speed relative to 0% AVs.

When the demand to capacity ratio is set to be 0.6, the average speeds for AVs and RVs are obtained for all AVs mode shares, as summarized in Figure 10.

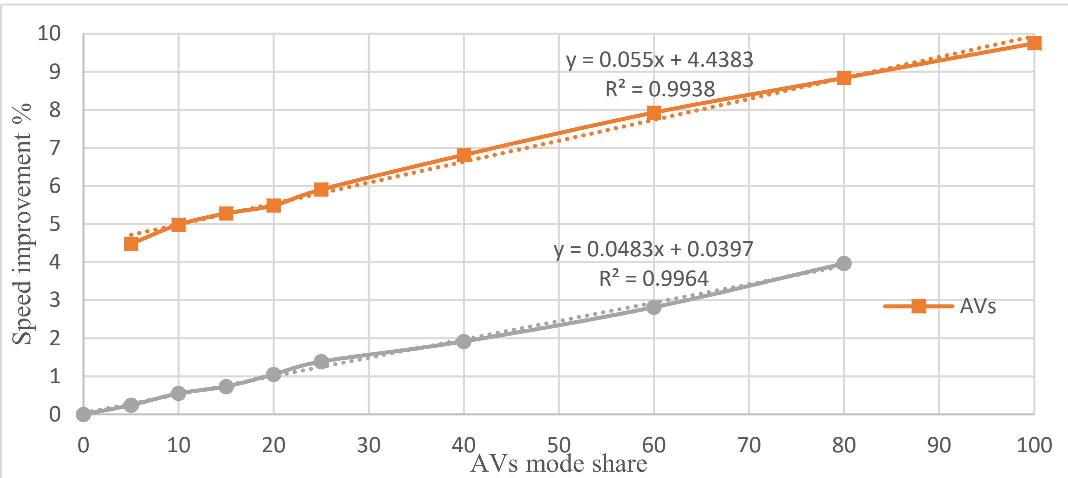


Figure 10: Average speed at 0.6 demand to capacity ratio

The data in Figure 10 shows that as the AVs mode share increases from 0% to 100%, the average speeds of AVs and RVs increase gradually as the AVs travel with a higher speed. The AVs average speed shows an improvement that ranges from 4.48% (at 5% AVs) to of 9.75% (at 100% AVs), relative to 0% AVs scenario. For RVs, the maximum increase in the average speed is 3.97% (at 80% AVs). In addition, the slope of each trend line, shown in Figure 11, indicates that the rate of improvement for AVs' average speed is (0.055), which is higher than the rate of RVs (0.0483). At a demand to capacity ratio of 0.8, the average speed data for AVs and RVs are presented in Figure 11.

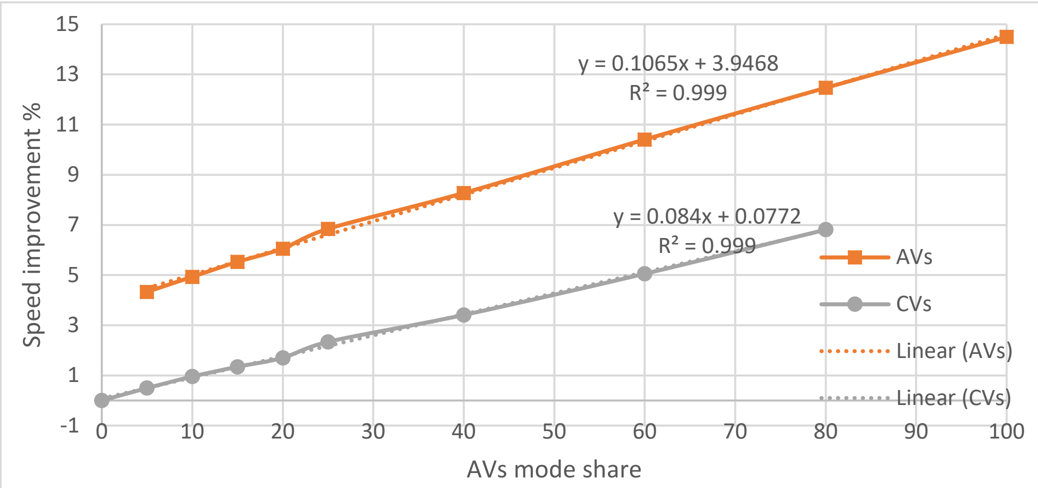


Figure 11: Average speed at 0.8 demand to capacity ratio.

The general trend of the average speed at 0.8 demand to capacity ratio is similar to 0.6 case as the average speed increases with the increase of AVs mode share, except that the percentage of improvement increases from 9.75% to 14.5% for AVs (at 100% AVs) and from 3.97% to 6.81% for RVs (at 80% AVs). This can be due to the fact that when the demand to capacity ratio increases from 0.6 to 0.8, the number of AVs increases, so their impact on average speed is higher. Moreover, when the demand to capacity ratio increases from 0.6 to 0.8, the rate of improvement (slope) almost doubled from 0.055 to 0.1065 for AVs and from 0.0483 to 0.084 for RVs.

The average speed data at a demand to capacity ratio of 1.0 were obtained as illustrated in Figure 12.

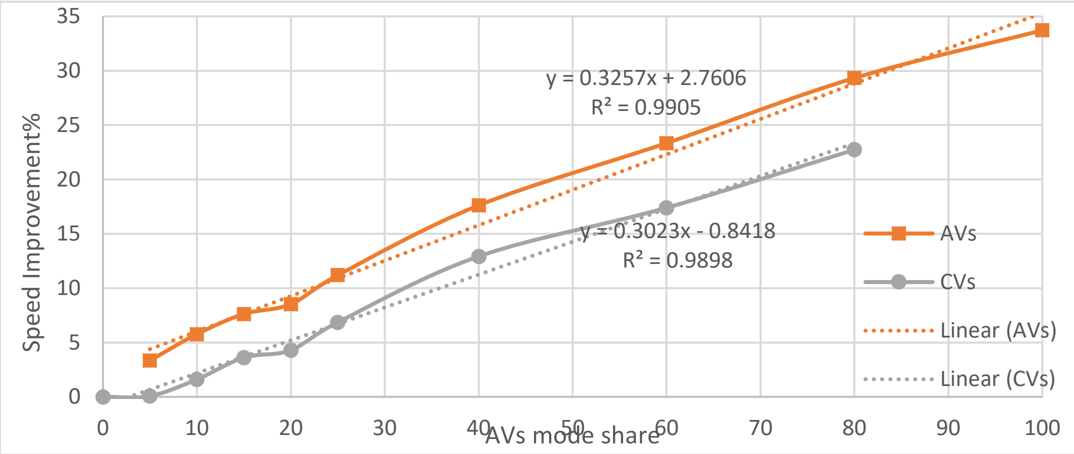


Figure 12: Average speed at 1.0 demand to capacity ratio.

In this scenario, the average speed for AVs improves by more than the double, compared to 0.8 case with 33.72% improvement (at 100% AVs), while the average speed improvement for RVs at 80% AVs increases to 22.73%, which is 3 times the improvement in 0.8 case. Moreover, the slope of each trendline increases significantly relative to the 0.8 case from 0.1065 to 0.3257 for AVs and from 0.084 to 0.3023 for RVs. This trend of change in improvement level is similar to the trend observed between 0.6 to 0.8 demand to capacity ratio, but with higher magnitude of the change.

Figure 13 provides the summary of the average speed data for the demand to capacity ratio of 1.2.

