ANALYZING THE FREEWAY CAPACITY AND EXAMINING THE IMPROVEMENTS VIA CONNECTED AND AUTONOMOUS VEHICLES

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ABSTRACT

Technology is getting better and improving each and every day. Transportation systems are getting smarter and more tolerant of human errors. In the near future, it won't be surprising to see autonomous vehicles on our roads. However, this can not happen in one night and there will be a transition phase where conventional and automated vehicles will coexist.

Connected vehicle technology will provide many opportunities. Reduced accident rates, reduced emissions, reduced parking requirements, reduced congestion and reliable journeying times are some of these advantages. Micro simulations have been broadly adopted for many evaluations, and there are serious challenges that should be answered. In this regard, simulation model calibration and validation are crucial for evaluating the potential improvements offered by connected car technology.

In this research, possible changes happening on the freeway merge sites through the usage of connected vehicle technology tried to be investigated by using a VISSIM simulation model that meets current peak capacities.

As a result of the experiments and investigations, it has been found that, when compared to traffic with only conventional vehicles, the vehicle capacity in the research area increases by an average of 5% for every 10% increase in autonomous vehicles. Additionally, it was shown that penetration rates up to 40% had the best results, outperforming all other percentages by a considerable margin. To conclude, the addition of autonomous vehicles for the enhancement of effective traffic management made a significant improvement to the transportation study. However, additional studies and applications of the same logics with various models is advised to improve future studies.

Key words: Traffic Simulation, Parameter Calibration, Connected Vehicle Technology, Freeway Capacity, Vissim.

OTOYOL BAĞLANTI KAPASİTESİNİN ANALİZİ VE BAĞLANTILI ARAÇ TEKNOLOJİSİ İLE YAPILABİLECEK İYİLEŞTİRMELERİN İNCELENMESİ

ÖZET

Teknoloji her geçen gün daha ileriye gidiyor ve gelişiyor. Ulaşım sistemleri giderek daha akıllı hale geliyor ve insan hatalarına karşı daha toleranslı oluyor. Yakın gelecekte otonom araçları yollarımızda görmek hiç de şaşırtıcı olmayacak. Ancak bu olay bir gecede gerçekleşmeyecek ve şuan kullanılan araçlar ile otonom araçların bir arada kullanıldığı bir geçiş aşaması olacak.

Bağlantılı araç teknolojisi beraberinde birçok fırsatı getirecektir. Azalacak kaza oranları, karbon emisyonları, daha az park gereksinimleri, trafik sıkışıklığı ve güvenilir yolculuk süreleri bu gibi avantajlardan bazıları olacak. Mikrosimülasyon modelleri birçok değerlendirme ve araştırma için geniş çapta benimsenmiştir ve yanıtlanması gereken ciddi soruları beraberinde getirmektedir. Bu bağlamda, simülasyon modeli kalibrasyonu ve doğrulanması, bağlantılı araç teknolojisinin sunduğu potansiyel iyileştirmelerin irdelenmesi için çok önemlidir.

Bu araştırmada, mevcut kapasiteleri karşılayan bir VISSIM simülasyon modeli kullanılarak, bağlantılı araç teknolojisinin kullanımıyla otoyol kavşak bölgelerinde meydana gelecek olası değişiklikler araştırılmaya çalışılmıştır.

Yapılan deneyler ve araştırmalar sonucunda, sadece konvansiyonel araçların kullanıldığı trafiğe kıyasla araştırma alanındaki araç kapasitesinin otonom araçlardaki her %10'luk artış için ortalama %5 oranında arttığı tespit edilmiştir. Ek olarak, %40'a varan girişim oranlarının en iyi sonuçlara sahip olduğu ve diğer tüm yüzdelerden daha önemli bir farkla gelişim gösterdiği ölçülmüştür. Bununla birlikte, gelecekte yapılacak çalışmaların iyileştirilmesi için ek çalışmalar ve aynı mantığın çeşitli modellerle uygulanması tavsiye edilmektedir.

Anahtar Kelimeler: Trafik Simülasyonu, Parametre Kalibrasyonu, Bağlantılı Araç Teknolojisi, Otoyol Kapasitesi, Vissim.

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Berkcan KÜÇÜKOĞLU

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LIST OF ABBREVIATIONS

AV	Autonomous Vehicles
CAV	Connected Autonomous Vehicles
CMU	Carnegie Mellon University
DCP	Data Collection Point
FHWA	U.S. The Federal Highway Administration
HGV	Heavy Goods Vehicle
MDOT	Maryland Department of Transportation
ODOT	Oregon Department of Transportation
PDOT	Pennsylvania Department of Transportation
N-Curve	Newell Oblique Curve
RTMS	Remote Traffic Microwave Sensor
SEA	Society Of Automotive Engineers
SRF	Safety Distance Reduction Factor
V2I	Vehicle-to-Infrastructure Communication
V2V	Vehicle-to-Vehicle Communication
V2X	Vehicle-to-Everything Communication
W-74	Wiedemann 74
W-99	Wiedemann 99

CHAPTER 1

1. INTRODUCTION

1.1 Study Purpose and Background

Although it will take some time, automation will be a part of our future. As is already common knowledge, technology is continually developing and getting better. Automobiles are becoming more intelligent and forgiving of human errors. There will be a long transitional period in which conventional and automated vehicles coexist. Not only one type of automated vehicle will begin to operate on our roads, but many more will gradually replace conventional vehicles in time.

In recent years, microscopic simulation models have played an important role in the evaluation of transportation system analysis, traffic strategies and alternatives. Impacts of autonomous vehicles usage on our networks can be estimated by microscopic simulation models. Obtaining the appropriate driving behavior parameters, which frequently change from study area to study area, is a problem when employing these software models. As a result, the model's default parameter settings are inappropriate for use in our research. This paper conducts a study of simulation model calibration and validation for selected study area and replacing the conventional vehicles with autonomous vehicles to identify and observe the changes happening on the freeway merge sites through the Connected Autonomous Vehicles (CAV) technology .

Fully autonomous vehicles will start to appear on our roads in future and having these fleets of Autonomous Vehicles (AVs) operating into our networks will require some preparation and lead us to ask and answer questions like what the impacts will be on our transport systems.

Calibrated VISSIM model and RTMS data from the Traffic Control Center of the Istanbul Metropolitan Municipality were used as references to research this subject.

1.2 Thesis Statement and Objectives

The two primary objectives of this research are to find the driving behavior parameters in the VISSIM simulation model that are compatible with current peak traffic capacity and to find and monitor the changes occurring at freeway merge sites using connected car technology. In order to verify our argument and offer a solution to our question, an appropriate study location in Istanbul with significant vehicle traffic from the O-2 Freeway has been simulated by using VISSIM. The map view of the chosen study area is displayed in Figure 1.1 down below. By making field observations, margin capacities, mainstream capacity, volumes of upstream directions, number of stops and more have been determined.

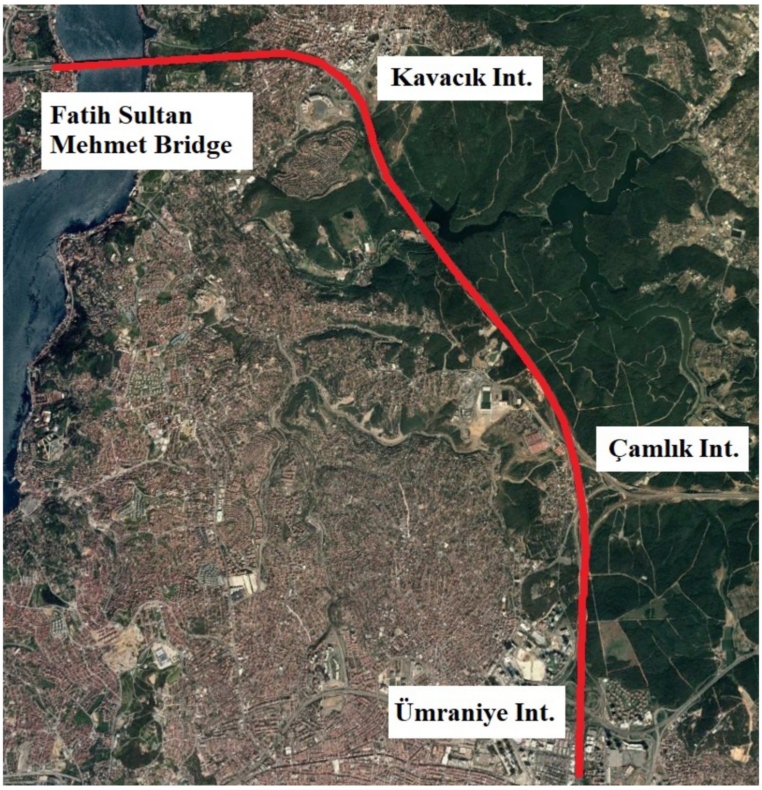

Figure 1.1 Schematic View of Study Area in O-2 Freeway in Istanbul, Source: Google Earth

1.3 Summary of Content

The remainder of the research is planned as follows. A brief review of the literature on VISSIM and AVs, driving behavior models, parameters, and the construction of the research network in VISSIM are covered in sections 2 and 3 of the study. This is followed by a calibration methodology as tested on a freeway in Istanbul, Turkey. The detailed discussion of the simulation outcomes in the final chapter is followed by our analysis and recommendations for additional study.

CHAPTER 2

2. LITERATURE REVIEW

Since simulations are safer, more affordable, and quicker than field implementation and testing, they are becoming an increasingly popular method of traffic analysis among professionals [1]. It is also an effective tool for working and evaluating the current state, proposed solutions, and alternatives. Despite the fact that the majority of studies investigated beyond the calibration of the model, the literature review for this study focuses primarily on the calibration of simulation, AVs, and VISSIM, which is utilized in this research.

There is a substantial amount of literature on the creation, verification, and use of VISSIM. The car-following model concept was approved for usage in Germany and internationally by Fellendorf and Vortisch [2] after they conducted an examination of the model for German and American conditions.

In a traffic network that interacts with light rail transit, Moen [3] carried out a comprehensive verification of VISSIM and tested it with CORSIM's capacity to model the performance of automotive traffic.

Gomes [4], with the “Congested Freeway Microsimulation Model Using VISSIM” was the one study that decided to adopt manual calibration. The authors of this study used a complex and crowded 24 kilometer stretch of freeway as their subject. There were mainly three bottlenecks, metered on-ramps, and high-occupancy vehicle lanes. The authors did not employ common metrics of effectiveness like volume, travel time, or delay because of the peculiar circumstances. Therefore, they made an effort to replicate the qualitative features of the road, such as bottleneck locations, queue lengths, and length of queues. Due to a lack of processing power, manual calibration was used in significant proportion.

For a 2-to-1 lane configuration freeway work zone with a 75 km/h speed limit, Kan [5] calibrated the VISSIM car-following parameters. With a total of nine different time intervals over the course of 48 minutes, they calibrated input demand volumes for a simulation program that matched the pattern of data gathered from a work zone. Finally, they made a comparison between the flow rate and speed statistics that were calculated in the microsimulation program and gathered in the field over the course of 48 minutes.

Manual calibration is still often employed, especially in private consultation, despite the fact that it is typically not advised due to the large number of parameter possibilities in microsimulation software. Due to the analyst's ability to view the model animation and contrast it with his or her experience, some of its benefits include being low on computational demand, relatively simple to implement, and compatible with qualitative effectiveness measures like bottleneck length, time, and location as well as general driver behavior. The biggest drawback is that the answer could not be as good as one produced by an automated procedure.

After a good amount of examination has been conducted on model calibration, articles and presentations showed that every single model has to be calibrated manually based on the chosen study location. The chosen location for this study starts from the Ümraniye Tepeüstü cloverleaf junction to FSM Bridge in Istanbul. The model is approximately 24 kilometers long and Istanbul traffic is known for its aggressive lane-changing characteristics, with drivers constantly overtaking and cutting off the other drivers while taking every chance to change lanes. [6]. Driving parameters are modified during the calibration procedure so that the model's outputs resemble actual traffic data [7].

To accurately reflect the site conditions, any VISSIM model should always be calibrated according to the study area. Only some designs, which are frequently not described in great detail, are applicable to the default driving behavior settings offered by the software developers. The procedure of calibrating parameters makes sure that the model properly reproduces the observed traffic conditions [8]. For the purpose of accurate simulation calibration, the parameters, descriptions, and optimization techniques for the VISSIM driver behavior models, which also include speed decisions, car-following, and lane-change characteristics, are briefly reviewed.

Along with it, a brief discussion is made on AV knowledge, vehicle-to-vehicle (V2V) communication, and vehicle-to-everything (V2X) communication. Since designing a new self-driving behavior or testing the effectiveness of existing ones are not within the scope in this study, it will be sufficient for us to know only what the

AVs are, the opportunities they will bring into our lives and understand AVs working principles.

2.1 VISSIM & Model Calibration Knowledge

VISSIM is a microscopic, stochastic, time-step-based simulation developed by PTV Group, where individual vehicles act as the simulation's most basic building blocks. It is based on the Wiedemann lane-changing and car-following "psychophysical" model [9]. Performance metrics including speed, travel time, queue length, level of service, and more are influenced by the features and behavior of individual vehicles.

There are two models of driving behavior parameters; Wiedemann 74 (W-74) and Wiedemann 99 (W-99). The W-74 model, generally used for urban arterials and merging area models, and W-99 model used for highways and freeway travel models [9]. In this research, as VISSIM User Manual advised, the Wiedemann 99 (W-99) car-following model was used [10, 11].

In 2004, the U.S. The Federal Highway Administration (FHWA) released the Traffic Analysis Toolbox Volume III: Guidelines for Applying Traffic Microsimulation Modeling Software, which covered all aspects of microsimulation modeling and included a chapter on calibration [12]. The Oregon Department of Transportation later created its Protocol for VISSIM Simulation, which applied the FHWA's guidance to specific modeling software and further refined the calibration process [13]. By looking at other protocols created, the volume calibrations should not exceed 10% of the count traffic volume and/or GEH<5 [14].

2.1.1 Desired & Traveling Speed Decision

Instead of specific driving features like the desired speed, Wiedemann parameters are typically utilized to calibrate simulation models. However, speed is usually considered as a critical parameter, which has great influence on average travel speeds, roadway capacity, and travel time. Default and linear distributions of desired speed in VISSIM are not suitable for real traffic conditions or conventional vehicle compositions [15]. In order to simulate human driving behavior, desired speed also must be described as a distribution rather than a set value. For a better simulation, the target speed, and average speed is accurately determined and calibrated in this study.

2.1.2 Car-following Models and Wiedemann 99

The movements of a following vehicle in response to the actions of the lead vehicle are described by a car-following model. In the middle of the 1950s, the first car-following models were proposed [16, 17]. Since then, several models have been developed including the Helly [18], Gipps [19], and Wiedemann [10] models, the intelligent driver model [20], the optimal velocity model [21], and the Gazis Herman-Rothery model [22].

Finding a set of model parameters that minimize the difference between the values of the simulated and observed variables is the process of calibration. According to the psycho-physical models, a driver's behavior will change based on the type of traffic situation they are in, such as whether they are in a free-flow condition, approaching the vehicle in front of them, following them, or braking. The relative speed and relative distance from the lead vehicle are typically used to represent the boundary characteristics defining the various states [10].

By calibrating the simulation parameters, the user of the simulation aims to replicate the field measurements. The W-99 [10, 11], a car-following model that is applied to freeway circumstances, has ten different car-following variables that impact how drivers behave. Those are called CC0, CC1, CC2, CC3, . . . , CC8, CC9 [9]. The whole car-following process is based on repetitive acceleration and deceleration of vehicles with drivers having different perceptions of speed difference, desired speed, and the safety distance between two vehicles. There are four possible driving states in the simulation: free driving, approaching, following, and braking. The driving behavior parameters used in the W-99 car-following model are briefly described below.

CC0 is the standstill distance, which defines the desired distance between two vehicles at stopped condition. The default value is 1.50 m. in VISSIM.

CC1 is the desired time headway for the following vehicle. On the basis of these values the safety distance can be computed as dxsafe = CC0 + CC1 * v, where v is the speed of the vehicle [9]. The default time distribution value is 0.9 sec. in VISSIM. Higher CC1 values characterize less aggressive drivers and more gaps.

