EVALUATION OF MANAGED LANE FACILITIES IN A CONNECTED VEHICLE ENVIRONMENT

SAFETY RESEARCH USING SIMULATION

UNIVERSITY TRANSPORTATION CENTER

Mohamed Abdel-Aty, PhD, PE, PI
Pegasus Professor, Chair

Yina Wu, PhD, Co-PI

Post-doctoral associate

Department of Civil, Environmental and Construction Engineering

Moatz Saad, PhD

Md. Sharikur Rahman, PhD

Department of Civil, Environmental and Construction Engineering

University of Central Florida

EVALUATION OF MANAGED LANE FACILITIES IN A CONNECTED VEHICLE ENVIRONMENT

Mohamed Abdel-Aty, PhD, PE, PI

Pegasus Professor, Chair

Department of Civil, Environmental and Construction Engineering

University of Central Florida

https://orcid.org/0000-0002-4838-1573

Moatz Saad, PhD Candidate

Graduate Research Assistant

Department of Civil, Environmental and Construction Engineering

University of Central Florida

https://orcid.org/0000-0003-1760-5711

Yina Wu, PhD, Co-PI

Postdoctoral Associate

Department of Civil, Environmental and Construction Engineering

University of Central Florida

https://orcid.org/0000-0001-6516-8144

Md. Sharikur Rahman, PhD Candidate

Graduate Research Assistant

Department of Civil, Environmental and Construction Engineering

University of Central Florida

https://orcid.org/0000-0001-7623-5437

A Report on Research Sponsored by

SAFER-SIM University Transportation Center

Federal Grant No: 69A3551747131

August 2019

DISCLAIMER

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated in the interest of information exchange. The report is funded, partially or entirely, by a grant from the U.S. Department of Transportation's University Transportation Centers Program. However, the U.S. Government assumes no liability for the contents or use thereof.

Table of Contents

List of Figures

List of Tables

1 Introduction

On freeways, managed lanes (MLs) have emerged as an effective dynamic traffic management strategy. They are vital for managing time and congestion through tolling while also providing drivers with more choices. They play an important role in improving traffic mobility, efficiency, and safety, in addition to generating revenue for transportation agencies. Managed lanes are designated lanes where the flow of traffic is managed by limiting vehicle eligibility (e.g., high occupancy vehicle [HOV] lanes, truck only [TO] lanes); restricting facility access (e.g., reversible lanes [RLs], express lanes [ELs]); employing fixed or dynamic price tolls (e.g., toll ways, express toll lanes [ETLs]); setting pricing and vehicle eligibility (e.g., high-occupancy toll [HOT] lanes, truck only toll [TOT] lanes); or setting vehicle eligibility and access control (e.g., bus rapid transit [BRT] lanes, dedicated truck lanes, transit ways) [1-3]. Figure 1.1, Figure 1.2, and Figure 1.3 show examples of express lanes with dynamic toll pricing, HOV lanes, and BRT lanes, respectively. This research also proposes a new designation for designated connected vehicle (CV) lanes.

Figure 1.1 - An example of high occupancy vehicle lanes, Nashville, Tennessee

Figure 1.2 - An example of bus rapid transit lanes, Boston, Massachusetts

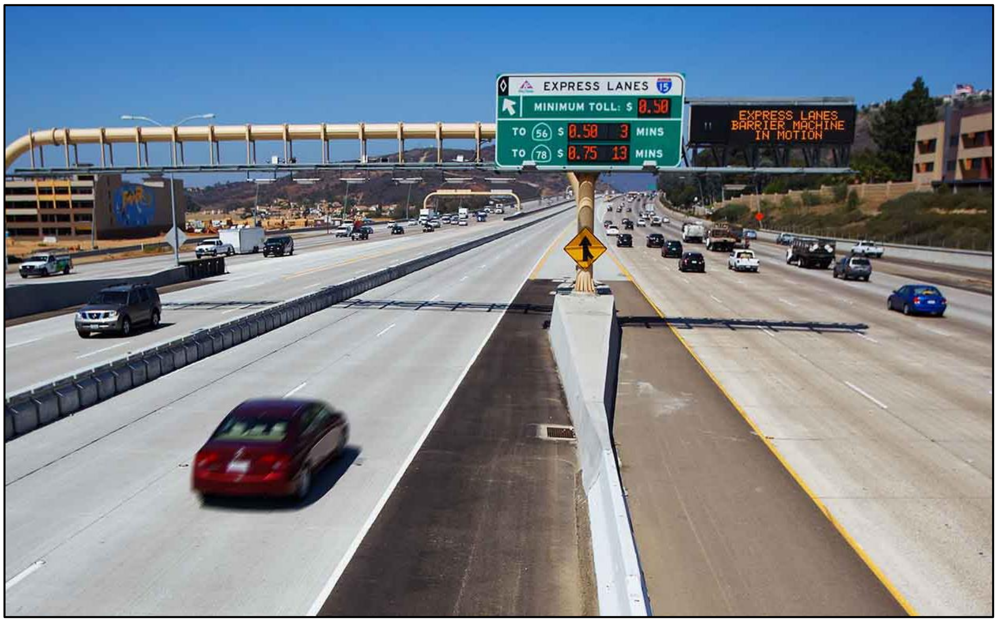


Figure 1.3 - An example of dynamic toll pricing lanes, San Diego, California

The route-miles of MLs from 1970 to 2015 are shown in Figure 1.4. The figure reveals a trend of ML growth over the years. Since 1995, HOT lanes and express lanes have grown drastically, and the growth of MLs is expected to continue. In 2013, the American Society of Civil Engineers (ASCE) estimated that the cost of congestion for wasting fuel and time was $101 billion annually and the average time spent for American drivers in traffic is about 38 hours annually. By 2020, MLs are projected to be expanded throughout the U.S. to reach 6,000 lane-miles (total length in miles multiplied by the number of lanes).

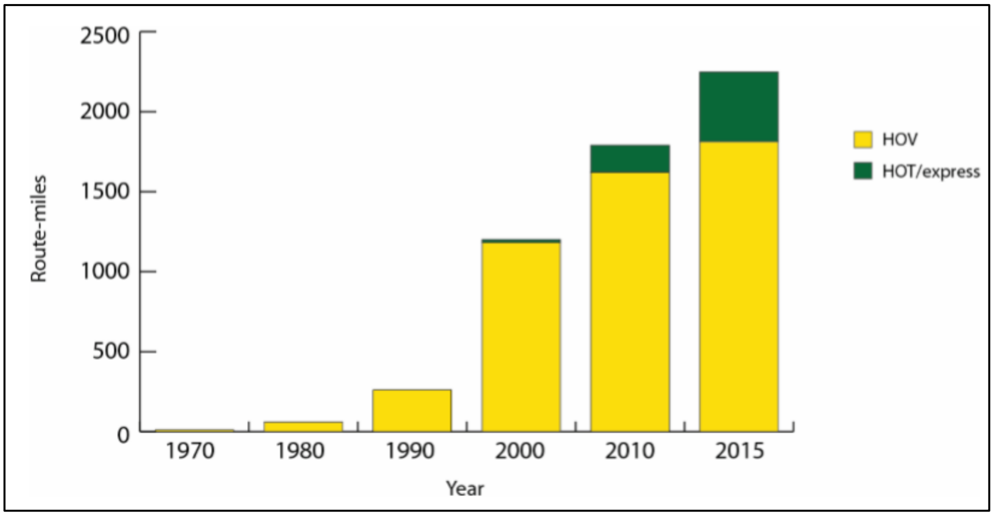


Figure 1.4 - Managed lanes growth from 1970 to 2015 (Source: [2])