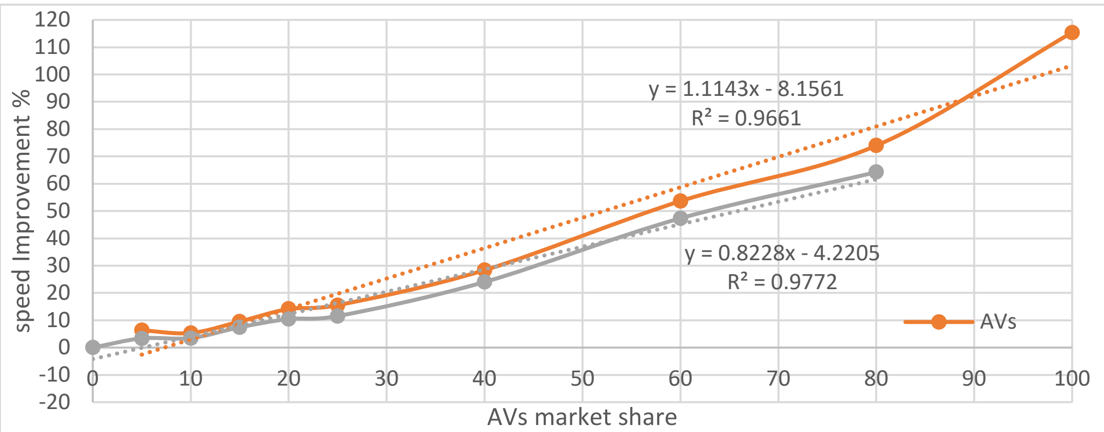


Figure 13 Average speed at 1.2 demand to capacity ratio

Figure 13 indicates a huge increase in average speed at 1.2 demand to capacity ratio, compared to the other cases. The percentage of improvement for AVs (115.39%) is 12 times higher than 0.6 case, 8 times higher than 0.8 case and 4 times higher than 1.0 case. Furthermore, the percentage of improvement for RVs significantly increases as well relative to the other cases. This is due to the fact that at low to moderate demand to capacity ratios (0.6 and 0.8), vehicles travel with a speed close to the posted speed, so the improvement in average speed is small. However, at high demand to capacity ratios (1.0 and 1.2), the baseline average speed (at 0% AVs) is relatively low as vehicles travel with a low speed due to high congestion. Therefore, any improvement in the average speed is obvious and significant, which is why 1.2 and 1.0 demand to capacity ratios have higher percentages of improvement than 0.6 and 0.8 demand to capacity ratios. This huge increase can also be noticed in the slope of trendlines for both AVs and RVs as they increase to 1.1143 and 0.8228 respectively.

4.1.2. Travel time. Considering different demand to capacity ratios, the simulation results shows the travel times for AVs and RVs, are discussed in this Section. The comparisons in this section show the percentage of reduction in travel time, relative to the 0% AVs. For demand to capacity ratio of 0.6, the results are depicted in Figure 14.

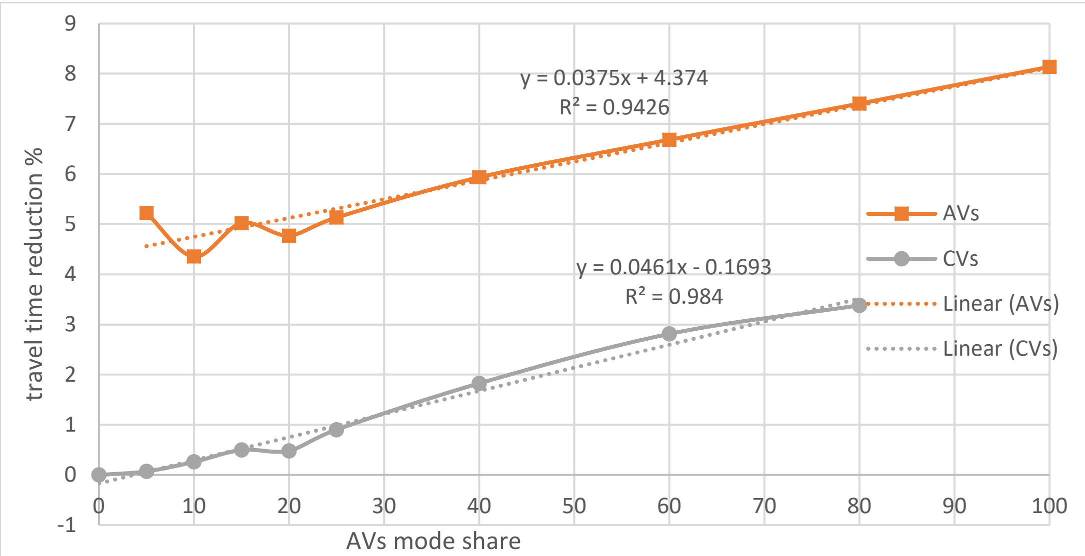


Figure 14: Travel time at 0.6 demand to capacity ratio

For the considered demand to capacity ratio (0.60), the travel time improves by 8.14 % for AVs and 3.38% for RVs, as the mode share increases from 0 to 100%. This reduction in travel time is because of the average speed increased (as observed earlier). However, it can be noted that from 0% to 25% mode share, the percentage of improvement for AVs fluctuates, then it increases at a constant rate. Similar to the average speed case, the travel time improvement for AVs is much higher than RVs as the mode share increases from 0% to 100% (8.14% for AVs and 3.38% for RVs), but the slope of RVs trend line (0.0461) is slightly higher than AVs' trend line slope (0.0375). This difference can be a result of the high fluctuations in the AVs data for low mode shares (5% to 25%).At 0.8 demand to capacity ratio travel time results are shown in Figure 15.

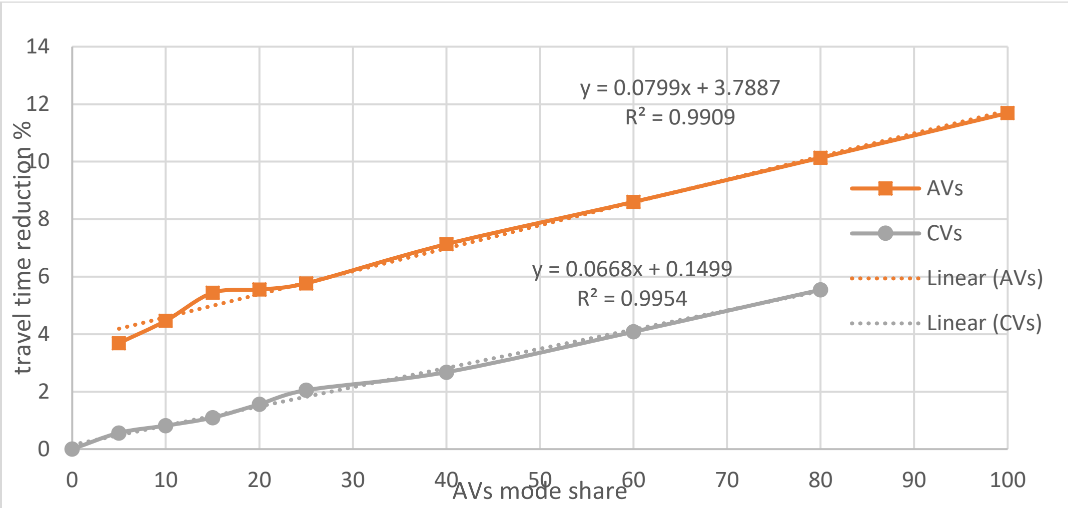


Figure 15: Travel time at 0.8 demand to capacity ratio

According to Figure 15, the demand to capacity ratio of 0.8 has a higher improvement percentage of travel time relative to 0.6 case as AVs' percentage of improvement increases from 8.14% to 11.69%, while RVs' percentage of improvement increases from 3.38% to 5.54%. This improvement in travel time is due to the fact the AVs travel with a smaller THW, compared to RVs. This, in turns, increases the number of gaps in the network, and thus decreases the travel time of vehicles. In the contrary of 0.6 case, AVs' travel time improved at higher rate (0.0799) than RVs (0.0668).

Travel time data at 1.0 demand to capacity ratio is illustrated in Figure 16.