CC2 defines the threshold that restricts longitudinal oscillation beyond safety distance in the following process. The default value is 4 m. in VISSIM.

CC3 characterizes the entry to the following state of driving. It initiates the driver to decelerate upon recognizing a slower leading vehicle. It defines the time at which the driver starts to decelerate before reaching the safety distance. The default value is -8.0 in VISSIM.

CC4 and CC5 control the speed oscillations after the vehicle enters the following state. Smaller values signify a driver's sensitivity to the leading vehicle's acceleration or deceleration. CC4 is used for negative speed difference and CC5 is used for positive speed difference. The default value of CC4 and CC5 is -0.35 and 0.35 in VISSIM.

CC6 stands for dependency of speed oscillation on distance in the following state. An increased value of CC6 results in an increase of speed oscillation as the distance to the preceding vehicle increases.

CC7, CC8, and CC9 parameters control the acceleration process.

Tables 2.1, 2.2, and 2.3 show the general parameters of W74, and W99 models respectively. The first column contains the name of the parameter used by VISSIM, along with the parameter description, their range, and default values in other columns.

Table 2.1 VISSIM General Model Parameters

Parameter	Parameter Description	Range	Default
Look Back Dist.Max.	Max. look back distance [m]	50 ~ 200	150
Look Ahead Dist.Max.	Max. look ahead distance [m]	100 ~ 300	250
Observed Vehs.	Number of observed preceding vehicles [veh]	1.00 ~ 5.00	2.00
Standstill Dist.	Standstill distance in front of static obstacles [m]	0.00 ~ 3.00	0.50

Table 2.2 Wiedemann 74 Car-Following Model Parameters

Parameter	Parameter Description	Range	Default
W-74-Avg	Average standstill distance	0.50 ~ 2.50	2.00
W-74-Add	Additive factor for security distance	0.70 ~ 4.70	2.00
W-74-Mult	Multiplicative factor for security distance	1.00 ~ 8.00	3.00

Table 2.3 Wiedemann 99 Car-Following Model Parameters

Parameter	Parameter Description	Range	Default
W-99-CC0	Desired distance between lead and following vehicle [m]	0.60 ~ 3.05	1.50
W-99-CC1	Headway Time [s] Desired time between lead and following vehicle	0.50 ~ 1.50	0.90
W-99-CC2	Following Variation [m] Additional distance over safety distance that a vehicle requires	1.52 ~ 6.10	4.00
W-99-CC3	Threshold for Entering following state [s] Time in seconds before a vehicle starts to decelerate to reach safety distance	-15.00 ~ -4.00	-8.00
W-99-CC4	Negative following threshold [m/s] Specifies variation in speed between lead and following vehicle	-0.61 ~ 0.03	-0.35
W-99-CC5	Positive following threshold [m/s] Specifies variation in speed between lead and following vehicle	0.03 ~ 0.61	0.35
W-99-CC6	Speed dependency of oscillation [1/ms]	7.00 ~ 15.00	11.44
W-99-CC7	Acceleration during the oscillation process [m/s2]	0.15 ~ 0.46	0.25
W-99-CC8	Standstill Acceleration [m/s2]	2.50 ~ 5.00	3.50
W-99-CC9	Acceleration with 80 km/h [m/s2]	0.50 ~ 2.50	1.50

2.1.3 Lane-change Model

The lane-changing model in VISSIM is based on the driver's response to the understanding of the surrounding traffic. It uses gap acceptance criteria in which a driver changes lanes provided the available gap is equal or greater than the critical gap. The decision to change lanes depends on the following conditions: the desire to change lanes, favorable driving conditions in the neighboring lanes, and the possible gap availability. Based on these conditions the lane-changing phenomenon is classified into two types: first one is optional lane change, which includes drivers who want to change from slow-moving lanes to fast-moving lanes, and second one is a necessary lane change in case of any lane closure due to work zones, incidents, route decisions and so on. A detailed description of the lane-changing algorithm is presented in Wiedemann and Reiter [23].

Necessary lane changes depend on the aggressiveness of drivers in accepting or rejecting gaps in the adjacent lanes, which is represented by parameters such as acceptable and threshold deceleration values of lane-changing and trailing vehicles and the safety distance reduction factor. Safety distance reduction factor, called SRF, refers to the reduction in safety distance to the trailing and leading vehicle on the desired lane and the safety distance to the leading vehicle in the current lane. The default value of SRF is 0.6, which means the safety distance during lane changing is reduced by 40%. A lower SRF value means that the safety distance for lane changing is reduced more, meaning that drivers have become more aggressive in accepting shorter gaps. Table 2.4 shows the lane-changing parameters. The first column contains the name of the parameter used by VISSIM, along with the parameter description, their range, and default values in other columns.

Table 2.4 Lane-Changing Model Parameters

Parameter	Parameter Description	Range	Default
Max.Decel. Own	Max. deceleration for leading (own) vehicle [m/s2]	N.A	-4.00
Max.Decel. Trail	Max. deceleration for following (trailing) vehicle [m/s2]	N.A	-3.00
Decel.ReteDist. Own	Reduction rate for leading (own) vehicle [m]	100 ~ 200	200
Decel.ReteDist. Trail	Reduction rate for following (trailing) vehicle [m]	N.A	200
Accepted Decel. Own	Accepted deceleration for leading (own) vehicle [m/s2]	-3.00 ~ 0.50	-1.00
Accepted Decel. Trail	Accepted deceleration for following (trailing) vehicle [m/s2]	N.A	-0.50
Min. Headway	Min. spacing (headway) [m]	0.50 ~ 3.50	0.50
Safety Dist. Fact.	Safety distance reduction factor	0.10 ~ 0.60	0.60
Coop Decel.	Max. deceleration for cooperative lane-change/braking [m/s2]	-6.00 ~ 3.00	-3.00

2.2 Connected Autonomous Vehicles

The current generation of advanced driver assistance systems has already developed to the point where some automated vehicles are already commonplace on our roads, which are able to steer, accelerate and decelerate by using information that they get about the driving environment around them. There are six levels of autonomy in vehicles [24]. This is also called SEA classification [25]. Table 2.5 shows the levels of AVs. The first column contains the level of the vehicle autonomy and along with the simple descriptions.

Table 2.5 Levels of Autonomous Vehicles

Levels of Vehicle Autonomy	Description
Level 0	Conventional / Non-Automation
Level 1	Only Cruise Control & Parking Assistance
Level 2	Partial Automation
Level 3	Conditional Automation
Level 4	High Automation
Level 5	Full Automation

In automation level definitions, level 0 and level 1 automation is self explanatory. At level 0, the automated system issues warnings like engine or brake problem and may momentarily intervene but has no sustained vehicle control. From level 1, the driver and the automated system start to share control of the vehicle. Examples are systems where the driver controls steering and the automated system controls engine power to maintain a desired speed, some parking assistance, where steering is automated while speed is under manual control. At level 1, the driver must be ready to retake full control at any time. At level 2, the automated system takes full control of the vehicle: accelerating, braking, and steering. The driver must monitor the driving and be prepared to intervene immediately at any time if the automated system fails to respond properly. A common example is adaptive cruise control which also utilizes lane keeping assist technology so that the driver simply monitors the vehicle. At level 3, the driver can safely turn their attention away from the driving tasks. The vehicle will handle situations that call for an immediate response, like emergency braking. The driver must still be prepared to intervene within some limited time when called upon by the vehicle to do so. At level 4, the driver's attention is not required for safety, like the driver may leave the driver's seat. An example would be a robotic taxi or a robotic delivery service. At level 5, no human or any human intervention is required at all. An example would be a robotic vehicle that works on all kinds of tasks, all over the world, all year around, in all weather conditions, non-stop [26].

2.2.1 Impacts of Autonomous Vehicles

The advancement of AV technology is increasing since it is the automotive industry's most important modernisation. There are currently some levels of uncertainty around the subject, but the long-term impact of this technology on society, mobility, and the economy might just be great. The following is a discussion of some potential effects of autonomous technology.

2.2.2 Society-wide Effects of Autonomous Vehicles

Having these fleets of AVs operating on our networks generates great opportunities. Users will see many benefits in the future, including decreased accident rates, less emissions, decreased parking requirements, improvements in traffic and reliable travel times, increased mobility, freed up commuting time, and redistribution of road space to other users.

According to studies done by CMU, PDOT, and FHWA, the use of residential roads will likely grow with the adoption of fully AVs, perhaps it helps reduce traffic on freeways. Autonomous technology might support automatic parking futures and lower parking requirements at destinations, which might potentially increase demand for public transportation in addition to promoting safe journeys at higher speeds. It benefits the seniors, children and disabled to boost their mobility and bring them to their destinations with absolute ease.

This study concentrates on the congestion improvements and reduced journey time part of the benefits. There is a potential for increased road capacity and reduced congestion through features such as coordinated driving, vehicle to vehicle (V2V) communication and vehicle to everything (V2X) communication as well.

CHAPTER 3

3. METHODOLOGY

3.1 Data Collection & Background

As it is described in Thesis Statement and Objectives part in Chapter 1, our aim is by introducing different percentages(10%, 20%, 30%, … , 100%) of AV compositions into the current traffic, and mix those AVs with conventional vehicles which meet daily network conditions, to determining an optimum penetration rate for these technologies and observing AV impacts on our freeway network. Finding traffic volume, lowering the number of stops and travel time improvements are mainly focused on this study. In order to perform this research, vehicle count data, speed data, VISSIM program and model calibration efforts are required.

There is a great deal of uncertainty over what the impacts on road infrastructure will be when the AVs start working on our roads. Because of the vehicle-to-infrastructure (V2I) communication, traffic signals, signs and any other traffic safety guiding elements will not be necessary. Therefore some of the road design criterias are neglected in this research. Additionally, the study area of the freeway is relatively straight and curves have extra-large radiuses (+1500m) and longitudinal grade less than 0.5% so the operation effects of the design on driving can be ignored.

3.1.1 Field Measurements

Having a fine-tuned and best-matched simulation model which represents the real-life behavior of drivers is so important for traffic engineers. Thus, before any analysis can take place, models need to be calibrated to be able to represent real-life conditions. For calibration, real life measurements and vehicle count data are required.

Due to the distribution of residential and business districts in Istanbul, the majority of Bosporus crossings happen from the Asian side to the European side in the morning hours, with the opposite flow appearing in the evening hours [27, 28]. Our research area starts from the Ümraniye-Tepeüstü cloverleaf intersection to the FSM Bridge in Istanbul. This study just considers the flows from the Asian-side to European-side direction. Before conducting any additional research, Yandex Navi and Google Maps were reviewed for finding the exact peak hours. As shown in Figures 3.1, 3.2 and 3.3, the whole study area was watched, examined and documented for this purpose from 06:00am to 08:00am, consecutive two week days, not mondays and fridays. The correct peak time was found to be accurate from 06:55am to 07:05am. After this point, the study area gets congested in high levels and traffic becomes a complete stop state.

Figure 3.1 06:30am, 6 Oct 2021, Traffic View of Study Area; Source: Yandex Navi

Figure 3.2 07:00am, 6 Oct 2021, Traffic View of Study Area; Source: Yandex Navi

Figure 3.3 07:30am, 6 Oct 2021, Traffic View of Study Area; Source: Yandex Navi

After figuring out the accurate peak time, three consecutive days for the video capture process were scheduled in the study area for confirming peak times and car counts. Small drone, compliant with regulations, were used for capturing the traffic congestion for this goal. Images and videos were taken from 3 different intersections in the study area. Figures 3.4, 3.5 and 3.6 show the congestion happening around 07:00am at 19 October 2021, 20 October 2021. and 21 October 2021.

Figure 3.4 07:00am, 19 Oct 2021, Kavacık Intersection; Source: Berkcan Küçükoğlu

Figure 3.5 07:00am, 20 Oct 2021, Çamlık Intersection; Source: Berkcan Küçükoğlu

Figure 3.6 07:00am, 21 Oct 2021, Ümraniye Intersection; Source: Berkcan Küçükoğlu

3.1.2 RTMS Data

Traffic data used in this research have been gathered through detectors and compared with the videos that had been shot to confirm values are correct. There are several Remote Traffic Microwave Sensor (RTMS) devices installed in the upstream (No.73, No.93, No.324, No.317, No.82, No.328, No.61, No.280, No.329, No.93, No.279, No.72) of the study area which provide presence indication and accurate measurements of volume, occupancy, and speed, during every two-minute interval in 7-days/24-hour period. The beginning time of the peak event during the morning hours was determined by analyzing the four-week RTMS data from 0:00am to 12:00pm, between 01.10.21 to 31.10.21 provided by Istanbul Metropolitan Municipality. The model's validity could be determined by simply determining the difference between the results observed and simulated are less than a defined acceptable difference. [29]. Through videos, car counts and RTMS values matched around 99,45% which confirms RTMS values are correct and usable. In this study, traffic conditions between 06:00am-01:00pm are modeled including an un-congested flow, transition condition, and congested flow conditions.

3.2 Experiment Design

As mentioned earlier, the study network is a part of O-2 freeway located at the Asian side of Istanbul. The research site's schematic layout is shown in Figure 1.1 at section 1.2. The subject direction was from Ümraniye to FSM Bridge.

3.2.1 Building Study Network in VISSIM

Each and every intersection is carefully examined and modeled after RTMS unit names. Figure 3.7 shows the consecutive RTMS unit diagram and the contribution of these units to the static route decision and vehicle count parameters.

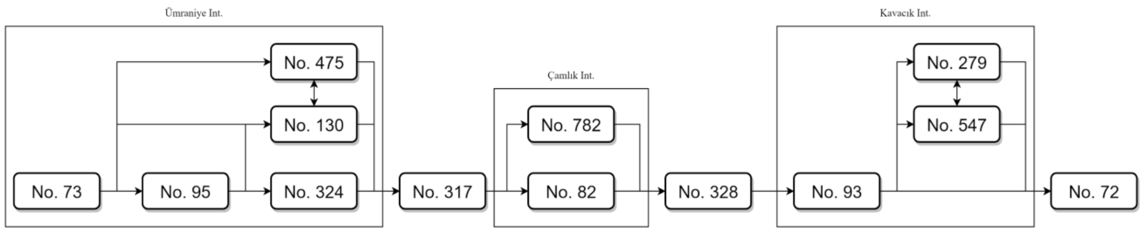

Figure 3.7 RTMS Diagram for Vehicle Flow and Static Route Calibration

Subtracting the consecutive RTMS vehicle counts in the study direction confirms that vehicle counts are valid and addresses the static routes percentages for model building.

The well-known microsimulation software, VISSIM version 2022.00.03(SP 03) [9] was used to create a microscopic model of the study area. The freeway model had four lanes and they were 3.5 meter wide each. Other parameters gathered from the field to maintain consistency with actual traffic conditions including speed restriction areas and signs, driving rules and other traffic safety elements were initially calibrated and modeled. Figure 3.8 shows the Network Editor window and model created in VISSIM.

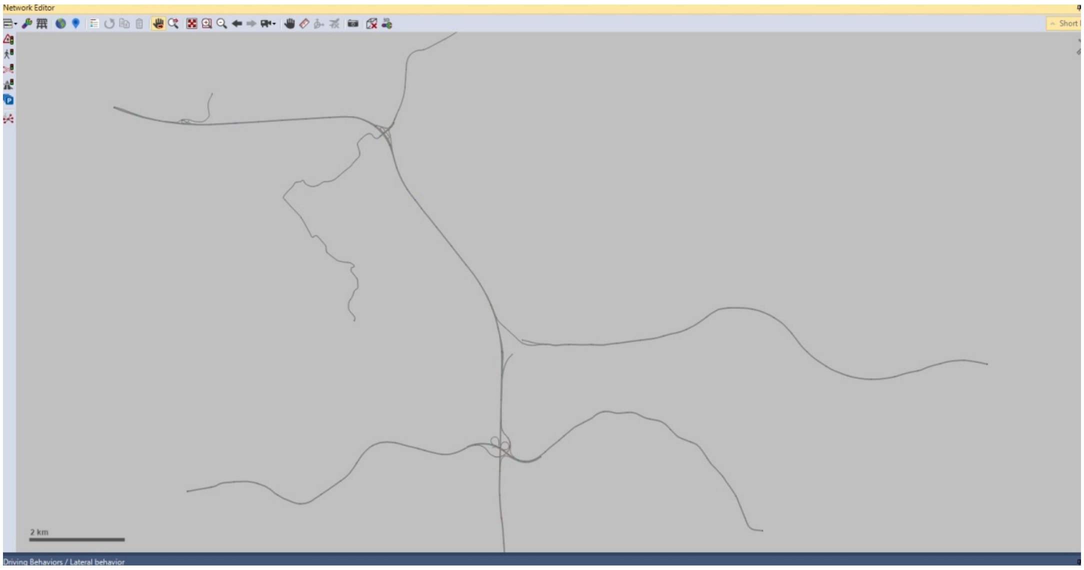

Figure 3.8 VISSIM Network Editor Window

Design speed for the O-2 freeway is 120km/h and other connector roads are 80km/h. To make the created model more responsive and realistic, all vehicles spawned in the system must hit the intersections at the same time. Thus, buffer time and buffer distance for each load is calculated and created by simply adding an extra 10km link before the mainstream RTMS unit No.73, and 6.6km before the connectors RTMS units No.130, No.475, No.782, No.279, and No.547 to solved this problem and added 5 minutes (300 secs.) of buffer time to whole simulations. All data collection points in the VISSIM network were placed 500 meters apart from each other, and nodes were created for each intersection. Figure 3.9 shows the data collection points chosen for the investigation and Figures 3.10, 3.11, 3.12 and 3.13 shows nodes created for our research purpose.