Several major cities in the United States, as shown in Figure 1.5, have introduced managed toll lanes systems such as ETLs and HOT lanes for increasing efficiency, alleviating congestion, and providing drivers with more alternative routes. In the U.S., 35 states use toll roads, with 6,233 miles of toll roads, bridges, and tunnels. There are also more than 50 million transponders along 46 priced MLs facilities. In 2016, more than 5.7 billion trips were taken on toll facilities, which generated $18 billion in toll revenues. Currently, there are over 300 MLs facilities in the U.S. Managed toll lanes are thought to be an appropriate option to deal with high congestion while also offering a viable cost-effective model for promoting economic development. Toll revenue has the potential to support half of the costs of the $1 billion assets of the facility [4].

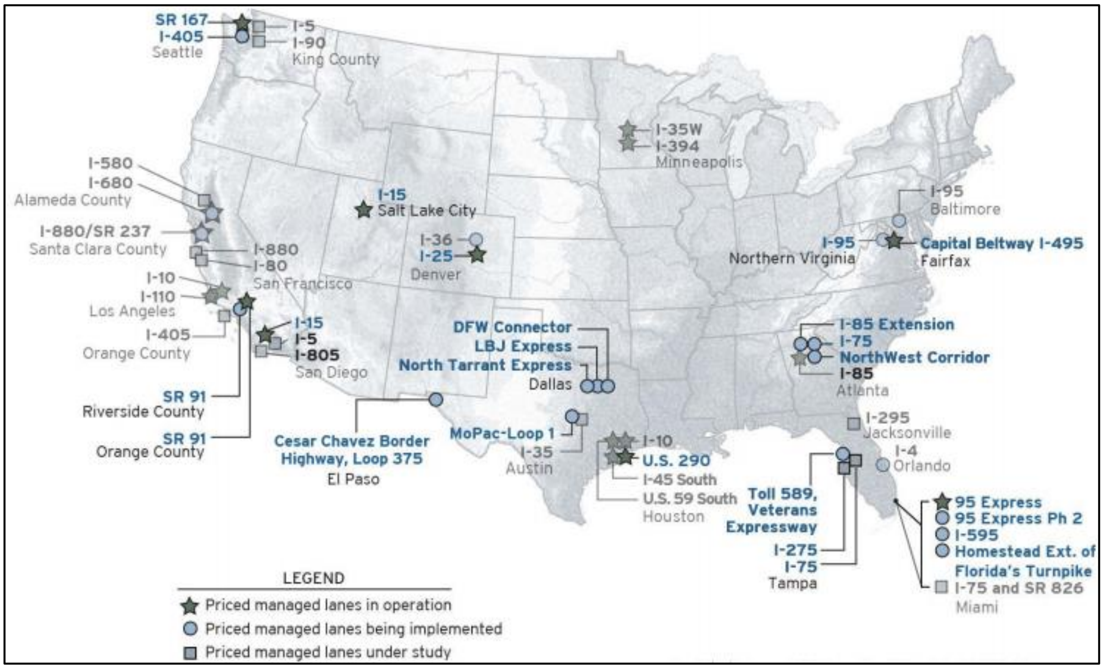


Figure 1.5 - Priced managed lanes in the U.S. Source: Atkins, 2013

The main objective of this study was to investigate the effect of different CV lane configurations and various market penetration rates on the safety and operation of the MLs network. Additionally, work will be done for studying the lower levels of automated vehicles (Level 1/Level 2) in a CV environment in the MLs network and determining the optimal market penetration rates of automated vehicle in the network under CV environment. This ongoing project is composed of four sections. Chapter 2 provides a brief review of previous studies of MLs, studies related to microsimulation and analyzing traffic conflicts, and studies related to connected and automated vehicles. Chapter 3 describes the microsimulation process for the studied corridor, which mainly included network building, calibration and validation, and CV scenario design. It also presents results and findings. Chapter 4 provides a description of the impact of dedicated lanes for CV platooning on expressways.

2 Literature Review

2.1 Managed Lanes Safety

The primary purpose of MLs is to manage and expedite the flow of traffic in a segment through access control (i.e., entrances, exits), vehicle eligibility (i.e., vehicle type, vehicle occupancy), or pricing strategies (i.e., dynamic tolls) [5]. As presented by the Federal Highway Administration (FHWA), MLs are a valuable option for transportation agencies to manage traffic congestion [6, 7]. The priced managed lanes system has risen dramatically in the U.S. in recent years due to improved time reliability, time savings, mobility, congestion management, and revenue generation [8]. The toll revenue is used to fund the facility through the dynamic tolls, which vary based on the time saved and the traffic periods. As the traffic increases in the MLs (i.e., peak period), the toll price increases to maintain the operating speed in the MLs [9, 10].

Limited research has been conducted on the safety benefits of improving the geometric design of the general-purpose lanes (GPLs) segments close to the access zones. The limitation of the geometric data availability and the small sample size are the main reasons behind limited studies of MLs [2]. A recent article conducted by Abuzwidah and Abdel-Aty [10] analyzed crash data for 156 segments on I-95 over the course of 9 years (2005 to 2013) using three methods: before-after with the comparison group (CG) method, the empirical Bayes (EB) method, and the cross-sectional (CS) method. The results showed that total crashes in the MLs decreased by 20% and severe crashes (fatal and injury) were reduced by 30%. Moreover, total crashes and severe crashes (fatal and injury) increased in GPLs by 19% and 8%, respectively [10].

The latest MLs guidelines report from the National Cooperative Highway Research Program (NCHRP) [2] pointed out that MLs provide better operational and safety performance than GPLs. Access zones are considered to be one of the most dangerous locations on the GPLs segments. Crashes frequently occur near the entrances and the exits of the MLs. One of the countermeasures suggested by NCHRP was to appropriately locate the access zones and the traffic control devices [2]. Designated access should be strategically positioned to minimize erratic weaving to or from nearby ramps [11]. Two types of crashes are common near the access zones: sideswipe and rear-end crashes. Sideswipe crashes happen due to lane-changing maneuvers upstream from the MLs entrances or exits. Meanwhile, rear-end crashes occur as a result of vehicles that decelerate before entering MLs [2]. Access zones crashes are fundamentally affected by access type, traffic periods, and weaving length upstream or downstream of the facility. Meanwhile, high crash frequency is associated with small access length and close access points to the on- or off-ramps [12-14].