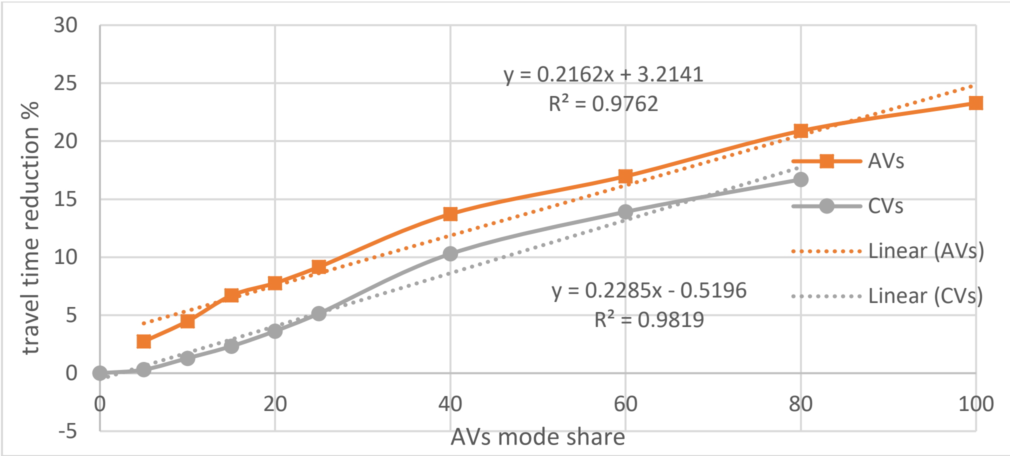


Figure 16: Travel time at 1.0 demand to capacity ratio

The percentage of travel time improvement for AVs (23.28%) is almost double the percentage in 0.8 case, while the percentage of improvement for RVs (16.69%) increased threefold compared to 0.8 case as indicated in Figure 16. Although the rate of improvement for both AVs and RVs increased relative to 0.8 case, RVs improvement was at a slightly higher rate (0.02285) than AVs (0.02162) similar to what was observed in 0.8 case. At this demand to capacity ratio the congestion is very high, and the network is saturated which means there are no gaps and the travel time for RVs is very high at 0% so providing any gaps (by increasing AVs mode shares) improves the rate of RVs significantly.

The travel time when the network is oversaturated at 1.2 demand to capacity ratio is obtained in Figure17.

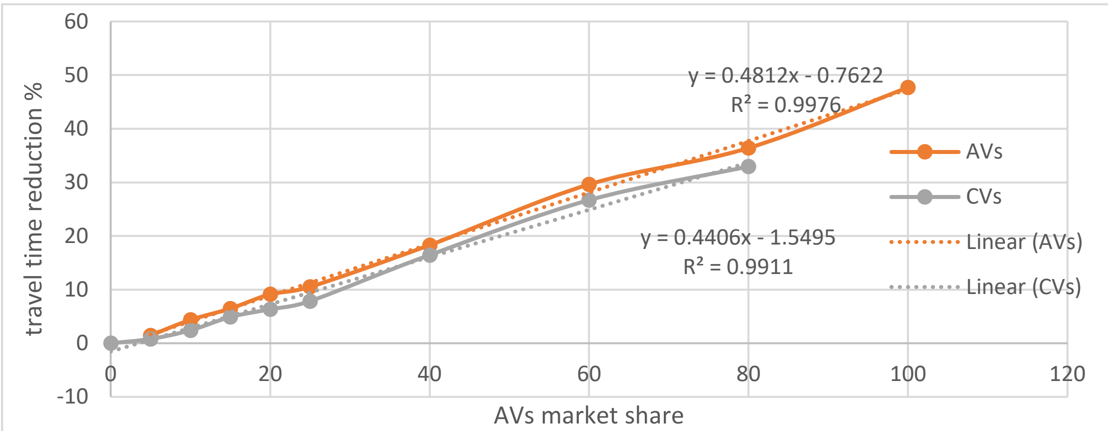


Figure 17: Travel time at 1.2 demand to capacity ratio

By comparing travel time results at 1.2 demand to capacity ratio with other cases, a significant improvement of travel time can be noted as the percentage of improvement for AVs (47.7%) is 6 times 0.6 case, 4 times 0.8 case and double 1.0 case. While the percentage of RVs (32.97%) is almost 10 times 0.6 case, 6 times 0.8 case and double 1.0 case. This significant increase can be noted also by comparing the rate of improvement for both AVs and RVs with the other cases.

As shown in Figure 17, the slope of AVs is close to the slope of RVs, which means that the difference between their values is relatively less than other cases, because when the congestion increases, and the network becomes oversaturated, all vehicles even RVs are forced to keep smaller gaps and move in a platoon like AVs.

4.1.3 Delay. The delays at different demand to capacity ratios are measured. The delay is calculated by subtracting the optimal travel time (when the vehicles travel with posted speed) from observed travel time (when the vehicles travel with a speed less than posted speed). In addition, the ratios shown in the delay comparisons are the percentage of reduction in delay, relative to the 0% AVs. For 0.6 demand to capacity ratio delay data is depicted in Figure 18.

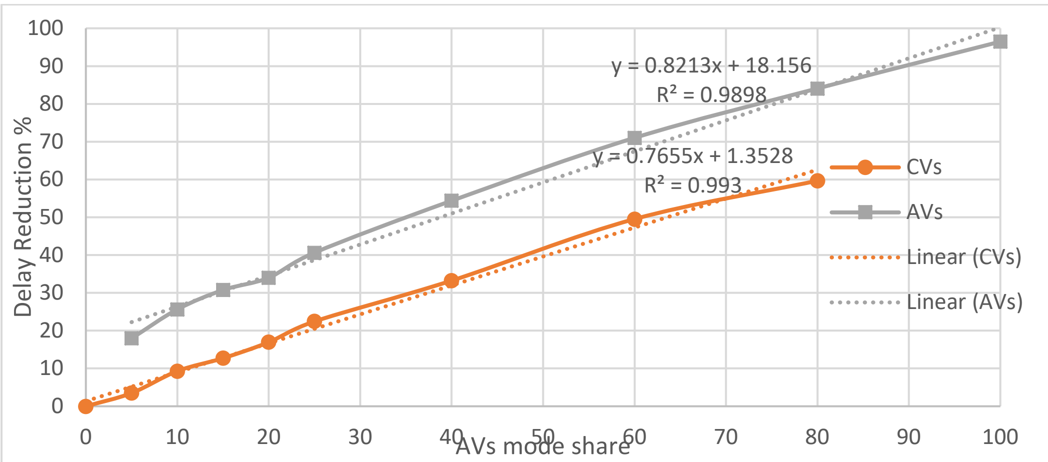


Figure 18: Delay at 0.6 demand to capacity ratio

Figure 18 indicates that the delay decreases as the mode share of AVs increases. As the mode share of AVs increased from 0% to 100 %, the total delay decreases (improves) by 96.47% for AVs and 59.67% for RVs, which helped to achieve the reduction in travel time, as observed in the previous section. However, the percentages of improvement for delay are much higher than travel time percentages because delay values are small in magnitude, so any small improvement in delay time will result in a significant percentage improvement in delay.

The slope of each trend line shows that the total delay for AVs improved at a higher rate (0.8213) than RVs (0.7655).

Delay data at 0.8 demand to capacity ratio were obtained and summarized in Figure 19.