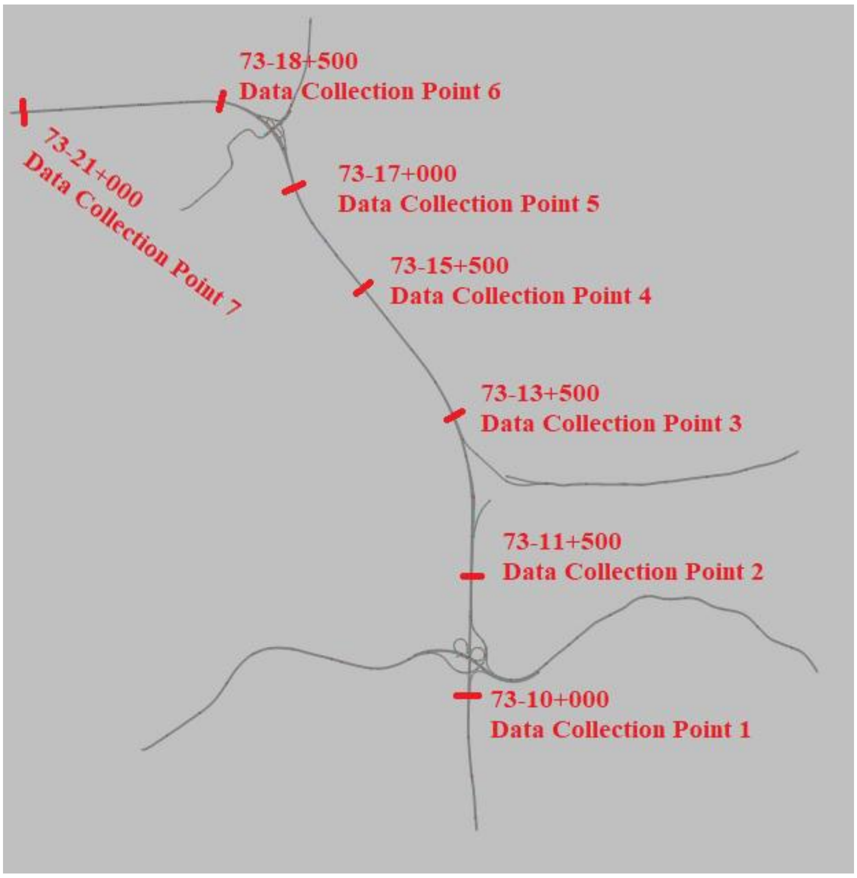

Figure 3.9 Chosen Data Collection Points for Analysis

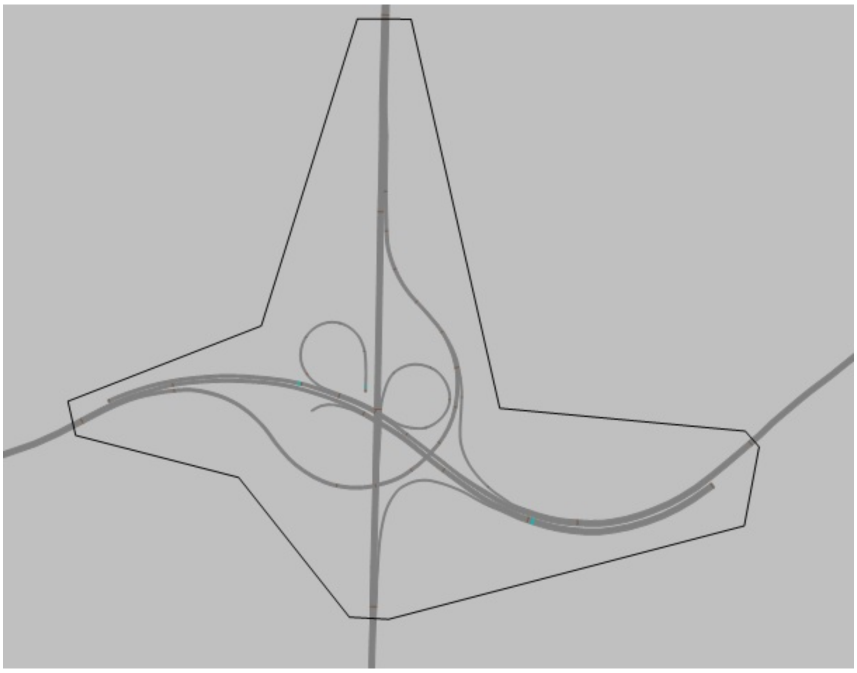

Figure 3.10 Ümraniye Intersection Node

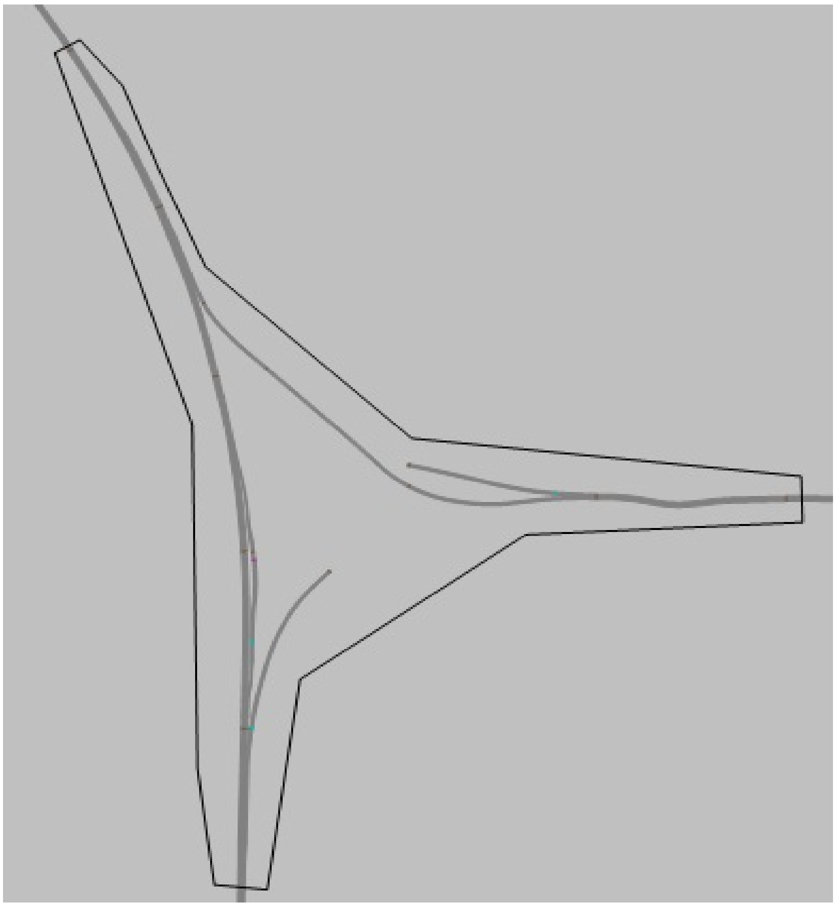

Figure 3.11 Çamlık Intersection Node

Figure 3.12 Kavacık Intersection Node

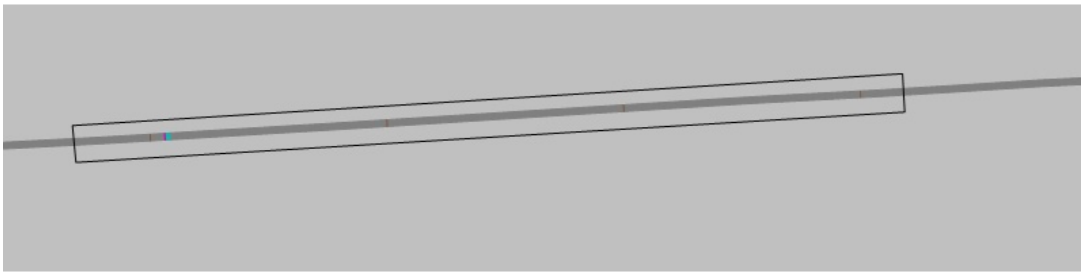

Figure 3.13 FSM Bridge Node

3.2.2 Parameter Selection & Calibration Effort

Driver behavior model of W-99 was selected to replicate freeway traffic conditions. In the first model, default driving parameters were used for calibration of the experimental driving model. Following a simple test scenario, the predicted traffic volumes and the total number of cars passing through detectors for every two-minute interval with the actual data were compared. A comparison between the modeled data and observed data reveals that there is a significant difference between these two sets and some vehicles at the intersections refused to merge into the mainstream and observed that they were waiting on the side of the road aimlessly. It justifies the need for a calibrated model based on actual traffic condition before making a scenario analysis. The goal of the calibration process is to determine the statistically significant values of model parameters using field data [12].

There are two types of methods for Driving Behavior Parameters calibration;

The first calibration of driving behavior is using trajectory data (lane-changing, acceleration, deceleration, etc.) extracted from video files using image-processing techniques [30, 31]. The second calibration technique employs the traffic flow measurement data (volume, speed, etc.) gathered by detectors [32-34]. Second method has been chosen because of insufficient tools for automatic image processing. However, videos and photos were still used to learn about headway time and following variation parameters.

The simulation and evaluation attributes were set to the following settings. The overall simulation time was calculated as 25200 seconds. At the beginning of the simulation, a 300-second warm-up time was also assumed. A five-minute time interval (300 sec.) was used for data gathering over the whole 360-minute simulation period, excluding warm-up times. The simulation results are unaffected by the simulation speed [9]. In each case, three independent runs with the same beginning condition and various seeds were made in order to remove the stochastic difference, and the average run time was reported. In order to achieve this, the following simulation parameters were utilized in VISSIM: initial random seed = 40; seed increment = 1; number of runs = 3; step time (resolution) = 10; simulation time = 25200; and maximum speed for simulation.

3.2.3 W-99 Values & Lane-Changing Parameters

The W-99 values of CC0 to CC9, which are related to the freeway traffic flow model, were examined and adjusted accordingly. On the basis of the literature, it can be concluded that the most impact on lane capacity is done by CC0, CC1, CC2, and CC4/CC5 parameters [5]. CC0 and CC1 determine the safety distance which in turn determines capacity. The sensitivity of safety distance with respect to CC0 is much lower as compared to its sensitivity with respect to CC1. For example, at operating speeds of 80km/h under normal traffic conditions, varying the CC0 value from 1.5m. to 3m., keeping CC1 fixed at 0.9, results in a small capacity drop from 2000 veh/h/lane to 1800-1900 veh/h/lane. But varying the CC1 value from 0.9 to 1.8, keeping CC0 fixed at 1.5m, results shows a significant capacity drop from 2000 veh/h/lane to 1100-1200 veh/h/lane. Since the objective of parameter calibration is to make the model as closely as possible to the real-life condition, CC0 and CC1 values are obtained from the images and videos gathered for this research. According to our inspected samples, driving behaviors of Istanbul drivers in the morning peak hours vary greatly. Some follow each other very closely, while others extend this follow-up time and leave a lot of space in between vehicles almost 2 times more than expected.

Figure 3.14 Ümraniye Intersection, Vehicle Headway and Following Variations
Source: Berkcan Küçükoğlu

Figure 3.15 Ümraniye Intersection, Vehicle Headway and Following Variations
Source: Berkcan Küçükoğlu

Figures 3.14 and 3.15 show the variations observed. Our research revealed that the headway distance ranges between 0.4 meters at the minimum and 2.65 meters at the maximum. Also, 20% of the samples that were examined standing closer than one or less meters apart, however 27% preferred standing spaces that were more than two meters apart. Between one and two meters, the remaining 53% favor various distances. In the end, the average CC0 value measures roughly 1.561 meters. This number is used as 1.56 meters in order to round the value and use a less complicated parameter. Figures 3.16 and 3.17 represent the approximate measured distances.

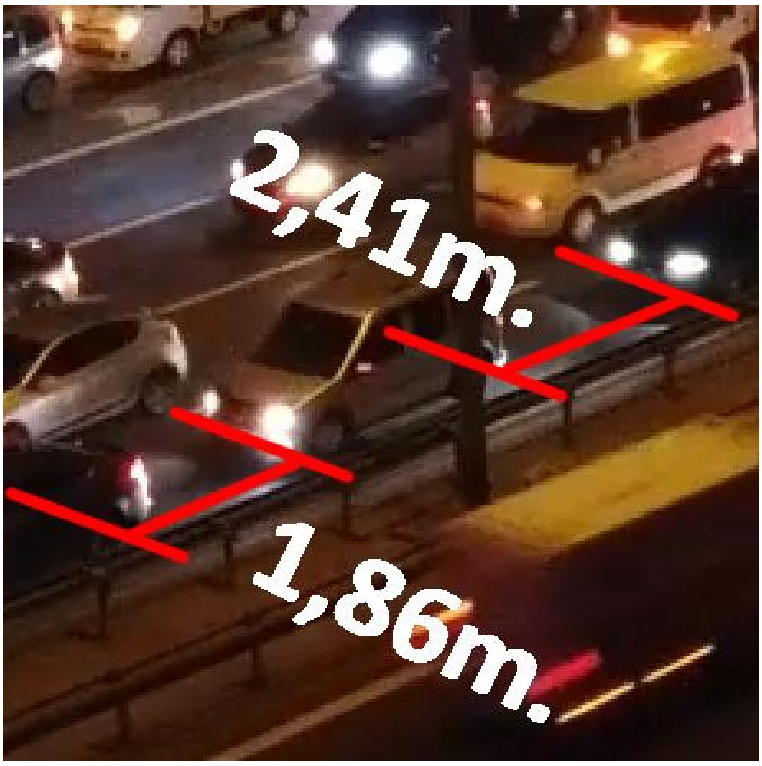

Figure 3.16 Ümraniye Intersection, Vehicle Headway Variations
Source: Berkcan Küçükoğlu

Figure 3.17 Ümraniye Intersection, Vehicle Headway Variations
Source: Berkcan Küçükoğlu

CC1 parameter is also gathered from the videos. According to our inspected samples, following variations and trying to keep up time is longer than expected. This is due to the early morning hours and the fact that drivers react slowly because they have just woken up. Figures 3.18 and 3.19 shows the two of the samples and their frame counters top on them.

Figure 3.18 Ümraniye Intersection, Vehicle Following Variations
Source: Berkcan Küçükoğlu

Figure 3.19 Ümraniye Intersection, Vehicle Following Variations
Source: Berkcan Küçükoğlu

In the video screenshots above, 1 second equals 25 frames. Therefore, 01:12 is about 37 frames and 01:16 is about 41 frames. An average of 38.71 frames per second were taken from the videos and if this value is divided to 25, the average value of reaction time is about 1.5482 seconds. This number is a time distribution in VISSIM, so the value is set as an average of 1.55 seconds in order to round the number and use a less complicated parameter.