2.2 Access zones

Managed lanes systems have been widely implemented on freeways to mitigate congestion and improve efficiency. Managed lanes are usually designed as concurrent with GPLs and separated by a barrier or painted stripe with several at-grade ingresses and egresses. However, this kind of design may result in weaving segments between ingress (egress) and on-ramp (off-ramp). For example, a vehicle from an on-ramp must cross multiple GPLs to get access to the ML. There are multiple approaches for providing access to MLs: continuous access, restricted at-grade access, and grade-separated access. Recently, there has been an interest in continuous access where vehicles could use the priced MLs at any point. Experiences from the design of access zones for MLs suggest several recommendations [11]. First, the geometric criteria for access zones should be the same as those used for freeway ramps, including locally recognized entrance and exit standards. Second, the location of ingress/egress facilities is influenced by some factors. For example, direct access ramps to/from local streets should be made with candidate streets that currently do not have freeway access to better distribute demand and prevent overloading existing intersections. For at-grade access with the adjacent freeway lanes, designated outlets should be strategically positioned to minimize erratic weaving to reach nearby freeway exits. Third, locate ingress/egress points associated with street access away from intersections that are operating at or near the traffic capacity. Fourth, vehicles entering the MLs facility should be required to make a maneuver to get into the lane. Fifth, the ramps to MLs should provide adequate space for possible metering and storage. Sixth, proper advance signing should be provided, and pavement markings should emphasize the mainline. Seventh, safety lighting should be applied for all ingress/egress locations using the same warrants applied for urban freeway entrance and exit ramps. Provision for entrance ramp metering (RM) and enforcement should be considered.

Weaving segments are some of the most critical areas on freeways, with more sideswipe and rear-end crashes than other segments [15-17]. Pulugurtha and Bhatt [18] explained that the high incidence of crashes in the weaving segments is due to the short weaving distances near the ramps. The weaving length is an important factor that affects the crash count [18-21]. Bonneson and Pratt [20] found that longer weaving segments have lower CMF, which indicates a lower number of crashes. Previous studies have explored the efficient weaving length near the access zones of MLs. One of these studies was conducted by the California Department of Transportation [12], which suggested a minimum distance of 800 ft. per lane change between the on- or off-ramps and the access zones. Another study conducted by the Washington State Department of Transportation (WSDOT) [22] proposed the minimum distance between the access zones and the on- or off-ramps to be 500 ft. per lane change. Meanwhile, the study recommended that the desired distance is 1,000 ft. per lane change. A study conducted by Venglar et al. [23] suggested that the range of the weaving length varied between 500 ft. and 1,000 ft. per lane change. They provided various cases of the weaving distance as shown in Table 2.1 [23]. Meanwhile, they concluded that the minimum distance between the ingress and the egress of the MLs was 2,500 ft. Additionally, Machumu et al. [24] recommended the minimum weaving distance near MLs based on travel speed, number of vehicles changing lanes, and the following distance. A weaving length of 800 ft. per lane change was recommended at sections with six lanes, while the length was suggested as 1,500 feet per lane change at sections with three lanes [24].

Table 2.1 - Weaving distances for MLs

Design Year Volume Level	Allow up to 10 mph Mainline Speed Reduction for Managed Lane Weaving?	Intermediate Ramp (between Freeway entrance/exit and MLs entrance/exit)?	Recommended Minimum Weaving Distance Per Lane (ft)
Medium (LOS C or D)	Yes	No	500
		Yes	600
	No	No	700
		Yes	750
High (LOS E or F)	Yes	No	600
		Yes	650
	No	No	900
		Yes	950

Source: Venglar et al. [23]

2.3 Microscopic Traffic Simulation

In this study, microscopic traffic simulation will be used to replicate the field corridor in order to study the safety and operation effectiveness of MLs in a CV environment. As indicated by Haleem [25], traffic simulation plays a vital role in better understanding the traffic of the real world and producing accurate results. Using traffic simulation has many advantages: (1) predicting driving behavior due to a specific action, (2) exploring why some events happened in the real world, (3) studying hotspot areas or regions with problems before carrying out solutions, (4) identifying the impact of any modifications on the traffic system, (5) being familiar with all variables, (6) discovering the drawbacks of the traffic system, and (7) efficiently simulating new ideas. Many studies used simulation experiments for carrying out conclusions for traffic safety studies. Lately, simulation has been a flexible and efficient tool for improving traffic safety analysis. It has also been proven that using simulation in traffic safety studies is a cost-effective way to test different scenarios that have been accurately replicated from the real world in a simulated environment [25].

According to Nilsson [26], simulation is one of the most widely used and efficient tools for studying roadway system operation and investigating traffic safety impacts. Compared to other methods, simulation is a more efficient and easier way to collect traffic data. It can test the impact of a treatment before implementing it in the field. It is also an alternative for evaluating different operations and improvements since field data collection is a costly and time-consuming process [26]. Simulation techniques can be used for analyzing risky driving factors in an environment that is similar to the real world [27]. They also allow testing multiple scenarios applicable to road geometry or traffic control devices [28]. In conclusion, because of the enormous amount of field data required for studying driver behavior, simulation techniques are the most appropriate tool for conducting this kind of study.

Simulation networks have to be validated with real-world data to study traffic safety and especially to explore driving behavior accurately [29]. Calibration and validation are the most important steps when utilizing simulation to replicate the real-world conditions. When studying weaving segments in simulation, several driving behavior parameters for car following and lane change should be adjusted to calibrate and validate the network [30, 31]. The car following model determines the longitudinal movement of the simulated vehicle, while the lane change model decides a vehicle's lateral movement.

2.4 Previous work related to MLs at the University of Central Florida

Several studies were conducted at the University of Central Florida (UCF) to evaluate the safety and operation effectiveness of MLs [31-36]. A study was conducted by Saad et al. [33] to determine the optimal access zone design of MLs using microscopic traffic simulation. Several scenarios were tested using Vissim simulation to determine the optimal access design while taking into consideration accessibility levels and weaving lengths. The studied accessibility levels varied from one to three along the studied network. Both safety (i.e., speed standard deviation, time-to-collision, and conflict rate) and operation (i.e., level of service, average speed, and average delay) performance measures were included in the analysis. Tobit models were developed for investigating the factors that affect the safety measures. Analysis of variance (ANOVA) and Level of Service (LOS) calculations were used to evaluate traffic operation. Figure 2.1 shows the conflict rate for various weaving lengths. The results of the safety and operational analysis suggested that one accessibility level is the optimal option in the 9-mile network. A weaving length between 1,000 feet and 1,400 feet per lane change was suggested based on the safety analysis. In addition, from the operation perspective, a weaving length between 1,000 feet and 2,000 feet per lane change was recommended. The results also showed that off-peak periods had better safety and operational performance (e.g., lower conflict rate, less delay) than peak periods.