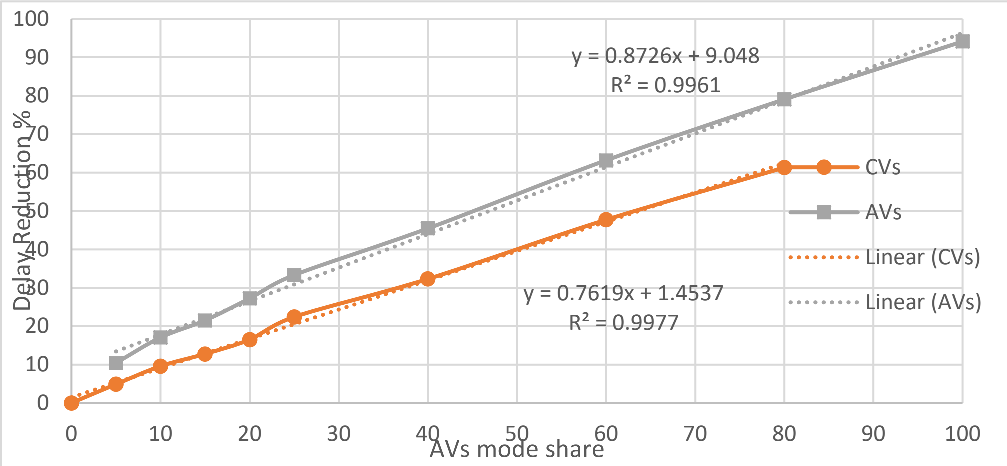


Figure 19: Delay at 0.8 demand to capacity ratio

In comparison with 0.6 case, the percentage of total delay improvement for RVs increases from 59.67% to 61.27%, while the percentage of improvement for AVs decreases from 96.47% to 94.09%. However, the slope for AVs trendline increases from 0.8213 to 0.8726 while the slope of RVs trendline slightly decreased from 0.7655 to 0.7619.

At 1.0 demand to capacity ratio delay data is presented in Figure 20.

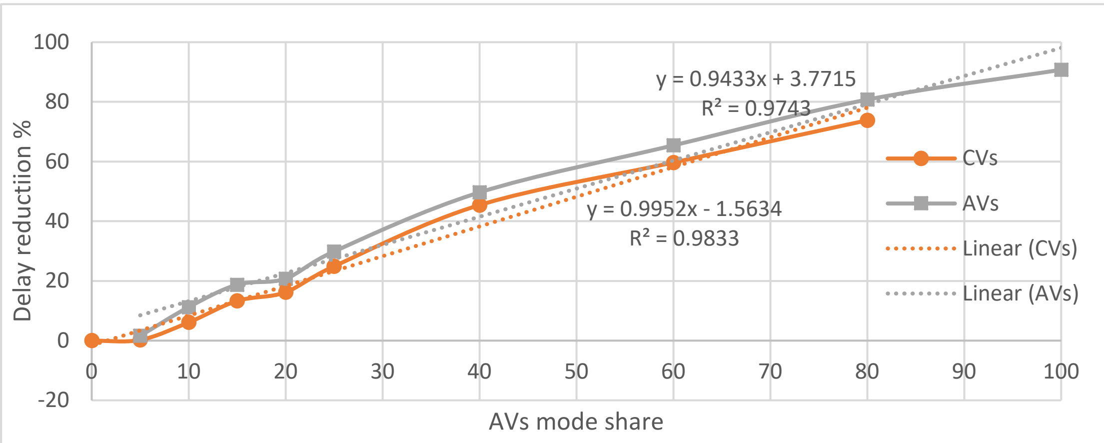


Figure 20: Delay at 1.0 demand to capacity ratio

According to Figure 20 the delay improves by 90.74% for AVs and 73.83% for RVs. It can be noted from Figure 19 that the difference between total delay percentages of AVs and RVs is relatively small, compared to 0.6 and 0.8 cases. Also, the slope of AVs' trend line (0.9433) is close to the slope of RVs' trendline (0.9952).

Delay data at 1.2 demand to capacity ratio is illustrated in Figure 20.

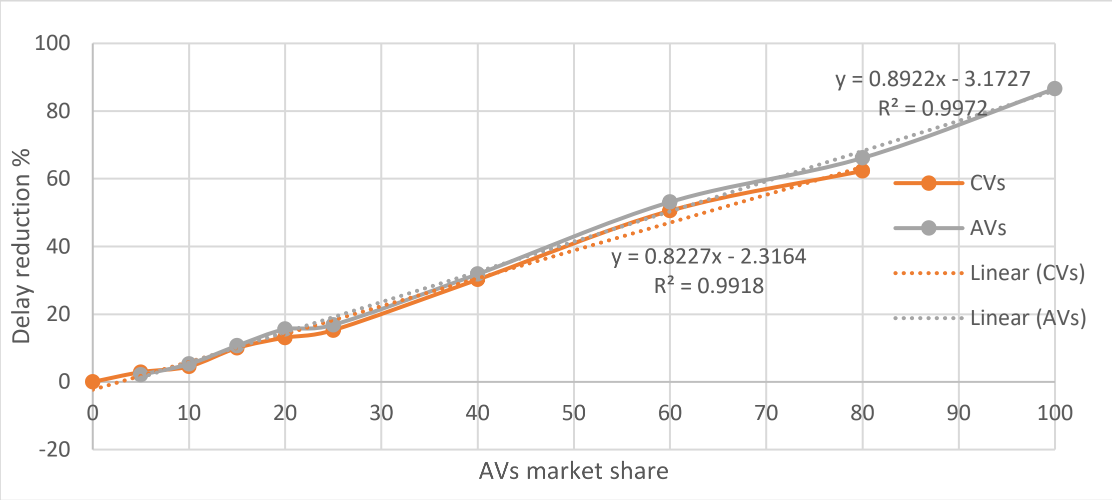


Figure 21: Delay at 1.2 demand to capacity ratio

Similar to other cases, the total delay improved as the mode share of AVs increased from 0% to 100% by 86.62% for AVs and 62.34% for RVs.

Similar to what was observed in the demand to capacity ratio1.0 case, the difference between AVs and RVs improvement is very small, compared to other cases. Figure 21 shows that total delay percentages for AVs and RVs are almost the same from 0% to 80% mode share. This small difference between AVs and RVs in this level of congestion is due to the high traffic flow with a small number of gaps, so the vehicles can't travel freely. All vehicle types are stacked and drive close to each other, so their travel time and their total delays are close.

In summary, the results of this section show that:

1) Increasing AVs fleet percentage yields an increase in average speed and a decrease in travel time and delay, as RVs are replaced with AVs that strictly keep the dominant speed without distribution and oscillation and travel with a smaller THW unlike RVs that travel with a random speed value with a larger THW. Therefore, this provides smooth uniform traffic flow and more gaps in the network.

2) The performance improvement increases as the demand to capacity ratio increases, which is consistent with (Aria el al., 2016) findings that positive effects of AVs are highlighted in a heavy traffic flow when the congestion increases and when the traffic flow becomes denser.
3) The network performance (average speed, travel time and delay) improvement rate increases rapidly when the AVs percentage exceeds 25%. As AVs percentage increases in the overall vehicles' fleet mix, and when they become the majority, their positive effects become more obvious

4.2 Results Relative to Different Demand to Capacity Ratios

In this section, performance measures (average speed, travel time and delay) are compared at different demand to capacity ratios for each AVs mode share, and the baseline scenario will be 0.6 demand to capacity ratio with 0% AVs.

4.2.1 Average speed. The average speeds for both AVs and RVs at different mode shares and demand to capacity ratios are compared. These comparisons show the ratios of reduction in average speed relative to 0.6 demand to capacity ratio with 0% AVs. The comparison of AVs average speed at low mode shares (5% to 20%) and high mode shares (25% to 100%) are summarized in Figure 22.