CC2 parameter is also tested from 4m to 12m for finding the best suited value for our study area. After making the changes and running the tests, results showed that there wasn't much of a difference. For the CC4 and CC5 car-following parameters, visual readings on the simulation suggested that an absolute value higher than 3 resulted in an unstable car-following process, and absolute values lower than 3 did not produce any significant variation of capacity. Therefore the CC4 and CC5 pair and CC2 were dropped from further consideration and set to the model default values. Rest of the parameters, CC3, CC6, CC7, CC8 and CC9 were not changed and set to their default values.

All the parameters described above have considered only the car following model. None of them have looked at the lane-changing parameters, which can be crucial as explained in the literature section. Drivers in Istanbul are frequently and aggressively cutting and overtaking other drivers, taking every opportunity to change lanes [6] and merge into the freeway traffic one way or another. The lane-changing distance is not a driving behavior parameter in the Wiedemann's algorithm. Vehicles can initiate the lane changing process by describing the position at which vehicles start to look for gaps in the adjacent lanes; it does not, however, affect any other aspect of the Wiedemann's algorithm. The first attempt to find the critical lane-changing parameter, safety distance reduction factor, which reflects the aggressiveness of drivers when changing lanes, was testing the default value of 0.6. After inspecting the simulation, observations showed some of the intersections are getting stuck and vehicles making queues of unexpected long lengths. Drivers refused to merge and wait at the intersection merging lane. This problem happened because of the default SRF value and it showed that the lane-changing parameter was definitely not working for our model. Since the SRF required a new value, different parameters from 0.2 to 0.6 were tested and changed the diffusion time from 60 seconds to 120 seconds for not letting any vehicles despawn during the simulation process. Some of the lane change values from earlier studies on this research area were utilized [35]. Tables 3.1, 3.2 and 3.3 shows the default W-99 values for Freeway (free lane selection) and lane-changing parameters default in VISSIM, their reasonable ranges and used values for the experiment simulation models.

Table 3.1 General Model Parameters and Used Values

Parameter	Range	Default	Used Value
LookAhead DistMax.	100 ~ 300	250	170
LookBack DistMax.	50 ~ 200	150	127
StandStillDist.	0.00 ~ 3.00	0.50	1.08
ObsrvedVehs.	1.00 ~ 5.00	2.00	3.40

Table 3.2 Wiedemann 99 Car-Following Parameters and Used Values

Parameter	Range	Default	Used Value
W-99-CC0	0.60 ~ 3.05	1.50	1.56
W-99-CC1	0.50 ~ 1.50	0.90	1.55
W-99-CC2	1.52 ~ 6.10	4.00	4.00
W-99-CC3	-15.00 ~ -4.00	-8.00	-8.00
W-99-CC4	-0.61 ~ 0.03	-0.35	-0.35
W-99-CC5	0.03 ~ 0.61	0.35	0.35
W-99-CC6	7.00 ~ 15.00	11.44	11.44
W-99-CC7	0.15 ~ 0.46	0.25	0.25
W-99-CC8	2.50 ~ 5.00	3.50	3.50
W-99-CC9	0.50 ~ 2.50	1.50	1.50

Table 3.3 Lane-Changing Parameters and Used Values

Parameter	Range	Default	Used Value
Max.Decel. Own	N.A	-4.00	-4.00
Max.Decel. Trail	N.A	-3.00	-3.00
Decel.ReDist. Own	100 ~ 200	200	152
Decel.ReDist. Trail	N.A	200	200
Accepted Decel. Own	-3.00 ~ 0.50	-1.00	-2.27
Accepted Decel. Trail	N.A	-0.50	-0.50
Min. Headway	0.50 ~ 3.50	0.50	1.92
Safety Dist. Fact.	0.10 ~ 0.60	0.60	0.33
Coop Decel.	-6.00 ~ 3.00	-3.00	-3.00

3.2.4 Desired Speed Distributions

RTMS measurement and statistics showed there was no discrimination in terms of speed readings by vehicles classes passing through the sensor. It was necessary to extract the speed data from the sensor readings and make an average speed distribution for each and every speed parameter. Cars, HGVs and Buses were used in this study, and these classes duplicated to their AV versions (Car-AV, HGV-AV, Bus-AV). Freeway speed restrictions were adopted for each vehicle class. Cars were driven at desired speeds of 120 km/h, while HGVs and buses were driven at speeds of 100 km/h during the simulation.

The desired speed distribution was composed of the speed intervals and the cumulative frequency of each interval. In this research, the traveling speed cumulative frequency curves were considered to be the desired speed distribution. Default speed distributions for 30km/h, 50km/h, 80km/h, 100km/h, 120km/h were modified according to RTMS readings. Desired speed distribution for each speed parameter can be seen in Tables 3.4, 3.5, 3.6, 3.7 and 3.8. Based on the data in tables below, the desired speed distributions were calibrated by setting the critical control points for the curves in Figure 3.20.

Table 3.4 Desired Speed Distribution for 30 km/h

Desired speed cumulative frequency	0%	20%	55%	82%	93%	100%
Desired speed distribution for 30 km/h	25	30	33	35	40	45

Table 3.5 Desired Speed Distribution for 50 km/h

Desired speed cumulative frequency	0%	20%	55%	82%	93%	100%
Desired speed distribution for 50 km/h	35	40	50	55	60	70

Table 3.6 Desired Speed Distribution for 80 km/h

Desired speed cumulative frequency	0%	7%	23%	49%	76%	97%	100%
Desired speed distribution for 80 km/h	50	60	70	80	90	100	110

Table 3.7 Desired Speed Distribution for 100 km/h

Desired speed cumulative frequency	0%	20%	31%	50%	78%	90%	100%
Desired speed distribution for 100 km/h	75	80	90	100	110	120	125

Table 3.8 Desired Speed Distribution for 120 km/h

Desired speed cumulative frequency	0%	20%	31%	50%	72%	78%	93%	98%	99%	100%
Desired speed distribution for 120 km/h	70	80	90	110	110	120	130	140	150	160

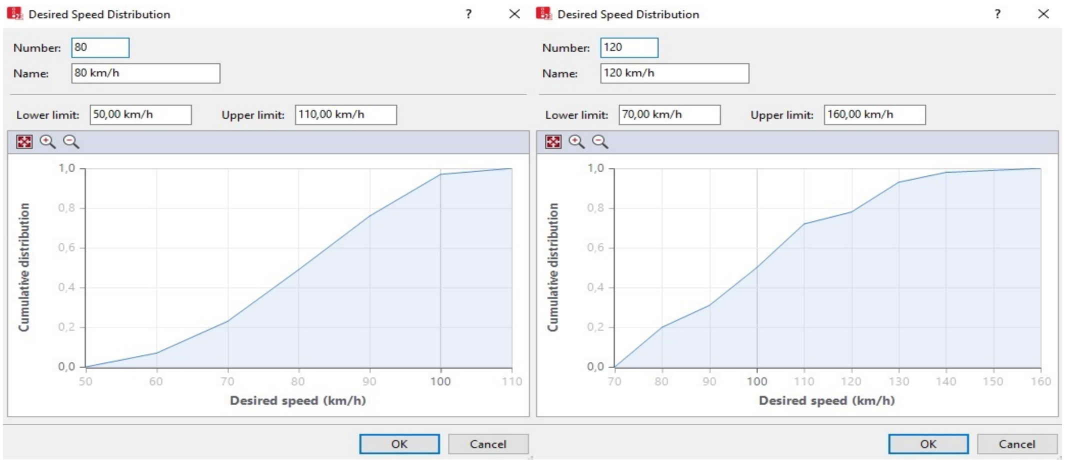

Figure 3.20 Calibrated Desired Speed Distributions for Conventional Vehicles

AVs are not like human drivers, which means they are more precise on the driving operations. They break more efficiently, take off more quickly and adjust traveling speed more precisely. For example, if an AV wants to set its speed to 80 km/h, it could apply the exact required throttle to achieve that speed and hold it. This can happen with almost a small margin of error.

There is no agreed upon definition of how the AVs behave or what the characteristics will be, however in accordance with the purpose of our research, linear speed distribution is used for only AVs desired speeds in this study. Based on the literature and PTV Groups presentations, the same calibrated distributions for human drivers with a speed difference of -2 km/h for the minimum speed and +2 km/h for the maximum values were used. Desired speed distribution for AVs can be seen in Figure 3.21.

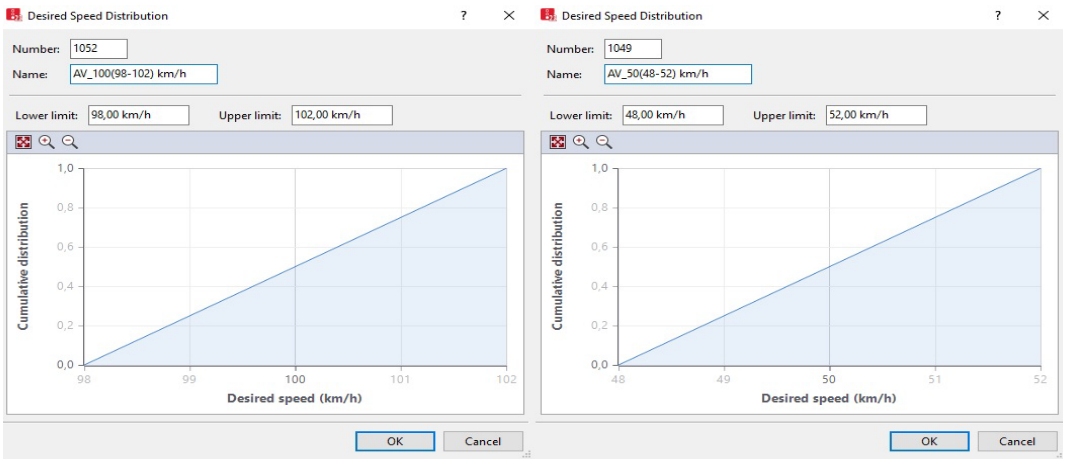

Figure 3.21 Calibrated Desired Speed Distributions for AVs

3.2.5 Vehicles and AV Compositions

As explained in the desired speed distribution section, six different vehicle classes for the experiment model which resemble similarities with the sensor data and videos captured for confirmation were used. Cars, HGVs and Buses and their AV versions (Car-AV, HGV-AV, Bus-AV) were used in this study. In VISSIM, there are already two predefined vehicle compositions, Default and Conventional. These two compositions obviously do not represent the RTMS data vehicle distribution.

Since more vehicle compositions were required, 239 new combinations were created for our vehicle distributions. For example, if there will be 1000 vehicles will spawn into the system for the next 10 minutes, and 250 of those vehicles are cars, 350 of them are HGVs and the rest are busses, this combination is considered 0.25-Car, 0.35-HGV, 0.40-Bus and name of the combination is 25C-35H-40B. Those combinations start from 2% Car to 90% Car, 2% HGV to 94% HGV and 1% Bus to 33% Bus. After simulating, and validating the vehicle compositions are working correctly, AVs are introduced into the traffic system by increasing their presence by converting each composition vehicles into AV versions of all vehicles. This conversion started with only 10% of the all vehicles becoming AVs, and in the end, all of the vehicles became AVs tested. Total number of 2631 vehicle combinations were created and used in this research.

3.2.6 Selected AV Behavior and Coexisting with Conventional Vehicles

Since there is no clarity on how AV systems will behave or what their attributes will be, default AV behaviors provided by the VISSIM and simple tuned AV behavior for this experiment were explored appropriately.

In VISSIM, there are predefined three different AV behaviors. For all of these behaviors, implicit stochastic is disabled, cooperative lane change is enabled and their CC2 is set to 0 meters. Table 3.9 shows the behavior names and their specific options defined for the behavior itself.

Table 3.9 AV Behaviors Provided by VISSIM and Their Definitions

Behavior Name	Specific Option Definition
AV cautious (CoEXist)	● Has slower acceleration parameters ● Uses enforce absolute braking distance option
AV normal (CoEXist)	● Has less gap time distribution and following parameters
AV aggressive (CoEXist)	● Has lesser gap time distribution and lower lane change clearance multiplayer ● Sees and interacts more objects and vehicles around

These three alternatives have been tested, and a decision has been made on which version to employ for our study. Cautious option has “Enforce Absolute Braking Distance” and this option forces AVs to calculate extra following distance and allows vehicles to safely stop any time even if the vehicle in front of it stops immediately. If this option is chosen, vehicles start having more gaps between them and it will be significantly bad for road capacity. The Normal and Aggressive options are nearly identical, however there is one small yet important variation between them. Normal option is only looking for one vehicle to interact with and two environmental objects, and depends on the leading vehicle most of the time, but aggressive option more likely knows nearly everything, can interact with more than 8 vehicles and more than 10 objects around it. Aggressive behavior can stack up vehicles tighter and follow leading vehicles more closely. It is considered that the adoption of the aggressive behavior is more appropriate for the conditions of Istanbul city and more reasonable for capacity increase.

Although the platooning option is rather a new concept, it is promising a good improvement on capacity increase. After experimenting with it, it concluded that platooning helps to our purpose, but it is decided to not use this option for our custom AV behavior. Platooning is the subject of another study by itself and the first versions of AVs that will enter the traffic are unlikely to have this feature implemented on. If 1 or 2 of every 10 vehicles will become autonomous in the beginning, there will not be enough AVs around to make a platoon. Therefore, platooning was excluded for this experiment.

Finally, our customized AV behavior has aggressive coexisting characteristics, general options enabled and platooning is turned off. Also, waiting time before diffusion was set to 120 seconds to match it with conventional vehicles and prevent any vehicles from despawning during the simulation. Table 3.10, 3.11 and 3.12 shows the selected AV parameters and options that were used in this research.

Table 3.10 AV Model Parameters and Selected Values

Parameter	AV Aggressive (CoEXist)	AV Modified Used Values
W-99-CC0	1.00	1.00
W-99-CC1	0.60	0.60
W-99-CC2	0.00	0.00
W-99-CC3	-6.00	-6.00
W-99-CC4	-0.10	-0.10
W-99-CC5	0.10	0.10
W-99-CC6	0.00	0.00
W-99-CC7	0.10	0.10
W-99-CC8	4.00	4.00
W-99-CC9	2.00	2.00

As shown in Table 3.10, selected AV behavior has the same parameters as AV Aggressive behavior. However, small changes could be seen in Table 3.11 and 3.12

Table 3.11 AV Lane-Changing Parameters and Selected Values

Parameter	AV Aggressive (CoEXist)	AV Modified Used Values
Max.Decel. Own	-4.00	-4.00
Max.Decel. Trail	-4.00	-4.00
Decel.ReteDist. Own	100	200
Decel.ReteDist. Trail	100	200
Accepted Decel. Own	-1.00	-1.00
Accepted Decel. Trail	-1.50	-1.50
Min. Headway	0.50	0.50
Safety Dist. Fact.	0.75	0.30
Max. Coop. Decel.	-6.00	-6.00
Wait Before Diffusion	60.00	120

Table 3.12 AV General Parameters and Selected Values

<table>
<tr><th>Features</th><th>AV Aggressive (CoEXist)</th><th>Default Values</th><th>AV Modified Used Values</th><th>Selected Values</th></tr>
<tr><td>Standstill Dist.</td><td>Unchecked</td><td>-</td><td>Checked</td><td>0.50 m</td></tr>
<tr><td>Coop. Lane Change</td><td>Checked</td><td>Max. Speed Dif.
10,80 km/h
Max. Coll. Time
10.00 s.</td><td>Checked</td><td>Max. Speed Dif.
10,80 km/h
Max. Coll. Time
10.00 s.</td></tr>
<tr><td>Enforce Abs. Breaking Dist.</td><td colspan="2">Unchecked</td><td colspan="2">Unchecked</td></tr>
<tr><td>Use İmp. Stochastics</td><td colspan="2">Unchecked</td><td colspan="2">Unchecked</td></tr>
<tr><td>Platooning Possible</td><td colspan="2">Unchecked</td><td colspan="2">Unchecked</td></tr>
</table>

As previously stated, the AV behavior functionality was examined with the fewest modifications possible. Overall results suggest that AV behavior is serving its purpose, and findings in sections 4.2, 4.3 and 4.4 reveal that AVs can enhance the traffic situation in a good way.

CHAPTER 4

4. ANALYSIS AND RESULTS

As described in section 3.2, the experimental design will be carried out in Chapter 4 utilizing VISSIM simulations. Network's current traffic characteristics will be assessed, and the presence of AVs with conventional vehicles will be explored. Based on simulation results, the ideal number of AVs required for change in the current condition will be determined by using measured data.