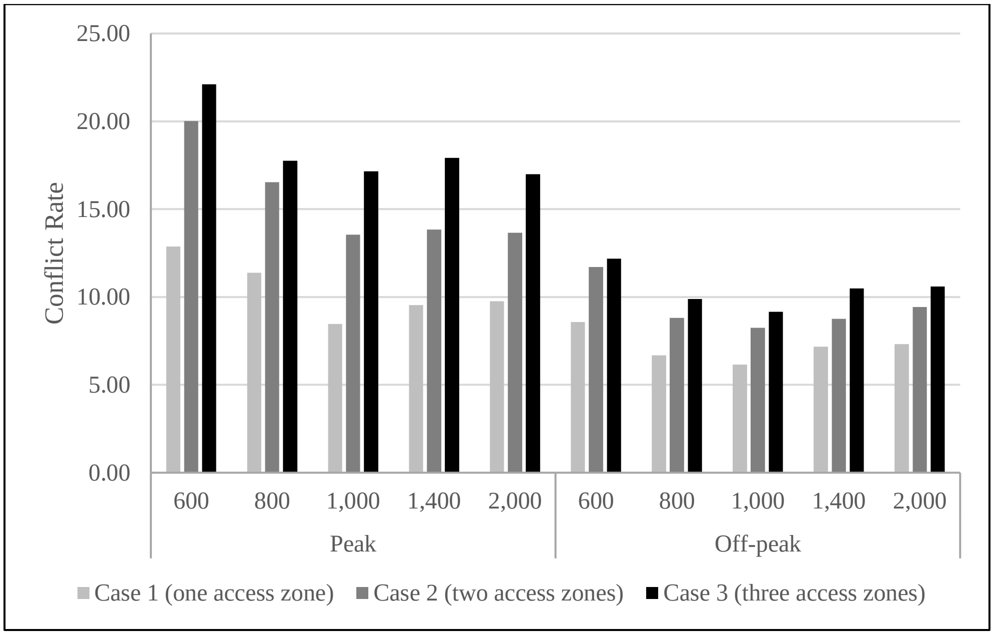
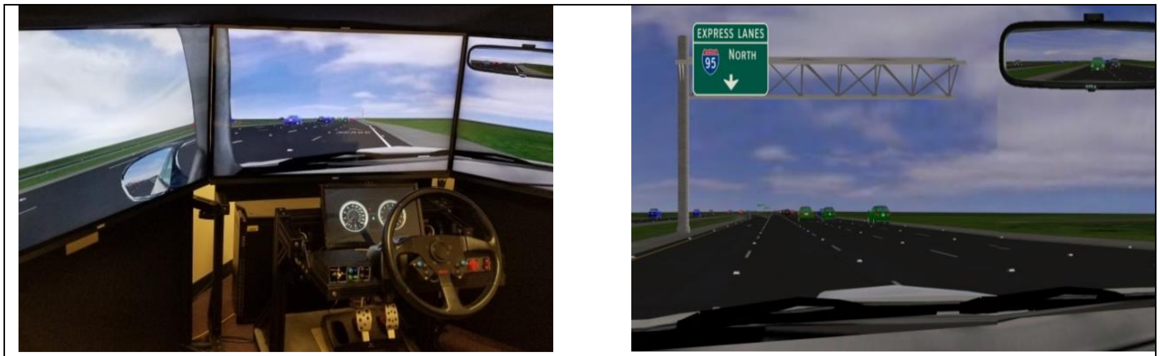


Figure 2.1 - Conflict rate for various weaving lengths (conflict/1,000 vehicle-mile per hour)

Another study conducted by Yuan et al. [35] aimed to investigate the safety effects of weaving length, traffic condition, and driver characteristics on drivers' mandatory lane change behavior based on a driving simulator study (Figure 2.2). A mixed factorial design with two within-subject factors (traffic volume: off-peak and peak; speed harmonization (SH): SH and Non-SH) and one between-subject factor (weaving length per lane change ($\boldsymbol{L_{LC}}$): 600 feet, 1,000 feet, and 1,400 feet) were employed in this study. Fifty-four licensed drivers were recruited to conduct this driving simulator experiment. Based on the experimental data, three lane change decision metrics (i.e., lane change merging gap, duration, and patience time), three lane change execution metrics (i.e., maximum longitudinal deceleration, lateral acceleration, and steering wheel angle), and two surrogate-safety metrics (i.e., number of conflicts and time exposed time-to-collision) were analyzed. Results indicated that for the ingress of MLs (entrance weaving segment), 1,000 feet $\boldsymbol{L_{LC}}$ would be recommended if the space is limited; otherwise 1,400 feet $\boldsymbol{L_{LC}}$ is preferable. For the egress of MLs (exit weaving segment), however, only 1,000 feet $\boldsymbol{L_{LC}}$ was recommended since the 1,400 feet $\boldsymbol{L_{LC}}$ was found to be significantly more dangerous than the 600 and 1,000 feet $\boldsymbol{L_{LC}}$. Moreover, the peak traffic condition could significantly increase the difficulty of lane change behavior on the weaving segments, and the speed harmonization could significantly improve the lane change safety on the entrance weaving segment.



(a) Appearance (b) A screenshot from a test scenario

Figure 2.2 - NADS MiniSim driving simulator at UCF

Another work completed by Cai et al. [34] investigated the optimal weaving distance in a freeway segment of Interstate 95 (I-95) in Miami, Florida, with four GPLs and two MLs. Three performance measurements were used for the safety evaluation: speed standard deviation, potential conflict, and time to collision. The results of the speed standard deviation and the potential conflicts revealed that 1,400 ft. per lane change increased the crash risk at the weaving segment. However, no significant difference could be found between 600 ft. and 1,000 ft. per lane change. Based on the traffic condition results, it was found that better safety performance could be found under the off-peak traffic condition. In addition, a variable speed limit (VSL) strategy was tested in the driving simulator experiment and was found to improve the safety of the studied network. The results of the driving simulator experiments were consistent with the results of the microsimulation with respect to the optimal weaving length. The study suggested that better results can be obtained if the drivers' lane change behavior observed in the driving simulator study could be used as input in the Vissim simulation using the Component Object Model (COM) interface [34]. Figure 2.3 shows the locations of the potential conflicts at weaving segments.