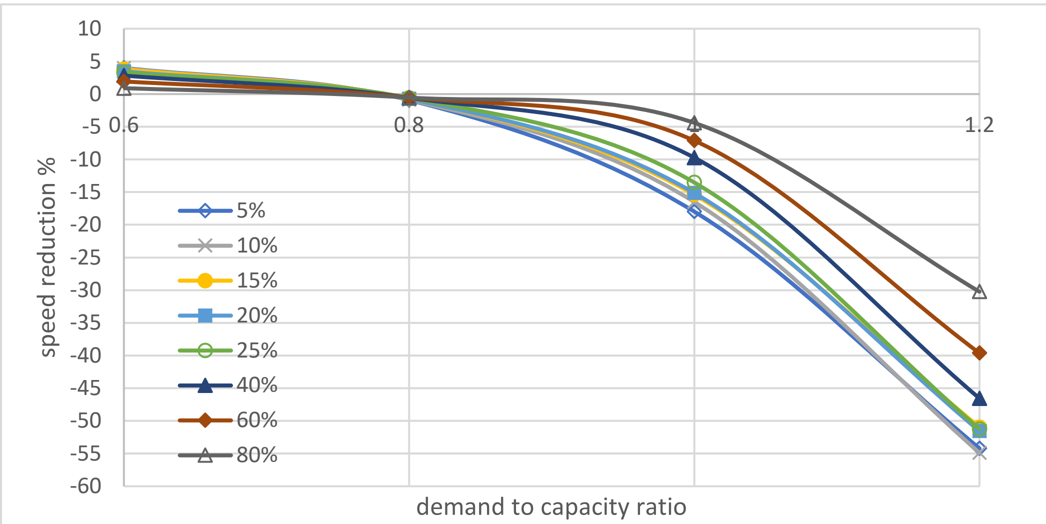


Figure 22: AVs average Speed

As the demand to capacity ratio increases, the average speed decreases as the network becomes more crowded and as density increases as indicated in Figure 22. In addition, the reduction in average speed due to congestion is less at high mode share, as 100% has the lowest reduction percentage among the other mode shares. Further, It can be noted from Figure 21 that all the curves have positive percentages (which means improvement in average speed) and negative percentages (which means reduction in average speed). At low mode shares of AVs all curves have positive percentages at 0.6 demand to capacity ratio while at high mode shares all curves have positive percentages from 0.6 to 0.8 demand to capacity ratios which means at low mode shares of AVs the average speed improves with the increase of AVs mode share relative to the base scenario and then it decreases from 0.8 to 1.2 demand to capacity ratios while at low mode shares of AVs the average speed increases with the increase of AVs mode share until the demand to capacity ratio is more than 0.8.

Figure 23 shows the results of RVs average speed performance.

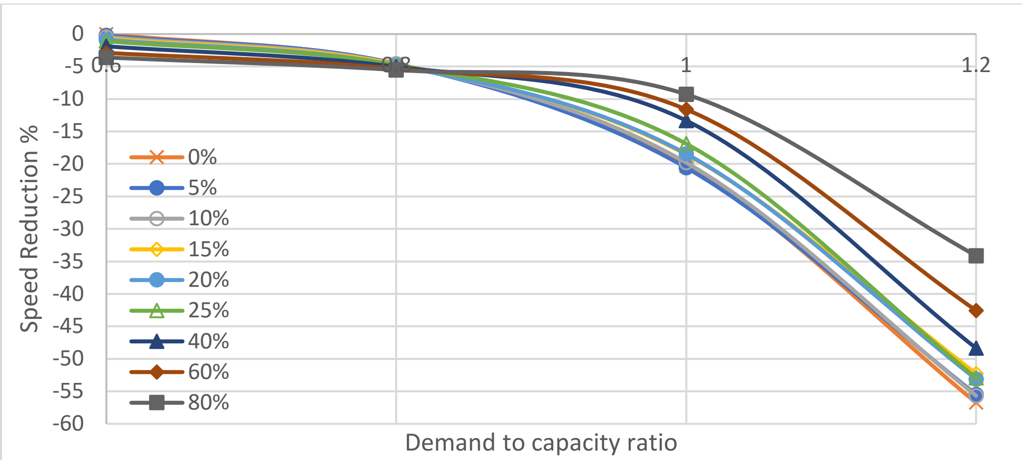


Figure 23: RVs average Speed

By Comparing AVs speed ratio with RVs, it can be noted that the speed reduction percentage at 1.2 demand to capacity ratio with 100% AVs is 6.8% as shown in Figure 22 which is close to the reduction percentage at 0.8 demand to capacity ratio with 0% AVs as shown in Figure 23. On the other hand, the speed reduction percentage at 1.2 demand to capacity ratio with 0% AVs is 56.74% as shown in Figure 22 that means having 100% AVs improves the network average speed at high congestion level instead of getting 56.74% reduction in average speed it becomes only 6.8%.

4.2.2 Travel time. Travel time data at different demand to capacity ratios and different mode shares for AVs and RVs are obtained. Figure 24 illustrates travel time data for AVs at low mode shares and high mode shares.

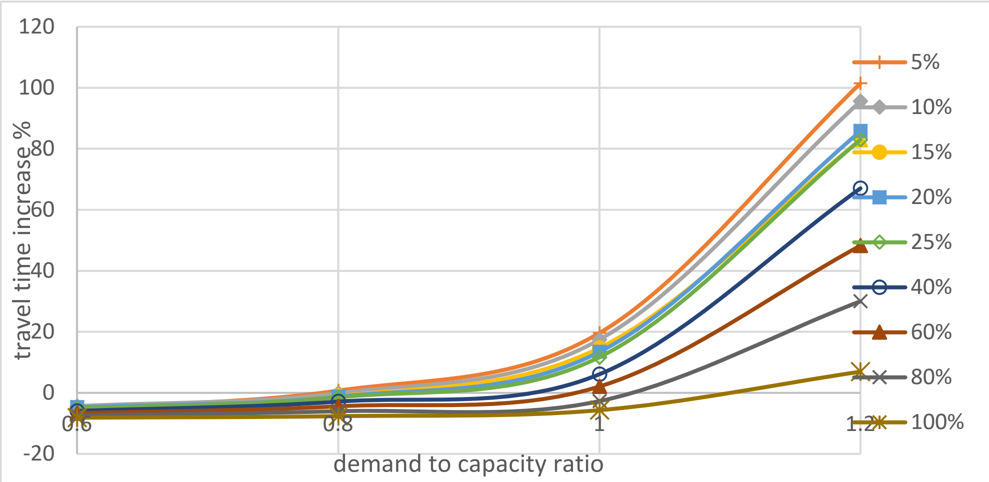


Figure 24: AVs travel time

Form Figure 24, it can be noted that the travel time increases as the demand to capacity ratio increases from 0.6 to 1.2, and as the network gets more crowded and traffic density increases. In addition, as the mode share increases, the increase of travel time decreases. At 1.2 demand to capacity ratio, the travel time increases by 101.453 at 5% while it increases by -6.94% at 100%. Moreover, it can be noted that there is a slight difference between the curves at low mode share values (5% to 20%), while there is a significant difference between the curves at high mode share values (25% to 100%).

Travel time data for RVs at low mode and high mode shares are obtained and summarized in Figure 25

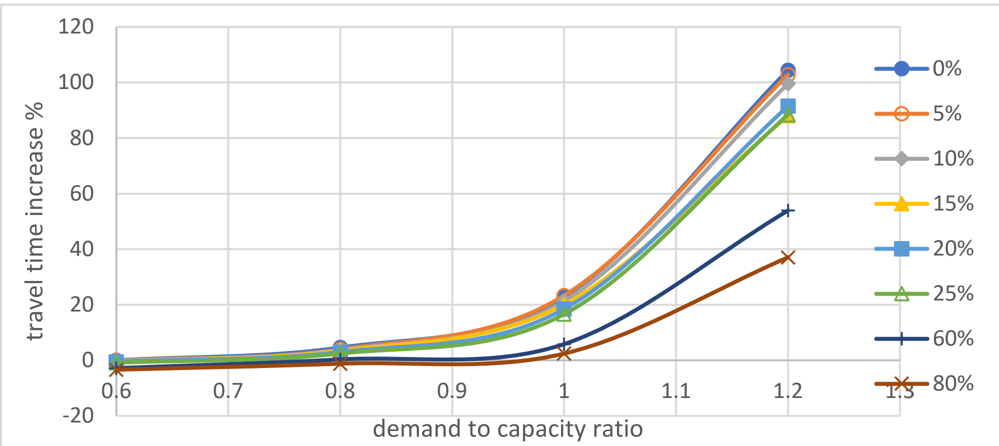


Figure 25 RVs travel time

Similar to what was observed earlier in the previous section the travel time increase at 1.2 demand to capacity ratio with 100% AVs (6.94%) is much lower than the increase at the same demand to capacity ratio with 0% AVs (104.5%) because RVs are replaced with AVs that perform better at high congestion with lower travel time values than RVs.