Four nodes and seven specific data collection points were chosen just before the intersections and between the intersections where vehicles can merge or freely drive. Total and average number of vehicles passing through the data collection points for each simulation, and total number of stops that happened for all experiments was analyzed. Findings of different calibrations have been presented in detail.

Data collection points 1 and 2 have been specially chosen to illustrate how all vehicles in the network could transform into AVs and to compare simulations of AVs and conventional vehicles. This case has been explored in section 4.2, and Figures 4.1 and 4.2 shows the cumulative vehicle counts at peak hours acquired after investigations. The behavior of AVs is quite a different story and involves a lot of uncertainty. Findings about this question are explained in sections 4.3 and 4.4. Data collection points 3, 4, 5 and 6 were used to show coexistence of AVs and conventional vehicles cases. The average number of vehicles passing through the data collection points has been examined from all conventional vehicles compositions to all AVs compositions. Figures 4.3 to 4.10 and Figures 4.11 to 4.16 shows the findings for all of these cases. Also, the average number of stops can be seen in Table 4.2. Results about the flow of traffic through the FSM Bridge were presented in section 4.4. The number of stops that occurred on the FSM Bridge is also explained in this section. The cumulative number of vehicles passing through the FSM Bridge during peak hours and after peak hours was shown using the data collecting point 7, which located the end of the FSM Bridge.

4.1 Current Traffic Conditions on Study Area and Calibration Verification

Testing the default parameters revealed that CC1 (Headway Time) and CC2 (Following Variation) are the two most important W-99 parameters affecting capacity. Moreover, only dramatic changes in CC1 and CC2 have a major impact on the network [5]. Also the default lane changing parameters were unsuitable for direct usage for our research area. Certain intersections were becoming blocked, and some vehicles were forming unusually long queues, refusing to merge or stay in the freeway mainstream. As explained in the methodology section, some of the calibration parameters were chosen from the previous experiments [35]. CC1 and CC2 values were selected and used according to our findings. For making sure, our conventional vehicles model correctly represents the observed traffic characteristics, results from each adjustment were compared with RTMS values. After several changes and tests, with the CC parameters given in section 3.2.3, the conventional vehicles simulation was 6,52% different from RTMS values. Table 4.1 shows the first and last calibration results and vehicle counts passing through the selected data collection points.

Table 4.1 Calibrated and Uncalibrated Simulations Similarity Percentages

Points	RTMS Values	Video Vehicle Counts	No Calibration Values	First Calibration Approach	Last Calibration Approach
DCP & RTMS Location A	1311	1262	664	881	1270
DCP & RTMS Location B	976	996	1215	946	1016
DCP & RTMS Location C	713	739	1212	1181	801
Difference (%)	3,01%		47,94%	33,84%	6,52%

As mentioned in the literature part of this research, if a simulation model is showing more that 90% resemblance [14] to the real world observation, it could be accepted that the model accurately represents the selected region.

4.2 All Conventional Vehicles Versus All Autonomous Vehicles

Cumulative vehicle counts at peak hours from the data collection points, number of stops, speed and average vehicles passing through the data collection points were studied in the next sections. The Newell oblique curve approach was employed for better understanding, graphs were made and displayed accordingly.

For this case, all vehicles are changed into AVs, and this raises additional questions. The goal of this study was not to calibrate a complete AV network structure or identify the ideal AV driving behavior. There is no agreement over the design of the AV driving behavior and its characteristics. As previously indicated, default AV behaviors existing inside VISSIM simply removes the stochastic driving behavior and makes parameters exact or exclusive for scenarios where both autonomous and conventional vehicles coexist. Even so, calibrated and approved all conventional vehicles simulation is compared with the all AV simulation that tuned accordingly and described in chapter 3.2.6.

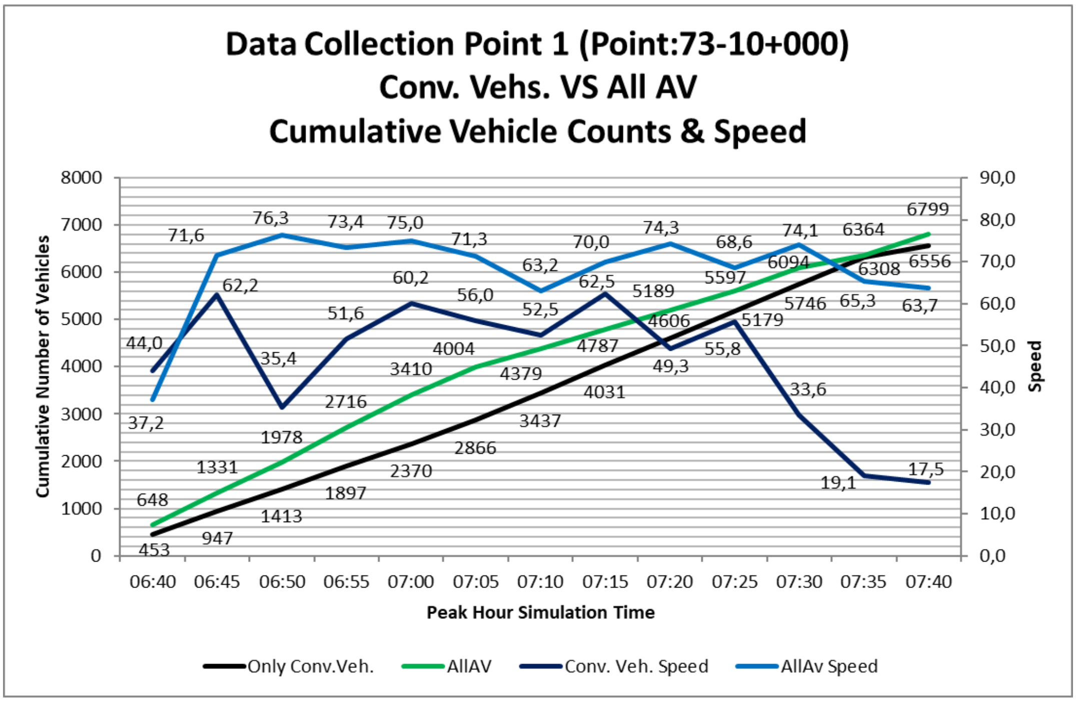

Figure 4.1 N-Curve for DCP1-73-10+000, Vehicle Counts at Peak Hour

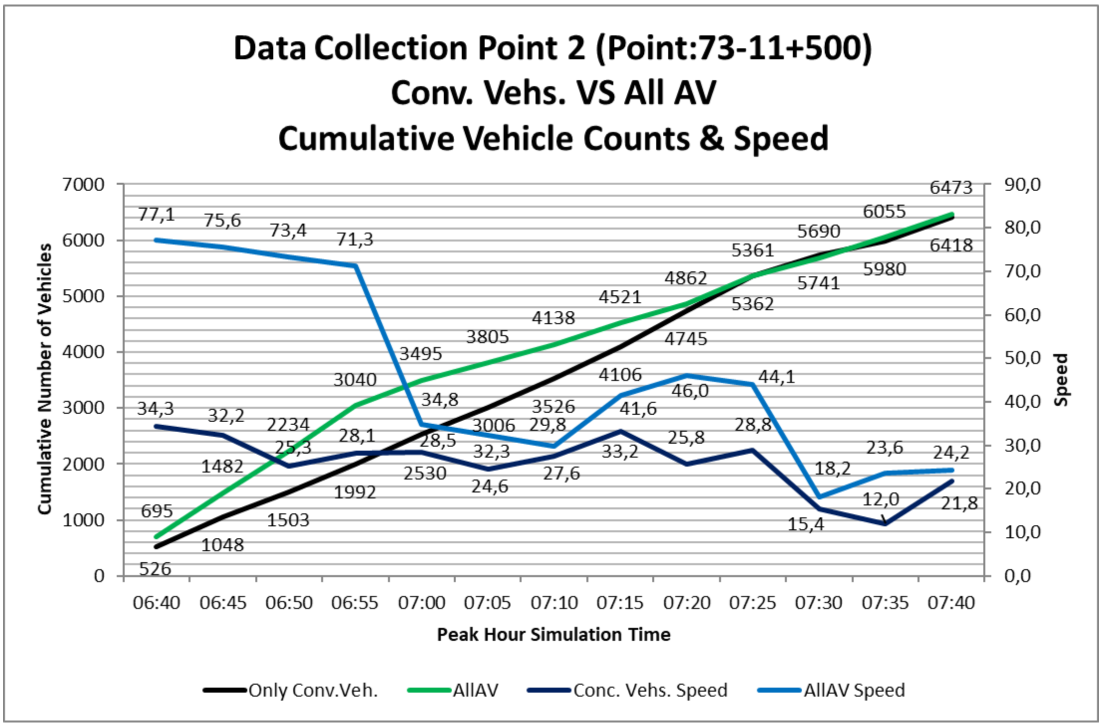

Figure 4.2 N-Curve for DCP2-73-11+500, Vehicle Counts at Peak Hour

Figures 4.1 and 4.2 belong to data collection point 1 and data collection point 2. Cumulative vehicle counts and corresponding speed at peak hour show that AVs reduce traffic congestions as expected. The graphs and measured results show around 20% to 25% increase in the number of vehicles passing through the data collection points. Additionally, it is noticeable that the traffic is more flowing and the vehicles maintain their speed more.

4.3 Coexistence of Autonomous Vehicles and Conventional Vehicles

The purpose of this thesis is to look at the changes that will occur as the number of AVs increases on the network. Models were created with the goal of increasing the number of AVs in the system by 10% each time and they will coexist with the conventional vehicles. Total number of vehicles is always preserved and conventional vehicles slowly swapped with AVs in each simulation.

As explained in section 3.2.6, one AV behavior in particular stands out as being more logical than the others and shows several characteristics expected to see in the future of autonomous driving, therefore it was chosen for experiments. Results indicate that a reasonable amount of vehicle capacity is gained into the network each time the percentage of AV present increases. Data collection points 3, 4, 5 and 6 have been chosen to demonstrate these findings. Average cars passing by the data collection points and cumulative vehicle count for each simulation have been investigated. The outcomes from data collection point 3 are shown in Figures 4.3 and 4.4. Results from data collection point 4 are displayed in Figures 4.5 and 4.6. Figures 4.7 and 4.8 represent the findings from data collection point 5. In the end, Figures 4.9 and 4.10 show the findings from data collection point 6 as discovered.