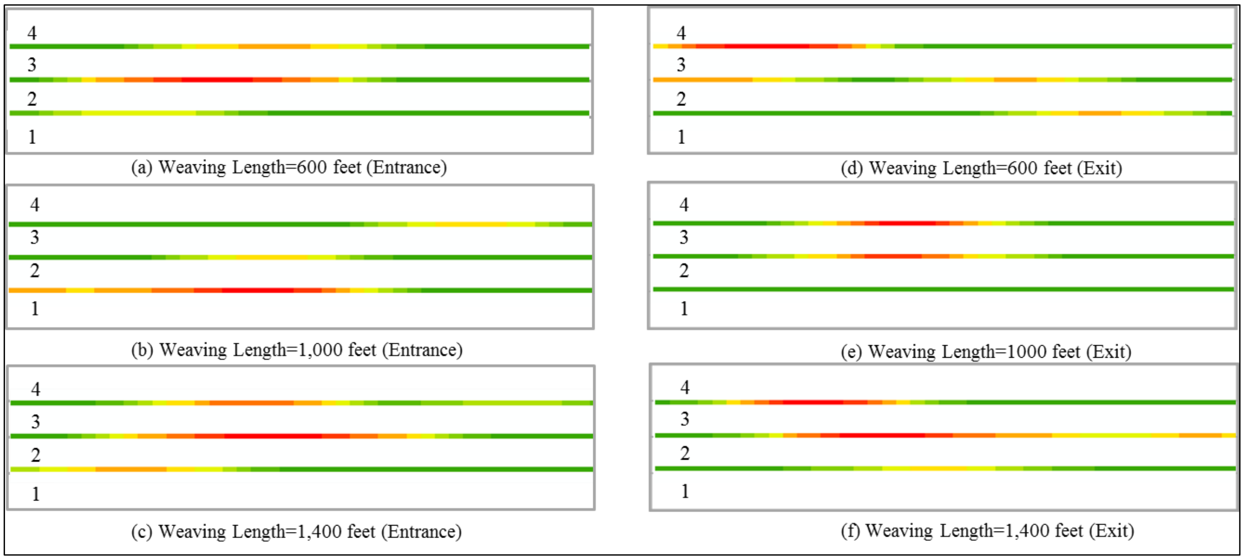


Figure 2.3 - Locations of the potential conflicts at weaving segments

Furthermore, in recent years, MLs have emerged as an effective dynamic traffic management strategy and are considered a safer option than toll plazas. One of the critical problems in toll plaza areas is driver confusion due to the various lane configurations and the different tolling systems. Two studies [37, 38] evaluated the factors that influence dangerous driving behavior at toll plazas. The studies used a hybrid plaza section of SR-408 in Central Florida, which consists of tollbooth and open road tolling (ORT) systems, as shown in Figure 2.4 [39]. The tollbooth section includes cash lanes and electronic toll collection (ETC) lanes. This design requires vehicles to decelerate or stop so drivers can navigate through different fare options, including cash toll and ETC. In the ORT section, drivers can navigate without stopping to pay tolls or changing lanes by using automatic vehicle identification (AVI) transponders. The studied section included the areas 1 mile before and 0.5 mile after the centerline of the mainline toll plazas. The crash reports from the toll plaza highlighted that the most dangerous locations along the toll plaza segment were the merging and diverging areas. Also, it was concluded that the most frequent types of traffic crashes at these locations were sideswipe and loss of control crashes. These two categories of traffic crashes were attributed mainly to unexpected lane changing at these sites.

The study used a driving simulator to assess driving behavior at hybrid plazas. Random effects models were applied to account for the data from the same participants, and different scenarios were assessed to test the effect of potential critical factors on risky driving behavior. The scenario variables included path decision making, signage, pavement marking, extending auxiliary lanes, and traffic conditions. Driver characteristics were also considered in the study. The results revealed that drivers at the ORT section performed less risky driving behavior than those who used the tollbooth. It was suggested to convert hybrid toll plazas to open-tolling system (e.g., MLs and all-electronic toll collection system (AETC)) [36-38].

Figure 2.4 - Hybrid mainline toll plaza [39]

2.5 Connected Vehicles

Connected and automated vehicles are the most recent development of information and communication technologies that can significantly improve the safety and efficiency of the transportation road network. In general, CV technologies utilize two main types of communication: vehicle-to-vehicle (V2V) and infrastructure-to-vehicle (I2V) through systems such as a dedicated short-range communication system (DSRC) and 5G cellular communication. With reliable connectivity of V2V communication, each CV would receive information about other CVs' statuses (i.e., position, speed, acceleration, etc.). A CV would also receive I2V information such as signal status, signal timing, etc. With the advent of V2V and I2V communications along with automated driving features, traffic safety and efficiency are expected to improve significantly in the transportation road network.

Connected vehicle technologies have great potential to reduce crash costs all over the world. The CV technologies would inform a vehicle about the traffic conditions in its surrounding environment, such as a nearby vehicle's position, speed, acceleration, signal status, and other traffic information through V2V and I2V communications. The V2V and V2I technologies are capable of minimizing driver error, which is considered a major cause alone or in combination with other factors in more than 94% of traffic crashes [40, 41]. The driving environment and associated driver-vehicle behaviors are expected to change with the introduction of connected and automated vehicles. At the operational level, these technologies are intended to help drivers and vehicles make safe and reliable decisions about acceleration, lane keeping, lane changing, etc. These technologies are expected to reduce crash risk, as the majority of crashes are due to human error. However, very little research has been conducted to estimate the safety impacts of CVs. The majority of the previous research was concerned about mobility and traffic operations in a CV environment rather than traffic safety. Fyfe and Sayed [42] combined Vissim and the Surrogate Safety Assessment Model (SSAM) with the application of the cumulative travel time (CTT) algorithm, which evaluates safety under a CV environment. The study showed a 40 percent reduction of rear-end conflict frequency at a signalized intersection with the application of CV. Olia et al. [43] experimented with CV technology in Paramics and estimated that the safety index improved up to 45% under the CV environment. Paikari et al. [44] also used Paramics to combine the V2V and V2I technologies and obtained higher safety and mobility enhancement on freeways under the CV environment. Vehicle platooning with CV technology is another key element of future transportation systems that can help us enhance traffic operations and safety simultaneously. Vehicle platooning refers to the strategies that several vehicles form a "platoon" that behaves as a single unit. Tian et al. [45] proposed a stochastic model to evaluate the collision probability for a heterogeneous vehicle platoon that can deal with inter-vehicle distance distribution. The results have great potential to decrease chain collisions and alleviate the severity of chain collisions in the platoon at the same time. According to the National Highway Traffic Safety Administration (NHTSA), CV technologies will prevent 439,000 to 615,000 crashes annually with the adoption of full V2V communication [46, 47]. Yue et al. [41] conducted a comprehensive study in an effort to examine the exact safety benefits when all vehicles are equipped with these technologies. They found that CV technologies could lead to the reduction of crashes involving light vehicles and heavy trucks by at least 33% and 41%, respectively. However, the safety impact of implementing I2V communication has not been sufficiently explored. Li et al. [48] investigated the I2V communication technology along with a VSL strategy under an adaptive cruise control environment. This simulation-based study indicated that the I2V communication system provides significant safety benefits in terms of surrogate measures of safety under an adaptive cruise control environment. One of the biggest issues facing CVs popularization is the market penetration rate (MPR). The full market penetration of CVs might not be accomplished in the near future. Therefore, traffic flow will likely be composed of a mixture of conventional vehicles and CVs. In this context, the study of CV MPR is worthwhile during the CV transition period. Rahman et al. [49] considered CV platooning to evaluate a longitudinal safety of managed-lane CV platoons on expressways based on simulation results. From their analysis, it is evident that ML CV platoons and all-lanes CV platoons significantly improved the longitudinal safety in the studied expressway segments compared to the base condition. In terms of surrogate safety measures, the managed-lane CV platoons significantly outperformed all-lanes CV platoons with the same market penetration rate. However, the study is limited to the HOV-type ML rather than a separated ML.

The CV technologies can also further increase the efficiency and reliability of automated vehicles by collecting real-time traffic information through V2V and I2V communications. There is a considerable amount of work in the literature describing the effectiveness of automated vehicles [50-53]. Morando et al. [54] investigated fully automated vehicle with level 4 automation and found the reduction of the number of conflicts by 20% to 65% with penetration rates of between 50% and 100%. None of the studies focused on a lower level of automation features under a CV environment that are available in the market with low penetration rates. Kockelman et al. [55] conducted a comprehensive study about the adoption of automated vehicles in United States based on a questionnaire survey. Most respondents were interested in lower-level automation technologies. This research team also estimated that lower levels of automation technologies would have adoption rates of more than 90% by 2045. Hence, it is worthwhile to study the safety benefits of lower-level automation under a CV environment using V2V and I2V communication technologies.