4.2.3 Delay. Delay data for both AVs and RVs at different mode shares and demand to capacity ratios are compared to the baseline scenario (0.6 demand to capacity ratio with 0% AVs).Delay data for AVs at low and high mode shares are indicated in Figure 26.

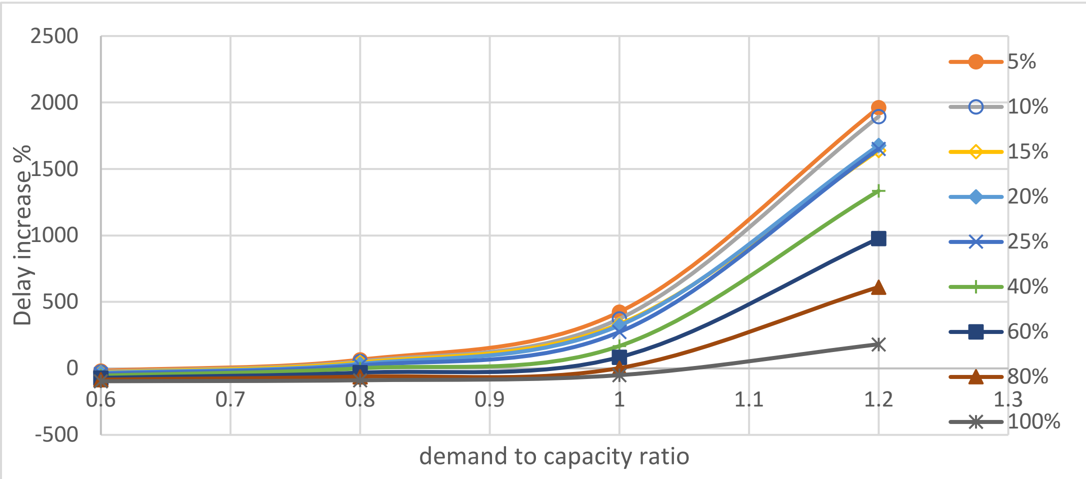


Figure 26: AVs delay

As illustrated in Figure 26, The total delay increases as the demand to capacity ratio increases from 0.6 to 1.2, the demand to capacity ratio increases as the number of vehicles in the network increases and the traffic becomes denser the delay increases this in turns increases the travel time as observed in the travel time section. Figures 27 depicts delay data for RVs at low and high mode shares.

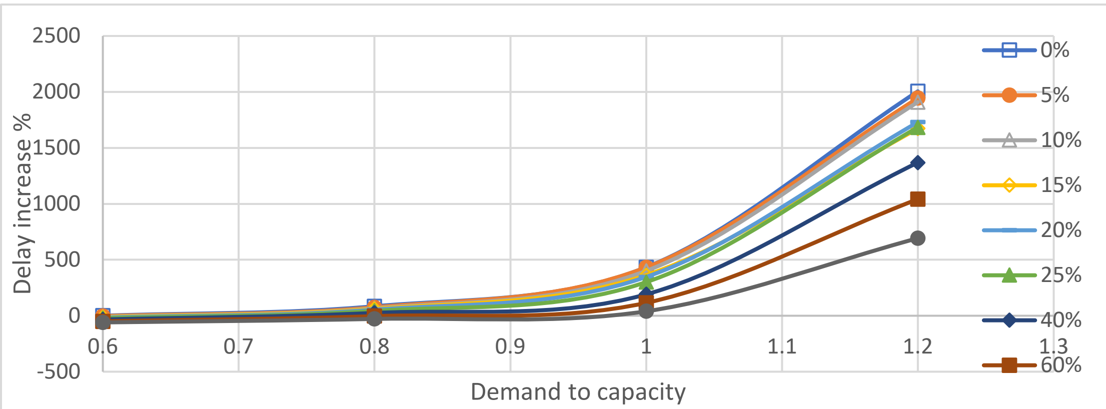


Figure 27: RVs delay

By comparing the increase of delay of 100% mode share at 1.2 demand to capacity ratio (181.7%) shown in Figure 26 with the increase of 0% mode share at the same demand to capacity (2005%) shown in Figure 27. It can be noted that the delay time at 100% is much lower than 0% mode share at the same level of congestion that means when AVs replace RVs in the network the delay time improves, and it achieves less increase in delay time with the increase of congestion

To sum up of what was observed in this section. The results show that

1) AVs high mode shares are less affected by the increase in demand to capacity ratio as they have high average speed and less travel time and delay, compared to low mode shares.
2) As the mode share of AVs increases in the traffic fleet and they replace RVs the performance of the network (in terms of average speed, travel time and delay) is less impacted by the increase of congestion.

4.3 T-test

Any of the traffic performance measures (average speed, travel time and delay) is a random variable that has natural variations. In this section, a test of hypotheses is conducted (using the t-test) to check that the variations of traffic performance measures are not random variations in the data, and that they are due to the difference between distributions. Therefore, this test is applied to determine whether the difference between the means of two scenarios or the means of AVs and RVs is due to random variations of the variables or due to the variations of the distributions. Dependent (paired) t-test is conducted to compare the means of overall speed values of the network at different mode share to determine whether there is a significant difference between the scenarios. The Pooled Variance independent t-test will be conducted to compare the means of the speed values of AVs and RVs in the same scenario (the same mode share value) to determine whether there is a significant difference between AVs and RVs speed values.

Two hypotheses tests are formed and evaluated. The Null hypothesis (H_0) which assumes that there is no difference between the two means [45].

H_0: $\mu_1 = \mu_2$

The Alternative hypothesis (H_a) which assumes that there is a difference between the two means [45].

H_a: $\mu_1 \neq \mu_2$

Where:

μ_1: the mean of the first scenario.

μ_2: the mean of the second scenario.

Δ = the difference between means.

When conducting the test two possible errors may occur

Type 1 error which is rejecting H_0 when it's actually true.

Type 2 error which is accepting H_0 when it's false.

No reasonable test procedure can guarantee a complete protection against these errors. So, there is a probability of making these errors. The probability of making type1 error is denoted by α and called level of significance. If $\alpha = 0.01$ that means that if the test procedure is used repeatedly on different samples H_0 would be rejected when it's true only 1 % of the time.

In this test procedure $\alpha = 0.05$ will be used.

t-test equation and tables is used to calculate P-value then compared with α .

if P-value $\leq$ α reject H_0

if P-value $>$ α accept H_0

4.3.1 Difference between scenarios. In this section, dependent (paired) t-test is carried out to examine the difference between scenarios' speeds. The following equation is used to calculate t value.

$$t = \frac{\bar{d}-\Delta}{\frac{s_d}{\sqrt{n}}}, \tag{17}$$

where

n = number of pairs

$\bar{d}$ = the mean difference

Δ = the difference between means

s_d = standard deviation of the difference

P-value is calculated from t curves with n-1 degree of freedom

- At 0.6

P-values at 0.6 demand to capacity ratio are calculated and compared with α. The results are summarized in Table 10.