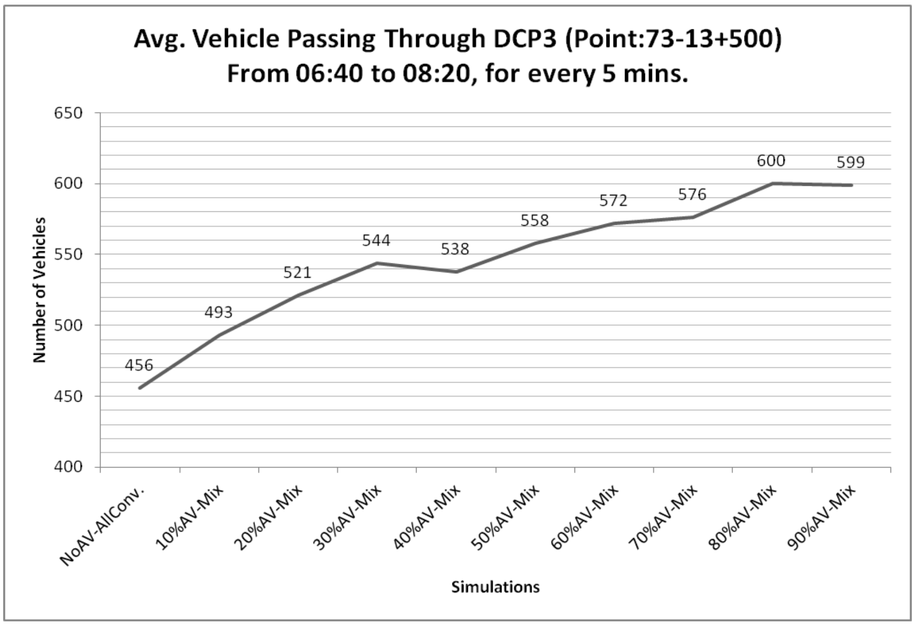

Figure 4.3 DCP-3 Avg. Vehicles Passing Through the Data Collection Point 3

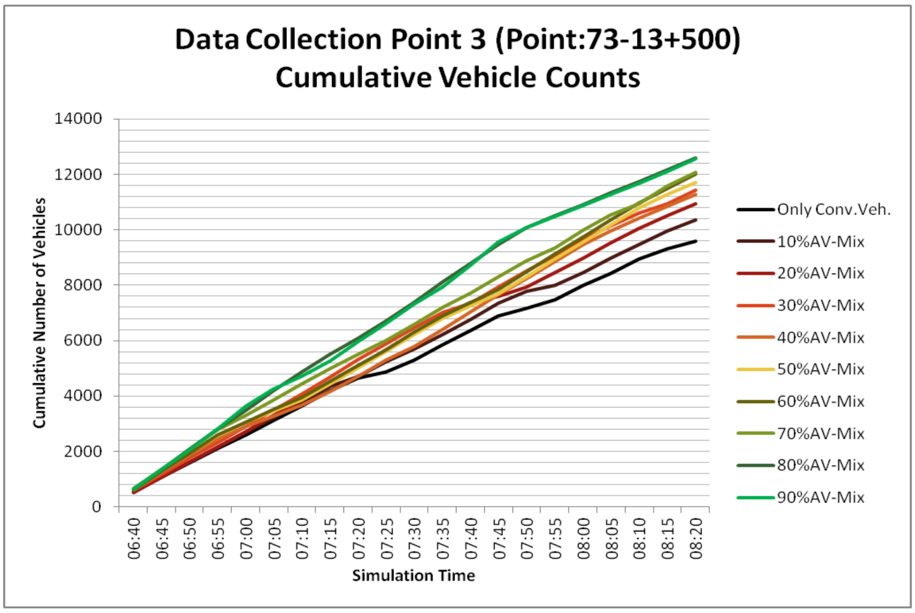

Figure 4.4 N-Curve for DCP3-73-13+500, Cumulative Veh. Counts at Peak Hour

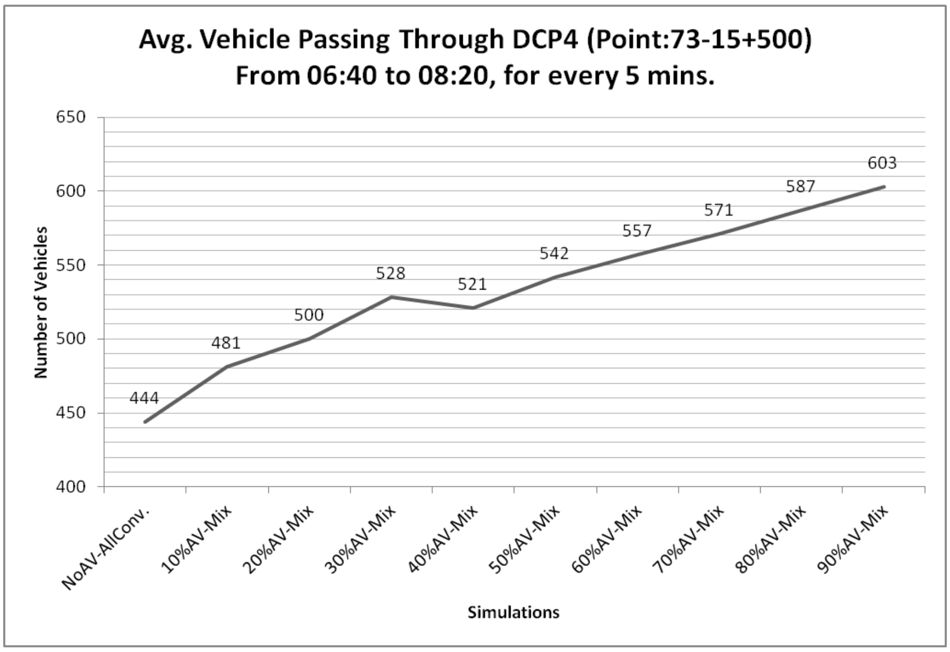

Figure 4.5 DCP-4 Avg. Vehicles Passing Through the Data Collection Point 4

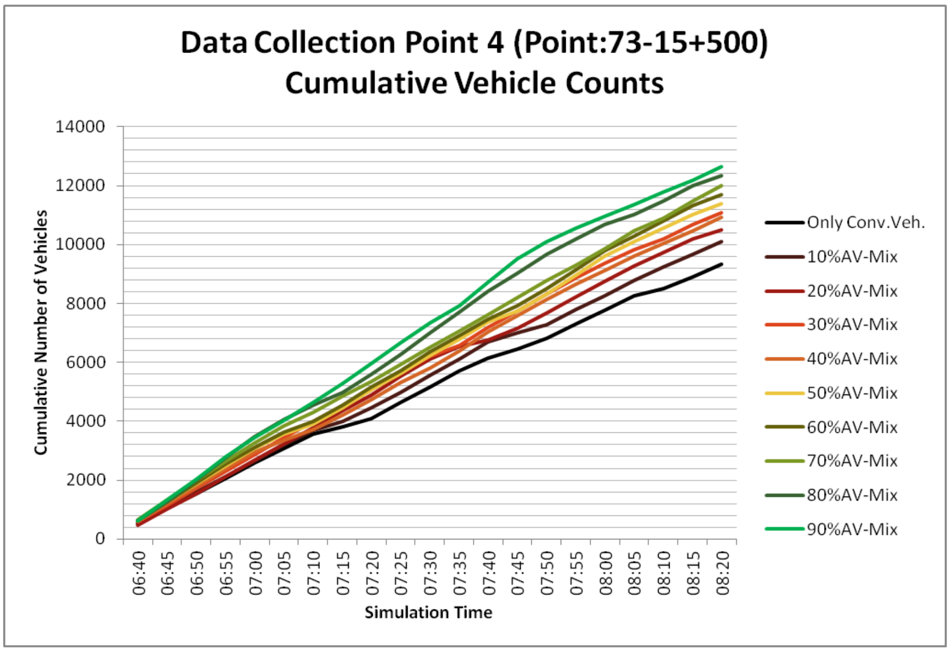

Figure 4.6 N-Curve for DCP4-73-15+500, Cumulative Veh. Counts at Peak Hour

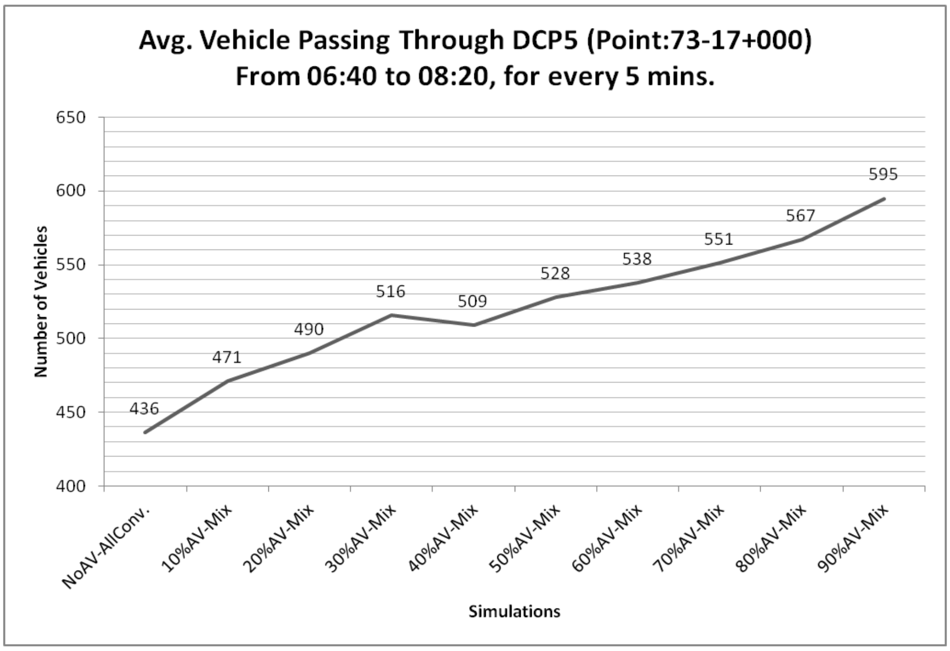

Figure 4.7 DCP-5 Avg. Vehicles Passing Through the Data Collection Point 5

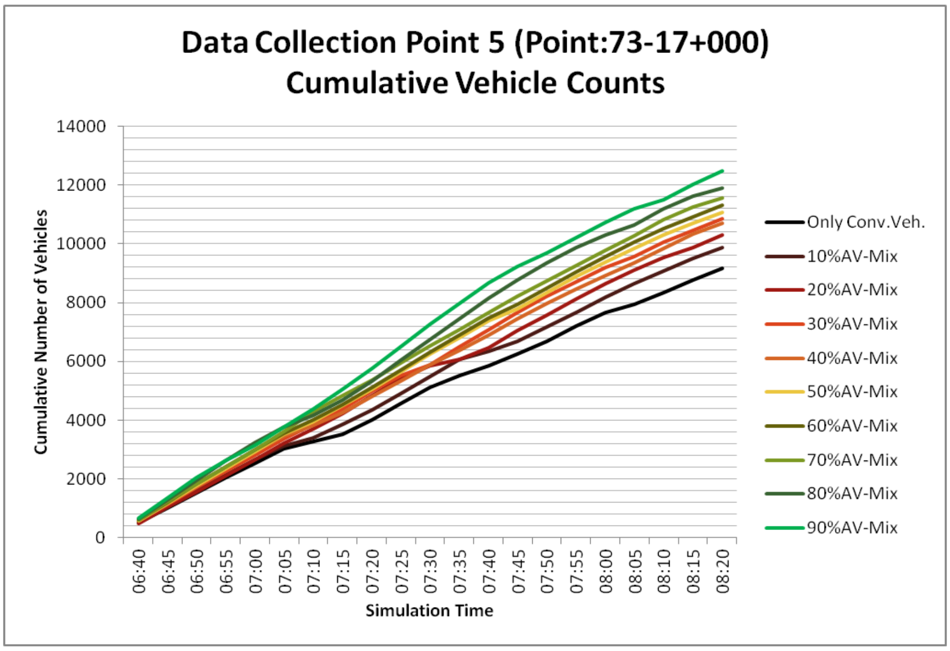

Figure 4.8 N-Curve for DCP5-73-17+000, Cumulative Veh. Counts at Peak Hour

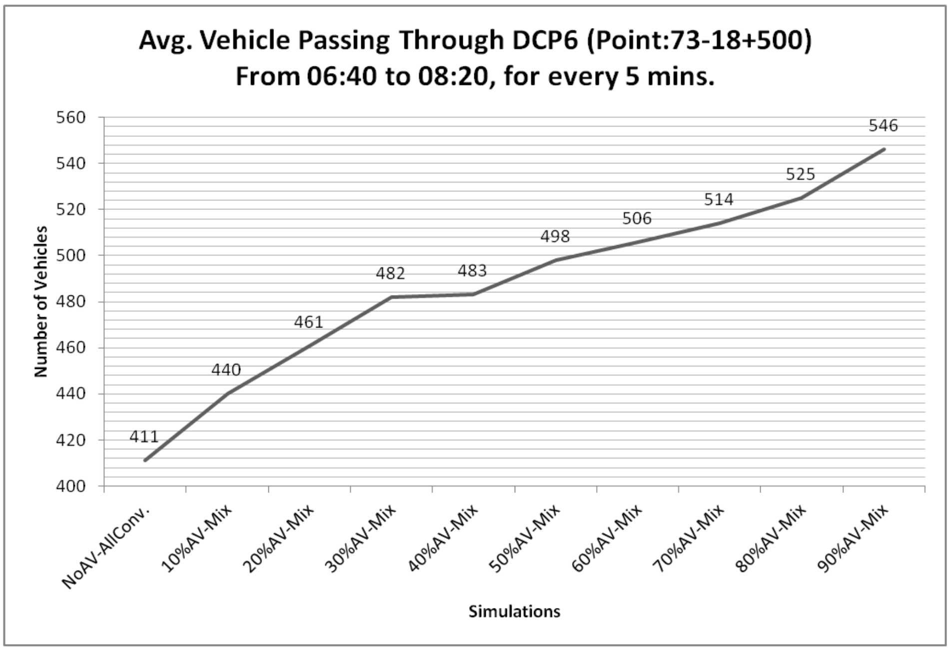

Figure 4.9 DCP-6 Avg. Vehicles Passing Through the Data Collection Point 6

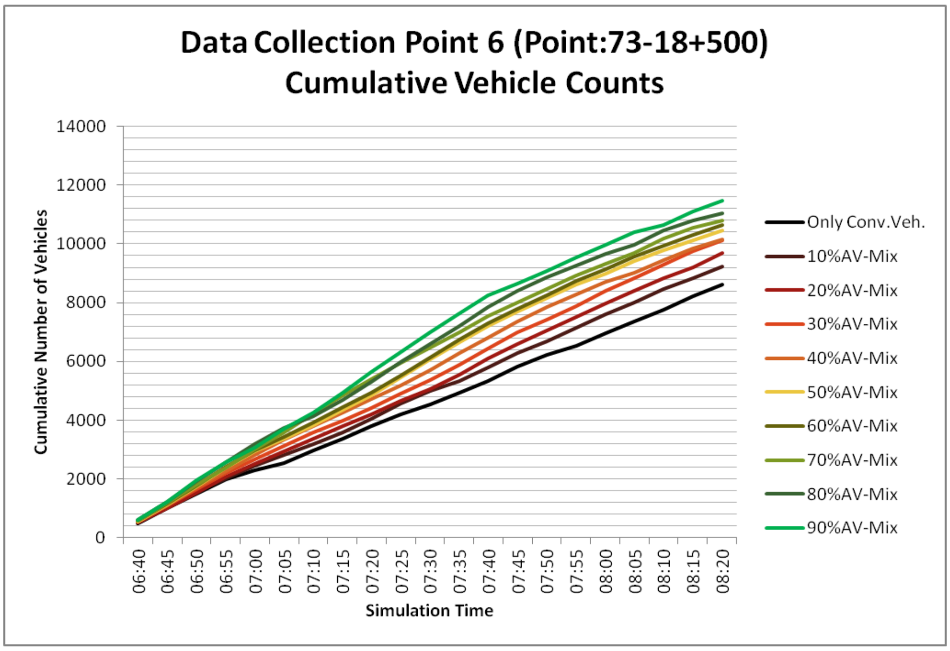

Figure 4.10 N-Curve for DCP6-73-18+500, Cumulative Veh. Counts at Peak Hour

Data collection points 3, 4, 5 and 6 are located at the start and finish of the Çamlık intersection as well as the start and finish of the Kavacık intersection. Also, these intersections have specific nodes placed around them as explained in section 3.2.1 for investigations about the number of stops happening during the simulation.

Cumulative number of stops on these intersections, including the Ümraniye intersection, were studied to support the findings. Figures 4.11 and 4.12 show the Ümraniye intersection node results. Findings from the Çamlık intersection node are displayed in Figures 4.13 and 4.14. In the end, Figures 4.15 and 4.16 are illustrates the results from Kavacık intersection node.