The driving behaviors of connected and automated vehicle are significantly different from conventional vehicles. From the modeling standpoint, capturing the effects of driving behavior of connected and automated vehicles is a very challenging task. An exhaustive summary of earlier studies employing simulation-based connected and automated vehicles are presented in Table 2.2 [46, 49, 50, 52, 56-67]. The table provides the simulation software used, the car following behavior employed, the area of interest (CV, automated vehicle, or both), and the measure of effectiveness. From Table 2.2, it is evident that most of the existing literature used Vissim as their simulation platform for the connected and automated vehicle. However, some studies used SUMO, Paramics, CORSIM, MovSim, and MATLAB in order to approximate the behavior of connected and automated vehicle. Those studies evaluated the effectiveness of connected and automated vehicle technologies considering full road networks of freeway and arterial sections but did not focus on segment and intersection safety concurrently.

Table 2.2 - Summary of previous simulation-based studies for connected and automated vehicles

Study	Car following model	Software	Area of Interest	Study area	Measure of effectiveness
Rahman et al. [49]	IDM	Vissim	Connected Vehicle	Freeway	Traffic Safety and Operations
Tajalli and Hajbabaie [65]	Vissim Default	Vissim	Connected Vehicle	Arterial	Traffic Safety
Mirheli et al. [50]	Vissim Default	Vissim	Connected vehicle	Arterial	Traffic Safety and Operations
Rahman and Abdel-Aty [46]	IDM	Vissim	Connected Vehicle	Freeway	Traffic Safety
Guériau et al. [58]	IDM	MovSim	Connected Vehicle	Freeway	Traffic Operations and Safety
Wan et al. [66]	PARAMICS Default	PARAMICS	Connected Vehicle	Arterial	Traffic Operations and fuel consumption
Genders and Razavi [57]	Modified driving behavior	PARAMICS	Connected Vehicle	Arterial	Traffic Safety
Wu et al. [67]	Vissim Default	Vissim	Connected Vehicle	Arterial	Traffic Operations
Guler et al. [59]	NA	MATLAB	Connected Vehicle	Arterial	Traffic Operations
Jin et al. [68]	Sumo Default	SUMO	Connected Vehicle	Arterial	Traffic Operations and fuel consumption
Jin et al. [60]	Optimal driving behavior algorithm	SUMO	Connected Vehicle	Arterial	Traffic Operations and fuel consumption
Lee and Park [61]	Vissim Default	Vissim	Connected Vehicle	Arterial	Traffic Operations
Letter and Elefteriadou [62]	CORSIM Default	CORSIM	Automated Vehicle	Freeway	Traffic Operations
Li et al. [63]	Vissim Default	Vissim	Automated Vehicle	Arterial	Traffic Safety and Operations
Fernandes and Nunes [56]	Gipps-model extension	SUMO	Automated Vehicle	Freeway	Traffic Operations
Talebpour and Mahmassani [52]	IDM	Own Simulator	Connected and Automated Vehicle	Freeway	Traffic Operations
Qian et al. [64]	SUMO Default	SUMO	Connected and Automated Vehicle	Arterial	Traffic Operations

It is also noted that the studies used default car following behavior, with the exception of six studies [46, 49, 52, 57, 58, 68]. It is worth noting that default car following behavior would not approximate the behavior of connected and autonomous vehicles in the real world. Some studies used a deterministic acceleration modeling framework such as the Intelligent Driver Model (IDM), which is considered to be more suitable to approximate CV behaviors in the real world [46, 49, 52]. Previous studies have shown that parameters of the default car-following model of a microsimulation software can be modified to model the behaviors of autonomous vehicles [54, 55, 69]. Those studies applied fully automated vehicle behavior in VISSIM and changed the parameters of the default car following model (Wiedemann 99) but did not focus on the lane changing model. However, it is intuitive that the lane changing behavior of a fully autonomous vehicle would also be significantly different from that of conventional vehicles. Therefore, a more realistic driving behavior model is required to simulate the behavior of automated vehicles under a CV environment.

2.6 Summary

In general, the literature supports the notion that MLs are an important countermeasure for improving the safety and the traffic operation of expressways. Nevertheless, little is known about the interrelationship between the MLs design and the efficiency of the network. Previous studies show that access zones are risky locations in the MLs segment. Hence, there is a need for studying the safety and operational impacts of access zones on the facility. Micro-traffic simulation was utilized, as it is a valid approach for studying the safety and operation effectiveness of the access zone design and can generate traffic conflict data. Previous studies proved that the simulated conflicts can be used as validated data to represent the real conflicts.

3 Impact of Connected Vehicles on Freeway Facilities with Managed Lanes

3.1 Overview

Connected vehicles are one of the most recent developments in traffic and safety engineering. They have the potential to revolutionize safety and efficiency by reducing the number of crashes and fatalities on the road. This technology enables vehicles, roads, traffic signals, and other infrastructure to communicate with one another about current road conditions, alerts, and signals.

The objective of the research presented in this chapter is to analyze the safety and operational effects of adding CVs and CV lanes to the MLs network. Several tasks were determined to achieve the goal of the study. The first objective was to build networks for the MLs in a CV environment. The second objective was to study the effect of different cases of CV lanes and CVs on the safety and operation of the whole network. The third objective was to determine the optimal market penetration of CV lanes by investigating different MPRs for different cases. A comparison between the different cases of MLs designs with the presence of CVs with different MPRs is generated for different traffic conditions.

3.2 Network of Interest

A 9-mile corridor located on Interstate 95 (I-95) in South Florida was used in this study, as shown in Figure 3.1. The corridor consists of four GPLs, two MLs, seven on-ramps, and nine off-ramps. The network of interest was built in VISSIM, which is a microscopic traffic simulation software, with the same geometric and traffic characteristics as the field network. The traffic characteristics (i.e., traffic volume, traffic speed) for each lane in the corridor was provided by the Regional Integrated Transportation Information System (RITIS) at 20-second intervals. In the simulated network, the traffic data was inputted at 15-minute intervals. The peak period was defined from 7:00 AM to 9:00 AM and the off-peak period from 9:00 AM to 11:00 AM. A 30-minute simulation was added at both the beginning and the end of the simulation for warm-up and cool-down [70, 71]. It is worth mentioning that the warm-up and cool-down periods were excluded from the analyses. In addition, multiple vehicle types were inputted to the simulated network including passenger cars (PCs), carpools, and heavy goods vehicles (HGVs). The percentages of the inputted vehicles were 85%, 10%, and 5% for PCs, carpools, and HGVs, respectively.