Table 10: T-test for the difference between scenarios' speed at 0.6 demand to capacity ratio

Scenarios	P-value	Decision
0% and 5%	2.56E-04	reject H_0
5% and 10%	1.42E-04	reject H_0
10% and 15%	2.55E-03	reject H_0
15% and 20%	2.50E-04	reject H_0
20% and 25%	4.50E-04	reject H_0
25% and 40%	09.52E-06	reject H_0
40% and 60%	4.50E-05	reject H_0
60% and 80%	6.67E-08	reject H_0
80% and 100%	4.57E-07	reject H_0

According to Table 10 all p-values are less than α which means that the null hypothesis is rejected, and that means increasing AVs mode share from 0% to 100% yields a significant improvement in average speed values

- At 0.8

Table 11 contains P-values at 0.8 demand to capacity ratio.

Table 11: T-test for the difference between scenarios' speed at 0.8 demand to capacity ratio.

Scenarios	P-value	Decision
0% and 5%	3.71E-03	reject H_0
5% and 10%	2.32E-03	reject H_0
10% and 15%	1.75E-04	reject H_0
15% and 20%	3.45E-03	reject H_0
20% and 25%	5.73E-04	reject H_0
25% and 40%	1.32E-04	reject H_0
40% and 60%	1.66E-05	reject H_0
60% and 80%	8.59E-08	reject H_0
80% and 100%	1.62E-05	reject H_0

Table 11 shows that there is a significant difference between each mode share average speeds at 0.8 demand to capacity ratio as all the values are less than α so the null hypothesis is rejected similar to 0.6 case any change in AVs mode share yields a significant difference in average speed.

- At 1.0

Table 12 indicates p-values and decisions at 1.0 demand to capacity ratio.

Table 12: T-test for the difference between scenarios' speed at 1.0 demand to capacity ratio

Scenarios	P-value	Decision
0% and 5%	0.905033	accept H_0
5% and 10%	0.117918	accept H_0
10% and 15%	0.228552	accept H_0
15% and 20%	0.050008	accept H_0
20% and 25%	0.026343	reject H_0
25% and 40%	0.003259	reject H_0
40% and 60%	0.011524	reject H_0
60% and 80%	0.001202	reject H_0
80% and 100%	0.006914	reject H_0

From Table 12 it can be noted that from mode share 0% to 20% the difference between consecutive scenarios insignificant thus the null hypothesis is accepted. At this ratio the network is crowded and at low mode shares AVs are interrupted by RVs, so they can't move freely with high speed thus the improvement in average speed is insufficient below 20 %. Above 20% the improvement is significant when the mode share increases to 25% to 100% and AVs are dominating the traffic fleet.

- At 1.2

P-values at 1.2 demand to capacity ratio are shown in Table 13.

Table 13: T-test for the difference between scenarios' speed at 1.2 demand to capacity ratio

Scenarios	P-value	Decision
0% and 5%	0.467	accept H_0
5% and 10%	0.868	accept H_0
10% and 15%	0.076	accept H_0
15% and 20%	0.322379	accept H_0
20% and 25%	0.744	accept H_0
25% and 40%	0.0185	reject H_0
40% and 60%	0.00361	reject H_0
60% and 80%	0.00352	reject H_0
80% and 100%	0.000363	reject H_0

Similar to 1.0 demand to capacity ratio at low mode shares the improvement in average speed is insignificant as shown in Table 13 from 0 to 25% the null hypothesis is accepted. Above 25% the improvent in average speed becomes significant.

4.3.2 Difference between AVs and RVs speed values. In this section, Independent (pooled variance) t-test is conducted to determine whether there is a significant difference between AVs and RVs average speed values in the same scenario, using the following equation:

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{{s_1}^2}{n_1} + \frac{{s_2}^2}{n_2}}} \tag{18}$$

where:

$\bar{x}_1$: mean of group1

$\bar{x}_2$: mean of group2

s_1 : sample variance of group1

s_2 : sample variance of group 2

n_1 : number of observations of group1

n_2 : number of observations of group 2

- At 0.6

Independent T-test was conducted between AVs and RVs average speeds, and P=values were calculated and summarized in Table 14.

Table 14: T-test between RVs and AVs speeds at 0.6 demand to capacity ratio

Scenarios	P-value	Decision
5%	1.9266E-08	reject H_0
10%	3.59779E-09	reject H_0
15%	1.98112E-08	reject H_0
20%	2.05817E-08	reject H_0
25%	5.01216E-09	reject H_0
40%	1.40731E-09	reject H_0
60%	3.17224E-12	reject H_0
80%	7.26973E-09	reject H_0

According to Table 12 there is a significant difference between AVs and RVs speed values at any mode share values as the congestion at this demand to capacity ratio is small, so AVs can travel freely with speeds significantly higher than RVs.

- At 0.8

p-values at 0.8 demand to capacity ratio are obtained and shown in Table 15

Table 15: T-test between RVs and AVs speeds at 0.8 demand to capacity ratio

Scenarios	P-value	Decision
5%	1.23986E-07	reject H_0
10%	8.15699E-08	reject H_0
15%	1.41604E-07	reject H_0
20%	5.60178E-08	reject H_0
25%	6.14618E-07	reject H_0
40%	2.82743E-08	reject H_0
60%	7.85416E-12	reject H_0
80%	4.085E-09	reject H_0

Similar to 0.6 case, there is there is a significant difference between the means of AVs and RVs speed values for the same reason that AVs travel much faster than RVs at low congestion.

- At 1.0

Table 16 shows p-values at 1.0 demand to capacity ratio

Table 16: T-test between RVs and AVs speeds at 1.0 demand to capacity ratio

Scenarios	P-value	Decision
5%	3.25E-03	reject H_0
10%	6.8E-03	reject H_0
15%	9.4E-04	reject H_0
20%	4.078E-03	reject H_0
25%	1.80E-03	reject H_0
40%	1.323E-02	reject H_0
60%	2.39E-03	reject H_0
80%	1.47984E-06	reject H_0

Also, as in case 0.6 and 0.8 there is a significant difference between AVs and RVs speeds and the null hypothesis is accepted.

- At 1.2

p-values at 1.2 demand to capacity ratio is indicated in Table 17.

Table 17: T-test between RVs and AVs speeds at 1.2 demand to capacity ratio

Scenarios	P-value	Decision
5%	0.538	accept H_0
10%	0.713	accept H_0
15%	0.658	accept H_0
20%	0.372	accept H_0
25%	0.441	accept H_0
40%	0.467	accept H_0
60%	0.235	accept H_0
80%	0.164	accept H_0

Unlike other demand to capacity ratios, it can be noted form Table 17 that there is no significant difference between AVs and RVs average speeds at all mode shares, which is consistent with Figure 14 because at this ratio the network is oversaturated. therefore, AVs are forced to travel with low speeds close to RVs speed values.

Chapter 5: Summary and Conclusions

5.1 Summary

Autonomous vehicles are the next generation vehicles that have drawn significant attention recently, as a lot of vehicles manufacturers and IT companies take a race in producing and developing these vehicles. Not only that, but it also has become a major concern to major cities such as Dubai to adopt this new technology as part of their transformation process. However, the introduction of this technology is expected to have various impacts. These impacts should be studied in order to evaluate and maximize the benefits of these vehicles and avoid and solve the risks and errors associated with them. The purpose of this research is to determine how the adoption of AVs can impact the traffic performance of Dubai's network.

The study was conducted on a section of E311 freeway. The study area encompassed about 10 freeway Km (with five lanes in each direction) and six junctions (two right-in-right-out junctions, a single point interchange and two full-cloverleaf junctions with additional ramps). VISSIM software was used to develop microsimulation model to evaluate different scenarios that represent different mode share of AVs and different demand to capacity ratios. this study considers various mode shares for AVs (0%, 5%, 10%, 15%, 20%, 25%, 40%, 60%, 80%, and 100%.). It should be noted that the 0% will be used as a benchmark for comparison purposes. Different traffic demand to capacity ratios are evaluated by considering demand to capacity ratios of 0.6, 0.8, 1.0, and 1.2 to represent uncongested, congested, very congested, and oversaturated conditions, respectively.

The following section provides the main conclusions of this research, based on the obtained results.