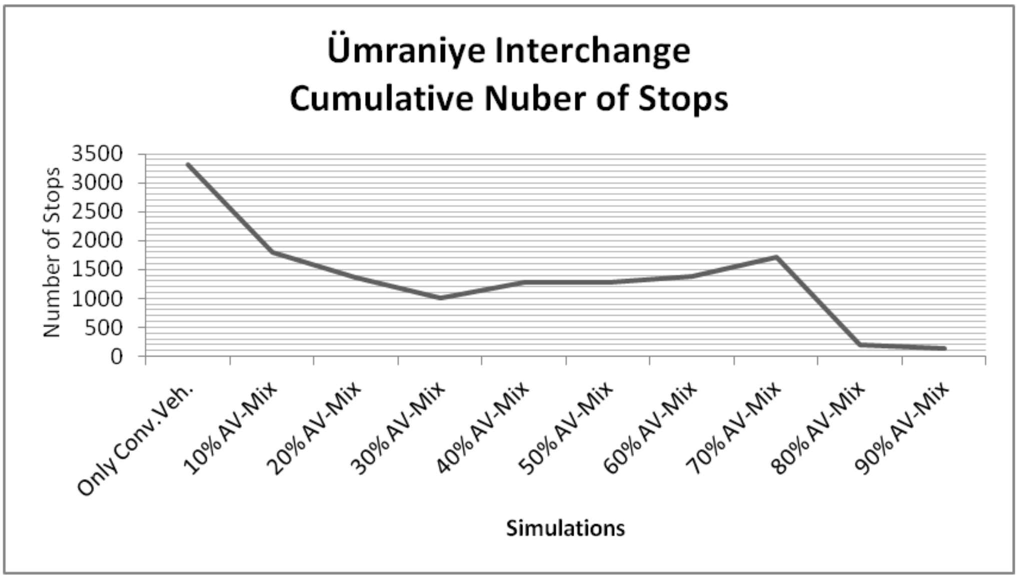

Figure 4.11 Ümraniye Node, Cumulative Number of Stops

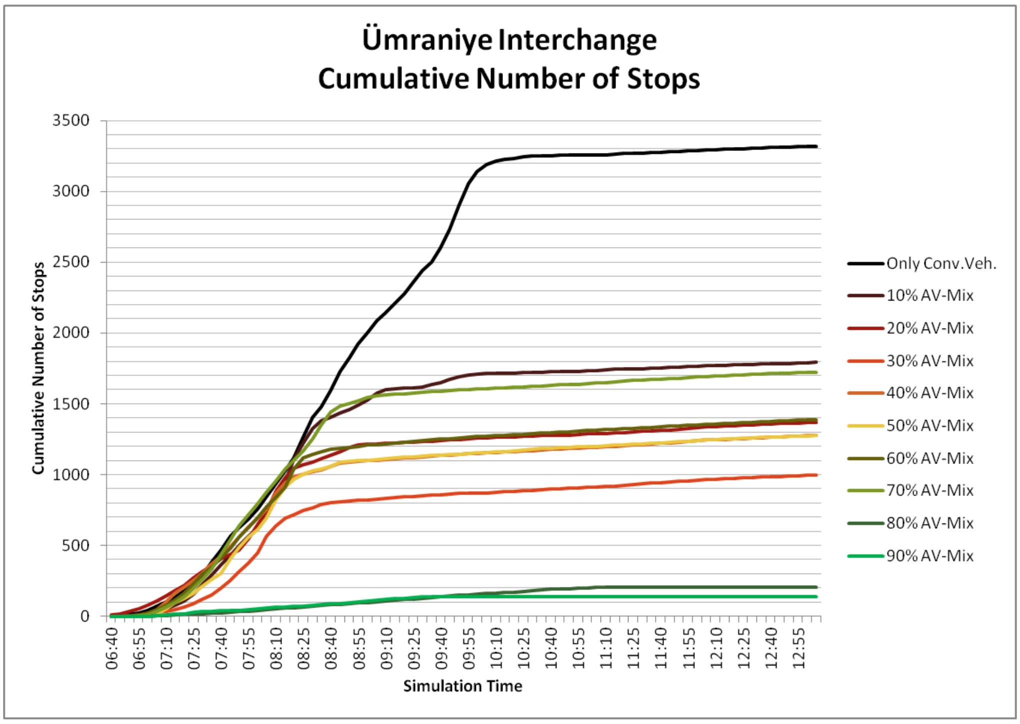

Figure 4.12 Ümraniye Node, Cumulative Number of Stops

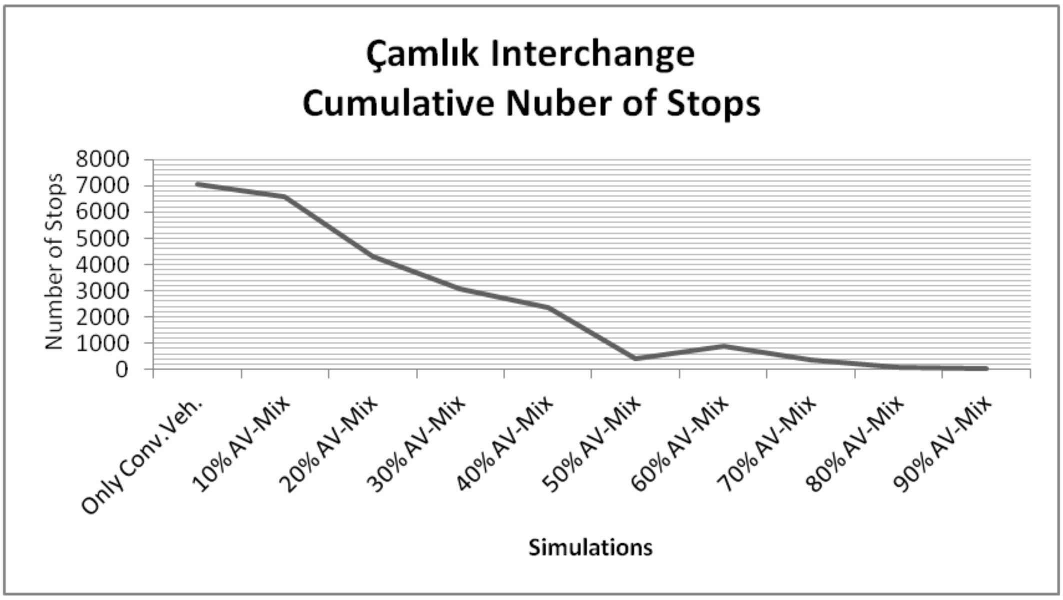

Figure 4.13 Çamlık Node, Cumulative Number of Stops

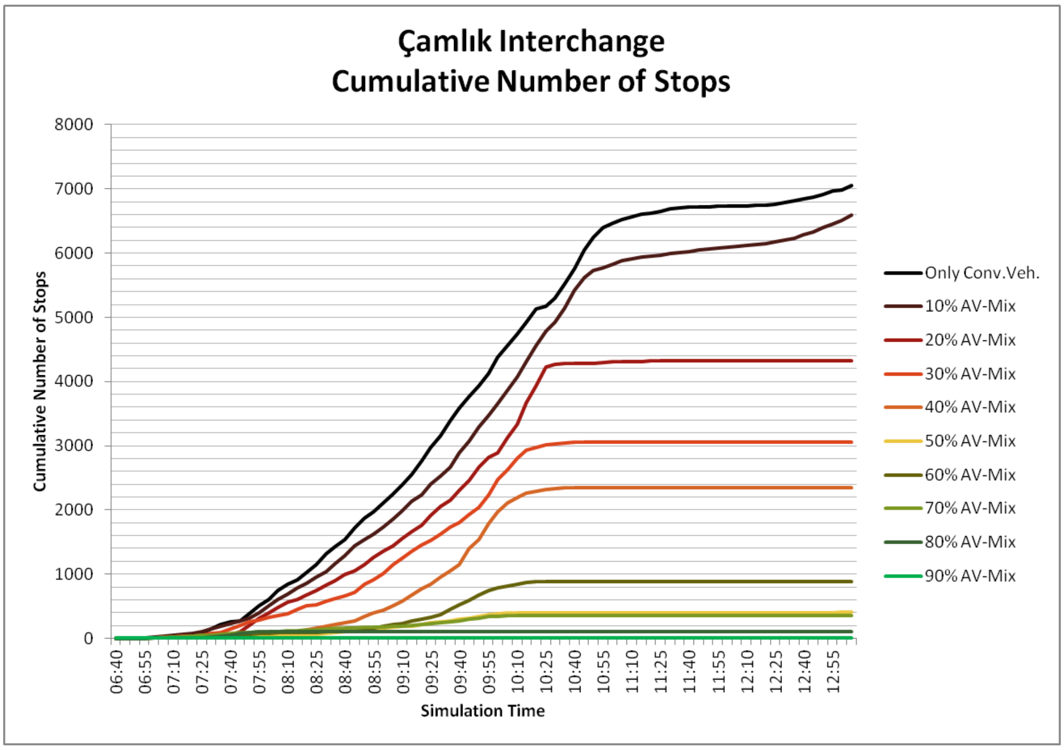

Figure 4.14 Çamlık Node, Cumulative Number of Stops

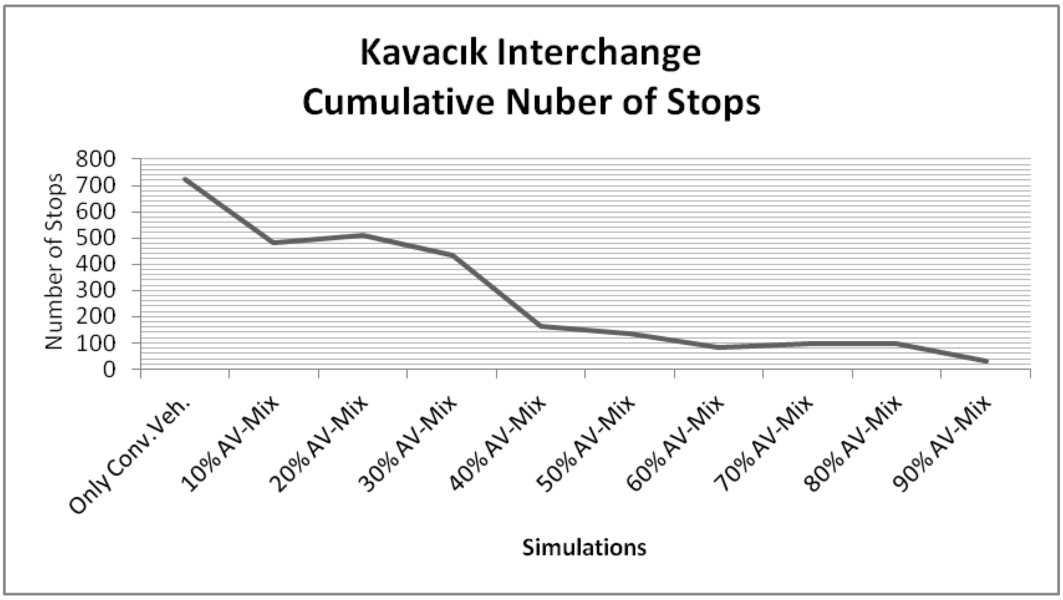

Figure 4.15 Kavacık Node, Cumulative Number of Stops

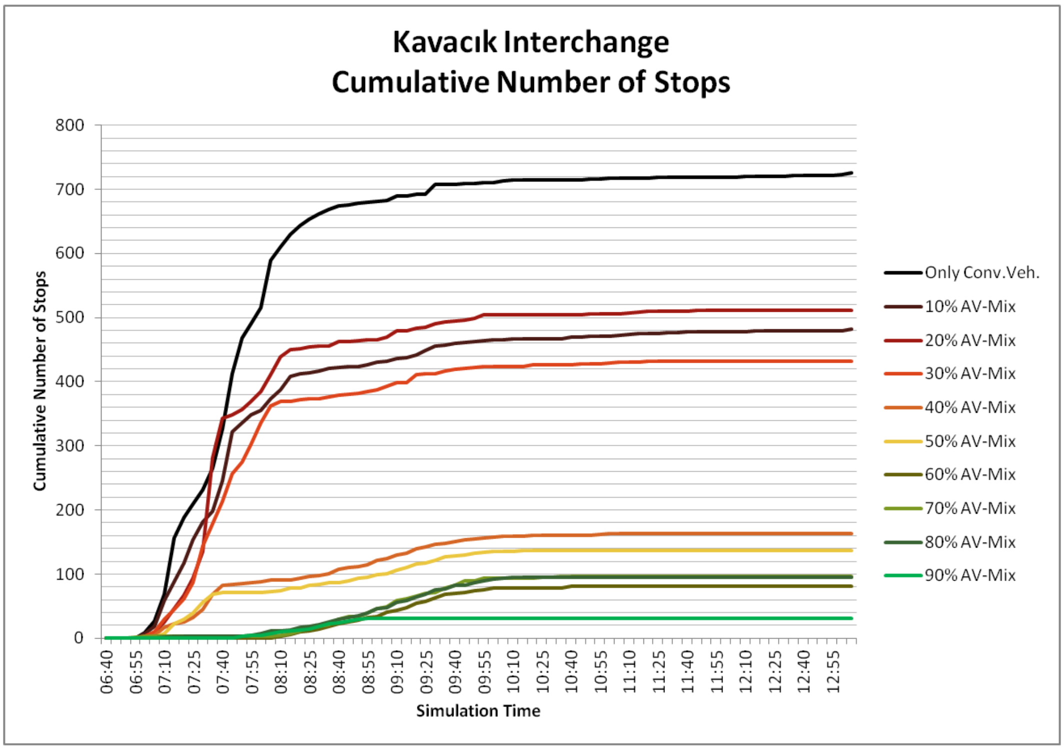

Figure 4.16 Kavacık Node, Cumulative Number of Stops

The table below shows the average number of stops happening for every 5 minutes on each node. The graphs and measured results show the average stop counts constantly decreasing for each simulation conducted.

Table 4.2 Average Number of Stops for All Nodes

Avg. Number of Stops /5mins.	**Ümraniye Interchange**	**Çamlık Interchange**	**Kavacık Interchange**
Only Conv.Veh.	43	90	9
10% AV-Mix	23	84	6
20% AV-Mix	18	55	7
30% AV-Mix	15	39	6
40% AV-Mix	16	30	2
50% AV-Mix	13	18	2
60% AV-Mix	10	11	1
70% AV-Mix	6	5	1
80% AV-Mix	3	1	1
90% AV-Mix	2	0	0

Table 4.2 makes it evident that when the network's AV percentage rises, the number of stops occur 25%–26% less often. The best AV penetration rate, based on this research, is between 40% and 50%. Additionally, after 80% AV-Mix, there are often 1 or 2 stops.

4.4 Total Number of Vehicles Passing Through FSM Bridge

The total number of vehicles crossing the FSM Bridge during peak hour can be seen below. Figures 4.17, 4.18 and 4.19 belongs to data collection point 7 and shows cumulative vehicle counts and avg. vehicles passing through the data collection point. There is also cumulative vehicle count comparison for all conventional vehicles and all AV at Figure 9.3. Lastly, the number of stops on the FSM Bridge node shown on Figures 4.20 and 4.21. Although the percentage of AVs is still rising in other simulations, it is not progressing as much as after the 40% or 50% results, which are the most desirable penetration based on the findings. Vehicles travel without stopping or encountering any difficulty due to traffic after 80% AV composition.

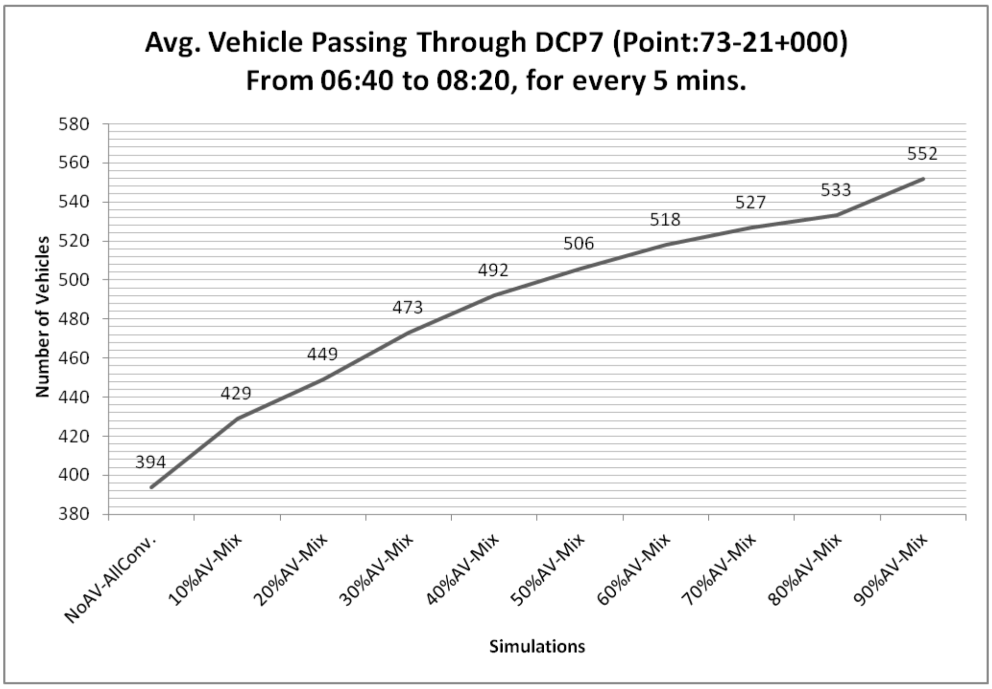

Figure 4.17 DCP-7 Avg. Vehicles Passing Through the Data Collection Point 7

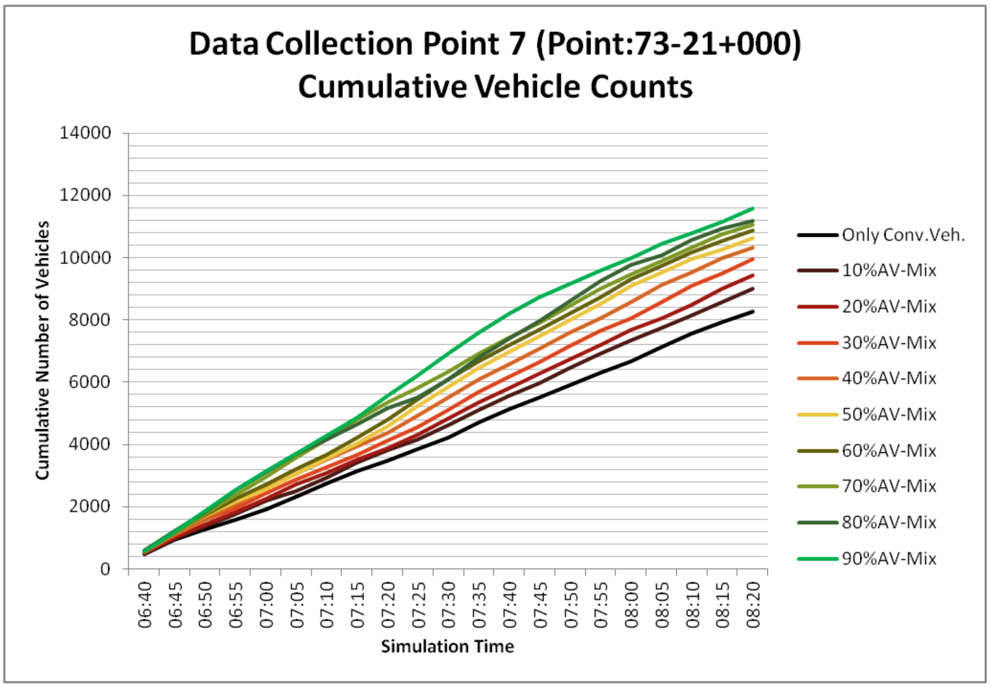

Figure 4.18 N-Curve for DCP7-73-21+000, Cumulative Veh. Counts at Peak Hour

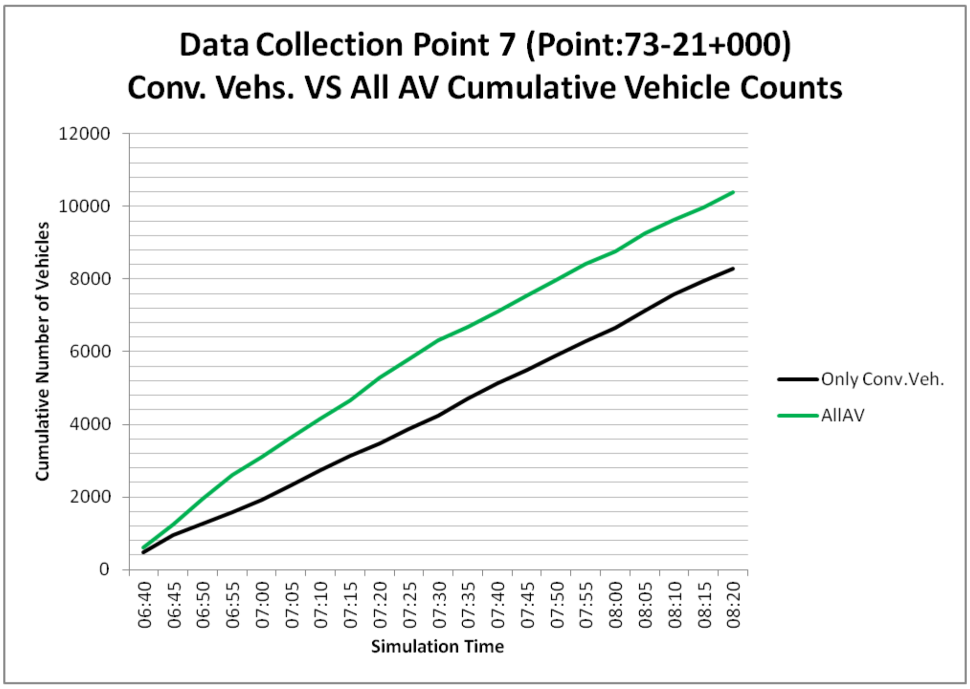

Figure 4.19 N-Curve for DCP7-73-21+000, Vehicle Counts at Peak Hour

To support the conclusions, the total number of stops on the FSM Bridge node were also investigated. The cumulative number of stops is shown in Figures 33 and 34, and Table 4.3 shows the average number of stops per 5 minutes during peak hours.