Ending point

Starting point

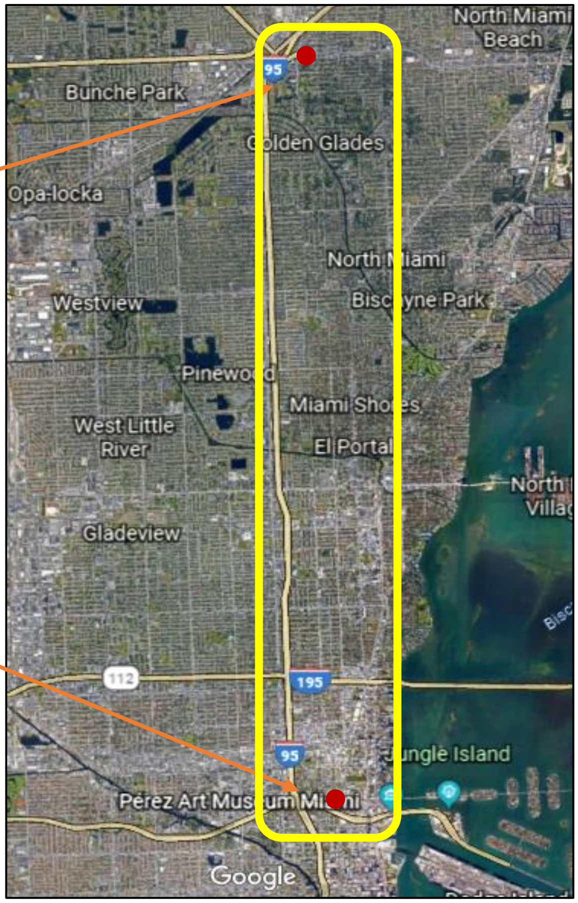


Figure 3.1 - Study area located on I-95 (Source: [72], Google maps)

3.3 Calibration and Validation

The field traffic and the simulated traffic were compared for the calibrating and validating process. In order to successfully calibrate and validate the simulated network, the difference between the simulated data and the field data needed to be minimized [31]. In this study, three hours of simulation data between 7:30 AM to 10:30 AM were used, and the warm-up and cool-down periods were excluded. The Geoffrey E. Havers (GEH) value was used for the calibration process. This method was proposed by the Wisconsin Department of Transportation (WisDOT) [72]. The GEH value depends on the traffic volume in the field network (V) and the traffic volume in the simulated network (E). A low value of the GEH (when the difference between simulated volume and field volume is less than five) is considered negligible and was suitable for the study. Previous studies indicated that if the percentage of GEH is less than five and is higher than 85%, the simulated network is considered well calibrated [34, 49, 74, 75]. The average GEH value (2.39) and the percentage of GEH values less than five (91.08%) indicated that the simulated network was well calibrated. The GEH formula is shown as follows:

$$GEH = \sqrt{\frac{2\,(E-V)^2}{(E+V)}} \tag{3.1}$$

Moreover, the difference between the field traffic speed and the simulated traffic speed was used in the validation process. Previous studies indicated that if the percentage of speed difference lower than five mph is higher than 85%, the simulated network is considered well validated. In this study, the average speed difference (1.9 mph) and the percentage of speed differences lower than five mph (95.56%) indicated that the simulated network was suitably validated.

3.4 Vehicle Classes

Four classes of vehicles were utilized in this simulation: passenger cars (PCs), heavy goods vehicles (HGVs), CVs, and carpools. According to the Florida Department of Transportation (FDOT) [75], the percentage of HGVs is 5% on freeways. Meanwhile, according to the 2015 U.S. Census American Community Surveys (ACS) for Miami-Dade [77], the percentage of carpools is 10% on freeways. Considering carpool percentage in this study was important because the policy of the FDOT is that carpools are allowed to use the MLs without paying tolls [77].

3.5 Connected Vehicles Environment

In PTV VISSIM 11, CVs could be added and tested in the MLs network. The driving behavior models of CVs were ready to use since they had already been calibrated and validated using real-world CVs data in a project named CoEXist, which is a project funded by European Union Horizon 2020 [78-80]. In the software, there are three types of CV driving logic: cautious, normal, and all-knowing. With cautious driving logic, vehicles always respect the road code and safe behavior, and with normal driving logic, vehicles have the capability to measure speeds of and gaps with the surrounding vehicles with sensors. The all-knowing driver logic predicts all other road users' behavior with V2V or V2I technologies [78]. In the all-knowing logic, the number of interaction objects and the number of interaction vehicle can be more than one (Figure 3.2). The figure shows one interaction objective and two interaction vehicles. However, in the cautious and normal logics, the vehicle can only have one interaction vehicle (Figure 3.3). Figure 3.4 shows the different vehicles' gaps between different driving logics. The cautious driving logic has the largest gap compared to other driving logics. The normal driving logic has gaps similar to human drivers but with higher safety. The all-knowing driving logic has smaller gaps but is still relatively safe. Figure 3.5 shows the different driving logic in PTV Vissim [80]. In this study, CVs followed the normal driving logic provided by PTV Vissim 11.

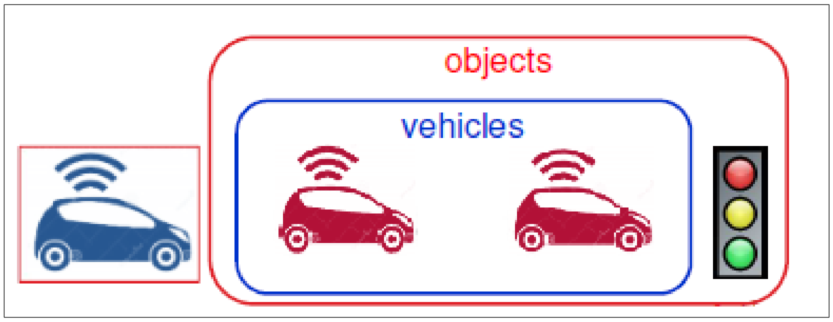


Figure 3.2 - Interaction objects and vehicles for the all-knowing logic

Figure 3.3 - Interaction objects and vehicles for the cautious and normal logics

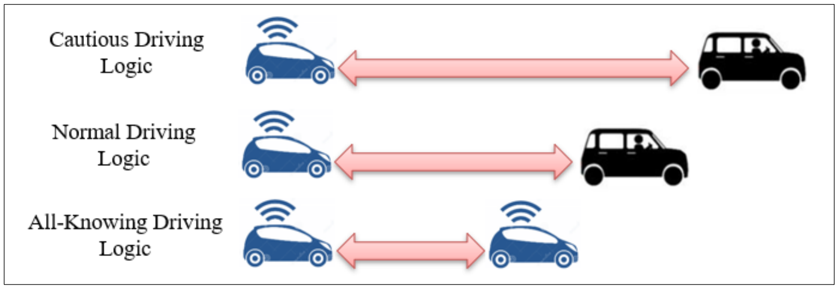


Figure 3.4 - Connected vehicles driving logics [81]

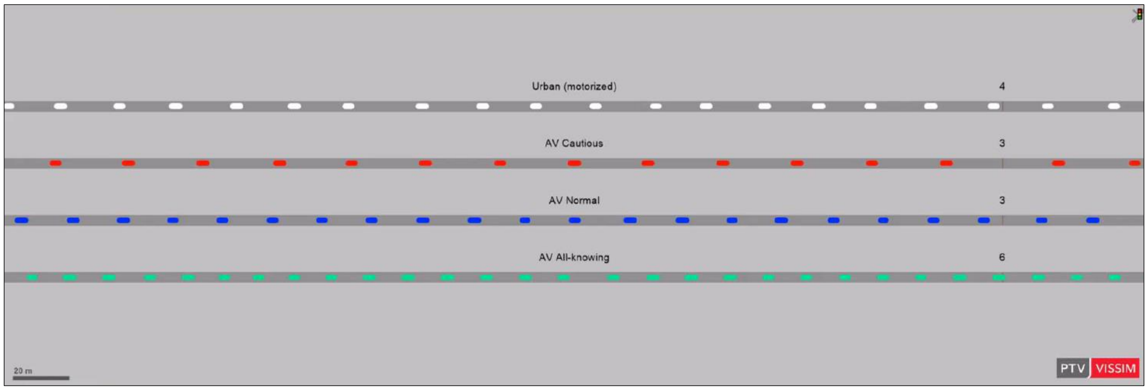


Figure 3.5 - Different driving logics in Vissim [78, 80]

The parameters of car following and the lane change models for all driving logics of CVs were calibrated and validated using real-world CV data [78-80]. Table 3.1 shows the calibrated car following parameters in PTV Vissim 11, which has ten car following parameters (CC0 to CC9) that are defined in the table. The calibrated lane changing parameters for CVs are shown in Table 3.2.