5.2 Conclusions

Considering the speed, travel time, and delay values obtained from the simulation outputs for all AVs mode shares and all congestion levels considered in the experimental design, the following can be concluded:

- The level of improvement in freeway performance increases as the mode share of AVs increases. In addition, the impact of AVs is higher under more congested conditions.

- RVs show performance improvements that are very close to those achieved by AVs at or above capacity.
- There is a significant difference between the AVs and RVs performance at demand to capacity ratio of 0.6 and 0.8, for all AVs mode shares. For higher demand to capacity ratios (1.0 and 1.2), there is a significant difference between the AVs and RVs performance at high AVs mode shares (above 25%).
- The highest percentage of improvement for average speed and travel time is achieved at 1.2 demand to capacity ratio with 100% AVs mode share. However, the highest percentage of improvement of delay is achieved at 0.6 demand to capacity ratio with 100% AVs mode share.
- At low mode share of AVs (from 5% to 20%) the improvement of average speed ranges from 6.33% to 14.15% at 1.2 demand to capacity ratio while the improvement at high mode shares of AVs (from 25% to 100%) ranges from 15.53% to 115.40% at 1.2 demand to capacity ratio.
- The percentage of reduction of travel time for AVs at low mode shares ranges from 1.47% to 9.14% while the reduction percentage at high mode shares of AVs ranges from 10.51% to 47.70% at 1.2 demand to capacity ratio
- The average delay for AVs at low mode shares improved by 2.07% at 5% AVs to 15.57% at 25% AVs at 1.2 demand to capacity ratio. While the percentage of reduction at high mode shares ranges from 16.84% to 86.62% at 1.2 demand to capacity ratio.
- At the same mode share, increasing the congestion yields a reduction in performance, but this reduction is less at high mode share values. This means that high mode shares of AVs are less affected by congestion, and they can perform better than lower mode shares.

In conclusion, AVs positively affect the network performance in terms of average speed, travel time and delay as AVs can travel with higher speed and with a smaller THW than regular vehicles. This will increase the number of gaps in the network, and thus increase capacity. Further, these positive effects are significant with large mode share of AVs, as regular vehicles are replaced by AVs, and as they become the majority in the traffic fleet.

As AVs require less lateral space, further improvements can be obtained by reducing lane width, and as a consequence, the number of lanes will be increased, and thus the road capacity will be increased. This can be done at 100% AVs mode share. At high mode shares, some of road lanes can be designated to AVs use only. These lanes can be narrowed so the number of lanes can be increased. Therefore, the results obtained from this thesis represent a lower bound of the actual improvements that can be achieved.

It is recommended for transport agencies to consider the following recommendations:

1. At the early stages of implementation (low AVs mode shares), the AVs can share the lanes with RVs and there is no need to modify the freeway cross-section (i.e. no need to change the lane width), as the number of AVs will not justify such change and the expected improvements are not high enough as well.
2. For the long-term plans, the transport agencies can plan for gradual change of the freeway lane width. Some lanes can be dedicated to AVs and accordingly a smaller width for these lanes can be applied. This will result in a higher number of lanes on the freeway as the AVs require smaller lane width. When the AVs mode share reaches 100%, all the freeway lanes will have smaller width and the total number of lanes on the freeway is expected to be much higher.

5.3 Future work

This research considered only the impacts of AVs on Freeway performance without any considerations of changing the lane width or changing any of the road characteristics. Therefore, future work can consider the following:

- Safety on both Freeways and intersections
- AVs' system failure and how they will perform in this case
- Performance of AVs on arterial streets' networks dealing with signalized junctions and roundabouts
- Capacity impacts of reducing lane width to get the expected higher values of improvements more than what was reported in this research.

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Appendix A

Considering the speed, travel time, and delay values obtained from the simulation outputs for all AVs mode shares and all congestion levels considered in the experimental design, the percentage of speed improvements for AVs and RVs are summarized in the Tables 18 and 19, respectively.

Table 18: Average speed improvement percentages for AVs

	Demand to Capacity ratio			
AVs mode share	0.6	0.8	1.0	1.2
5%	4.480602	4.33141	3.346118	6.329714
10%	4.983866	4.932443	5.770795	5.322659
15%	5.278834	5.52853	7.62401	14.96167
20%	5.486156	6.055703	8.518851	14.15253
25%	5.905125	6.843714	11.19122	15.52921
40%	6.81594	8.274807	17.61675	28.33558
60%	7.927285	10.40646	23.34695	53.63629
80%	8.838578	12.46561	29.33062	73.95463
100%	9.746211	14.49599	33.71592	115.3939

Table 19: Average speed improvement percentages for RVs

	Demand to Capacity ratio			
AVs mode share	0.6	0.8	1.0	1.2
5%	0.243338	0.492696	0.080972	3.359298
10%	0.551509	0.954635	1.610659	3.473866
15%	0.731608	1.344433	3.613593	11.9025
20%	1.051236	1.699911	4.282509	10.47829
25%	1.387936	2.338812	6.860873	11.51815
40%	1.916883	3.410339	12.92358	24.00551
60%	2.815556	5.052958	17.39545	47.33813
80%	3.965799	6.809604	22.73268	64.23883

The percentages of travel time reduction for AVs and RVs are presented in Tables 20 and 21, respectively.

Table 20: Travel time improvement percentages for AVs

	Demand to Capacity ratios			
AVs mode shares	0.6	0.8	1.0	1.2
5%	0.328163	3.690421	2.729199	1.470488
10%	0.669309	4.464582	4.483493	4.355536
15%	1.175858	5.43793	6.698759	10.52983
20%	1.338672	5.551698	7.771201	9.142178
25%	1.960159	5.768067	9.156461	10.51287
40%	3.469065	7.130411	13.71359	18.30204
60%	5.134995	8.600062	16.97798	29.62379
80%	6.600265	10.13742	20.87873	36.41146
100%	8.137926	11.69227	23.28329	47.69703

Table 21: Travel time improvement percentages for RVs

	Demand to Capacity ratios			
AVs mode shares	0.6	0.8	1.0	1.2
5%	0.070532	0.565203	0.303289	0.799748
10%	0.259935	0.81635	1.290757	2.411344
15%	0.49742	1.095733	2.325075	8.01515
20%	0.480563	1.560861	3.63451	6.341237
25%	0.902529	2.05016	5.14739	7.852647
40%	1.825319	2.677651	10.28564	16.45352
60%	2.812359	4.081867	13.90707	26.69549
80%	3.382888	5.543002	16.69655	32.96612

Finally, the delay improvements for AVs are illustrated in Table 22, while the values for RVs are shown in Table 23.

Table 22; Delay improvement percentages for AVs

	Demand to Capacity ratios			
AVs mode shares	0.6	0.8	1.0	1.2
5%	17.96159	10.42575	1.607591	2.066885
10%	25.632	17.04898	11.22892	5.263599
15%	30.75683	21.50262	18.74688	17.39857
20%	34.00479	27.21968	20.7497	15.5712
25%	40.64393	33.30374	29.87921	16.84266
40%	54.37905	45.43159	49.66882	31.8309
60%	71.02078	63.16755	65.42202	53.13976
80%	84.07906	79.02794	80.75725	66.1617
100%	96.47415	94.09442	90.74282	86.61859

Table 23: Delay improvement percentages for RVs

	Demand to Capacity ratios			
AVs mode shares	0.6	0.8	1.0	1.2
5%	3.501177	4.880225	0.234069	2.876839
10%	9.305782	9.582162	6.103599	4.556007
15%	12.72224	12.76263	13.2988	15.80713
20%	16.94675	16.49172	16.19109	13.08928
25%	22.44414	22.40117	24.91873	15.27285
40%	33.24432	32.27769	45.42199	30.22117
60%	49.53414	47.68623	59.70036	50.56866
80%	59.6704	61.27407	73.82784	62.34323

Vita

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