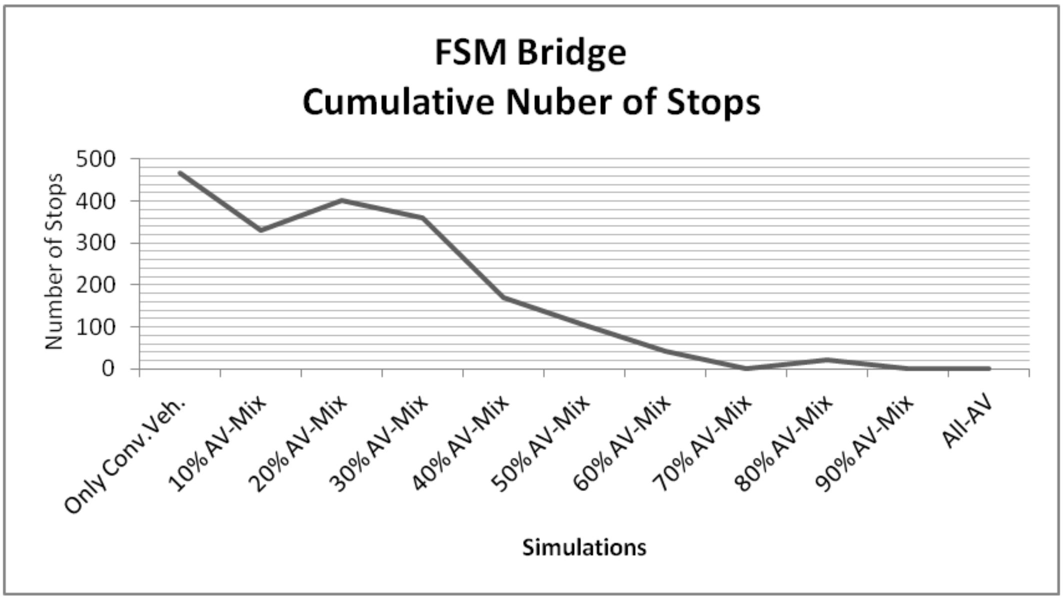

Figure 4.20 FSM Bridge Node, Cumulative Number of Stops

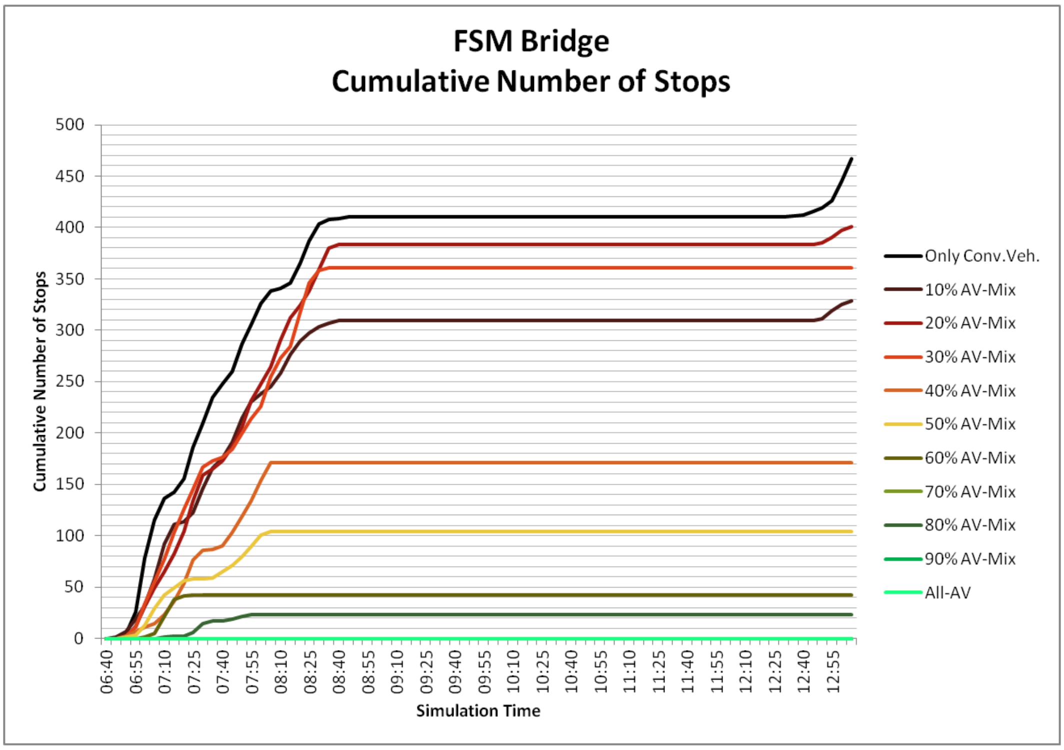

Figure 4.21 FSM Bridge Node, Cumulative Number of Stops

Table 4.3 Average Number of Stops for FSM Bridge Node

FSM Bridge Node / Simulations	Avg. Number of Stops /5mins.
Only Conv.Veh.	6
10% AV-Mix	4
20% AV-Mix	5
30% AV-Mix	4
40% AV-Mix	2
50% AV-Mix	1
60% AV-Mix	1
70% AV-Mix	0
80% AV-Mix	0
90% AV-Mix	0

Overall results indicate that our AV behavior is accomplishing our purpose and AVs can improve traffic conditions during peak hours when they coexist with conventional vehicles. When considering the entire simulation, about a 10% vehicle count improvement is observed, however when only the peak hours are focused on, a significant difference could be visible. Additionally, the results section 5.1 includes a detailed description of the improvements made during peak hours.

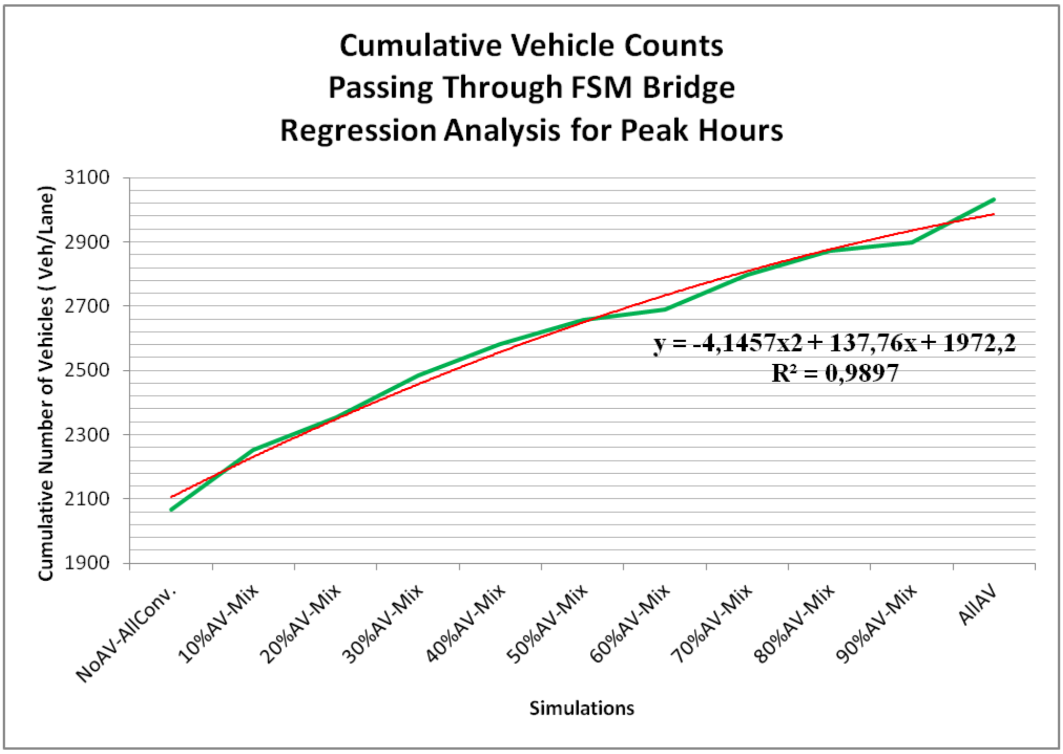

Figure 4.22 Regression Graph of the Total Vehicle Counts Passing Through the FSM Bridge for Peak Hours

Regression analysis was performed and a graph was drawn to determine how the AV % would increase the number of vehicles. For this purpose, the number of vehicles per lane at FSM Bridge crossings at peak hours was studied. The peak hour improvements are shown in Figure 4.22 according to the polynomial regression function $y = -4.1457x^2+137{,}76x+1972{,}2$ based on the number of vehicles per lane. Also analyzing the simulation's regression graph reveals that the R^2 value is 0,9897.

CHAPTER 5

5. RESULTS, CONCLUSION AND DISCUSSION

This chapter gives an overview of the entire research process, highlights its shortcomings, and suggests additional research for the future.

5.1 Summary and Research Findings

The primary objective of this study was to examine the effects of AVs in mixed traffic at highway margin locations for various AV combinations and a peak hour traffic demand situation. Examining the driving behavior parameters of the existing traffic performances was the second purpose. The experiment has been designed to effectively achieve the objectives of this investigation. Figure 5.1 shows the study's executive summary and simple workflow.

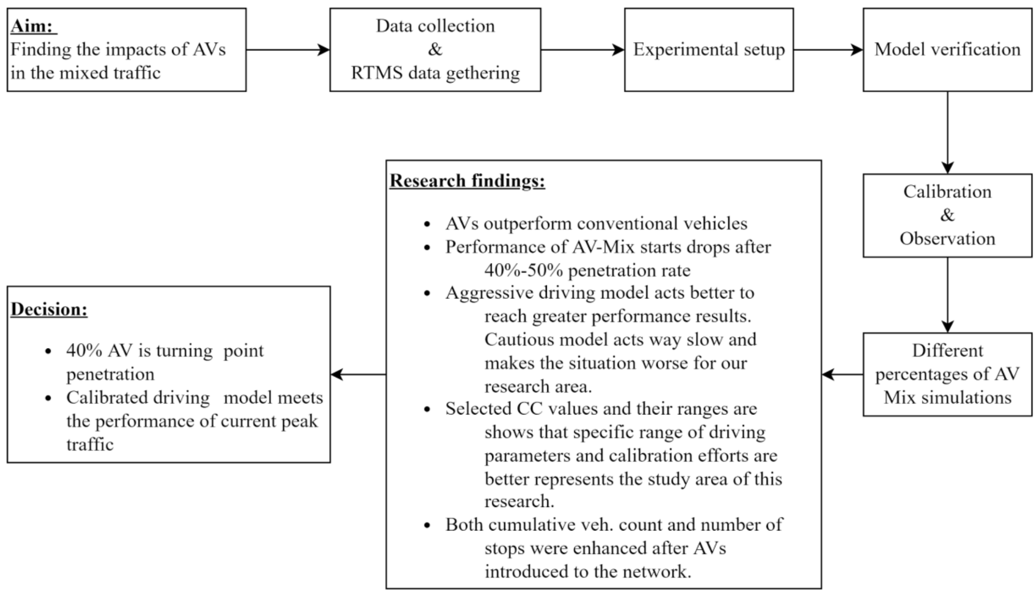

Figure 5.1 Summary of the study and workflow

It is discovered that the constant increase in AVs in the study area is expandable up to a particular limit, which was displaced for peak traffic demand instances. For the peak hour demand, optimal penetration levels are observed at penetrations of 30%, 40%, and 50%, respectively. In general, the study corridor's average travel and delay times have decreased while AV presence in the system has significantly increased for high AV penetration rates up to the optimal penetration. The results of this investigation demonstrates a considerable enhancement can be achievable with the AV aggressive behavior among of the three AV driving modules: normal, cautious, and aggressive.

The total number of 39 runs were chosen from the findings to get average results, despite the fact that the number of simulations explored in this study was rather modest. A total of 2631 vehicle combinations were created and tested from 0% to 100% AV, increasing by 10% to find an optimal penetration rate for these technologies and observe AV effects on our freeway network. The best cumulative vehicle count in our system is achieved when 4 out of 10 vehicles become AVs, according to the findings.

Table 5.1 Cumulative vehicle counts for FSM Bridge node and increments in different mix simulation

Simulations for FSM Bridge Node (Peak Hours)	**Total Number of Vehs.**	**Veh. Gain (%) vs/previous sim.**	**Cumulative Veh. Gain (%)**
Only Conv.Veh.	100,00%	-	-
10% AV-Mix	108,88%	8,88%	8,88%
20% AV-Mix	113,85%	4,97%	13,85%
30% AV-Mix	120,13%	6,27%	20,13%
40% AV-Mix	124,86%	4,74%	24,86%
50% AV-Mix	128,48%	3,61%	28,48%
60% AV-Mix	130,06%	1,58%	30,06%
70% AV-Mix	135,27%	5,21%	35,27%
80% AV-Mix	138,83%	3,55%	38,83%
90% AV-Mix	140,08%	1,26%	40,08%
AllAV	146,57%	6,49%	46,57%

The eventual goal is to eliminate traffic-causing stops and increase the number of vehicles passing through the FSM Bridge. Table 5.1 shows the overall results and percentage gain for each 10% AV increase in the network. Final findings show that our AV behavior is fulfilling its objective, and conventional vehicle model calibration represents the peak hour traffic. When AVs coexist with conventional vehicles, traffic conditions are improved during peak hours. Around 10% improvement can be seen when the full simulation is taken into account, but when only the peak hours are considered, it is possible to observe a sizable enhancement variation up to 45%. The penetration rate of AV is not required to be higher in order to receive all the benefits, and optimum penetration rate is found around 40%. Also, the technology and infrastructure needed to support an increase in the number of networked AVs in future.

5.2 Discussion

The study described in this paper intends to show possible changes occurring on freeway merging sites through the use of connected vehicle technology. The goal was also to calibrate a car-following model that can be used in a study area located in Istanbul, asian side, at morning peak hours. Several conventional car-following models were calibrated and validated by using RTMS data, and the calibrations were made, then analyzed for optimized values. Introducing different percentages of AV compositions into the current traffic, and mixing those AVs with conventional vehicles tested. The results suggest that AVs increased total vehicle capacity during peak hours. The results are encouraging, and usage of AVs in the future might stop traffic from occurring during rush hours.

Beyond these, calibrating a small number of parameters may not be the best approach to reach a more accurate representation of the drivers' behavior. For the calibration of driver behavior parameters and autonomous driving behaviors, more study is required. The next part will include recommendations for future research.

5.2 Conclusion and Future Work

In terms of the future studies, this study made an effort to construct and link several intersections depending on possible technology used today. As it is explained in field measurements, image recognition systems or better equipment could be used in order to record the section of the road better. More precise results can be obtained and study areas could be derived differently.

The impact of different vehicle accelerations can also be simulated by vehicle classes using the appropriate driver behavior characteristics from the created charts.

If the impact of HGVs or Buses accelerations or decelerations affects the car following model, for example, these values may need to be calibrated one by one according to vehicle classes and peak hour behaviors. It may be necessary to deploy specialized buses and trucks equipped with data gathering systems to conduct this research and collect the necessary data.

In order to eliminate the confusion happening in case all vehicles in the system become autonomous, more research should be done on AV's behavior. The freeway designs may eventually bring the fully automated lanes, which may display different car-following behavior than it does at the moment. Instead of comparing the existing settings with a certain number of AVs added to the study system, simulations of the "all vehicles are autonomous vehicles" type of model could be run, with just AV behaviors being examined.

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