Table 3.1 - Car following parameters for different driving logics [80]

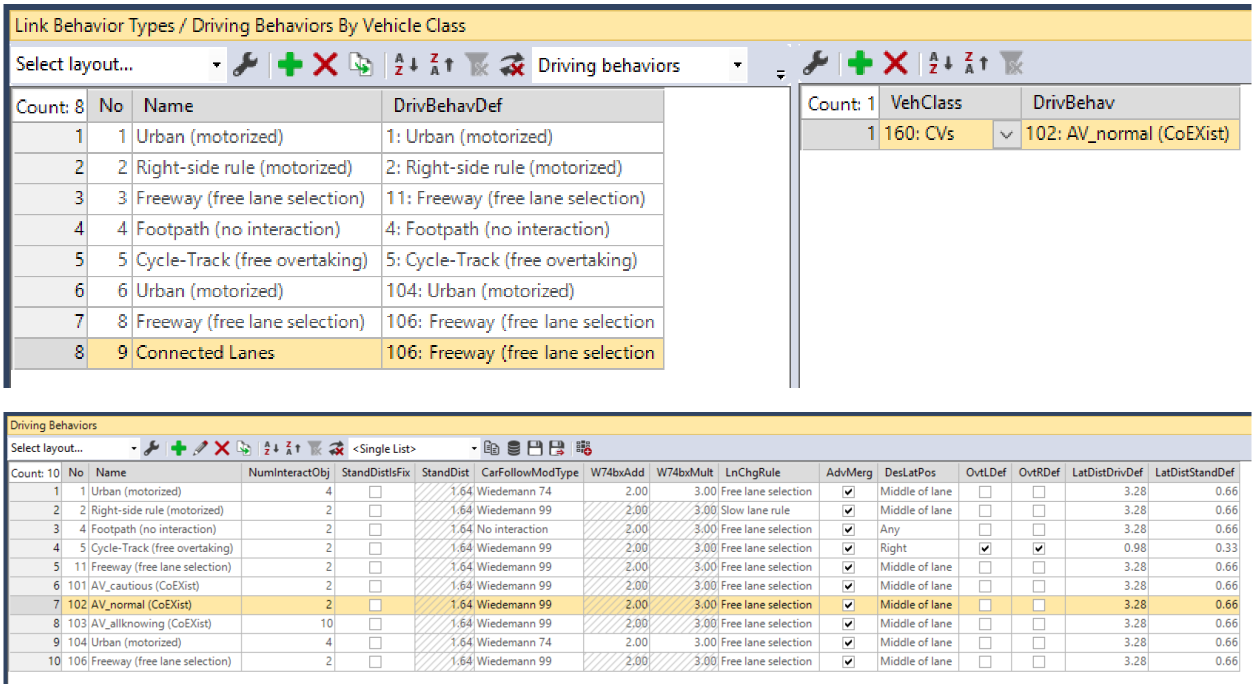
Car following parameter	Description	Human Driving Behavior (Default)	All Knowing Driving Logic	Normal Driving Logic	Cautious Driving Logic
CC0	The average standstill distance (m)	1.50	1.00	1.50	1.50
CC1	The headway time (s)	0.90	0.600	0.90	1.50
CC2	The distance difference in the oscillation condition (meter)	4.00	0	0	0
CC3	Controls the deceleration process	-8.00	-6.00	-8.00	-10.00
CC4	Defines negative speed difference	-0.35	-0.10	-0.10	-0.10
CC5	Defines positive speed difference	0.35	0.10	0.10	0.10
CC6	The distance influence on speed oscillation	11.44	0	0	0
CC7	The acceleration at the oscillation condition (m/s^2)	0.25	0.10	0.10	0.10
CC8	The desired standstill acceleration (m/s^2)	3.50	4.00	3.50	3.00
CC9	The desired acceleration at 50 mph (m/s^2)	1.50	2.00	1.50	1.20

Table 3.2. Lane change behavior for different driving logics [80]

	All Knowing Driving Logic		**Normal Driving Logic**		**Cautious Driving Logic**	
	Own	Trailing Vehicle	Own	Trailing Vehicle	Own	Trailing Vehicle
Maximum Deceleration (m/s^2)	-4.00	-4.00	-4.00	-3.00	-3.50	-2.50
-1 m/s per distance	100	100	100	100	80	80
Accepted deceleration	-1.00	-1.50	-1.00	-1.00	-1.00	-1.00
Waiting time per diffusion (s)		60	60			60
Min. net headway (front to rear) (m)		0.5	0.5			0.5
Safety distance reduction factor		0.75	0.6			0.6
Maximum deceleration for cooperative braking (m/s^2)		-6.00	-3.00			-2.50

3.6 Dedicated Connected Vehicles Lanes

Dedicated connected vehicle lanes (CVLs) were utilized in this study to investigate the impact of CVs in the MLs network with the presence of dedicated CV lanes. In this study, several scenarios were studied with the presence of CVLs. For instance, some scenarios allowed CVs to use either CVLs or MLs, while other scenarios restricted CVs to use only CVLs. These scenarios were important for deciding the effect of CVL presence in the MLs network. In order to assign CVs in a dedicated lane in Vissim, the normal behavior was used as shown in Figure 3.6.



Link Behavior Types / Driving Behaviors By Vehicle Class

Count: 8	No	Name	DrivBehavDef
1	1	Urban (motorized)	1: Urban (motorized)
2	2	Right-side rule (motorized)	2: Right-side rule (motorized)
3	3	Freeway (free lane selection)	11: Freeway (free lane selection)
4	4	Footpath (no interaction)	4: Footpath (no interaction)
5	5	Cycle-Track (free overtaking)	5: Cycle-Track (free overtaking)
6	6	Urban (motorized)	104: Urban (motorized)
7	8	Freeway (free lane selection)	106: Freeway (free lane selection
8	9	Connected Lanes	106: Freeway (free lane selection

Count: 1	VehClass	DrivBehav
1	160: CVs	102: AV_normal (CoEXist)

Driving Behaviors

Count: 10	No	Name	NumInteractObj	StandDistIsFix	StandDist	CarFollowModType	W74bxAdd	W74bxMult	LnChgRule	AdvMerg	DesLatPos	OvtLDef	OvtRDef	LatDistDrivDef	LatDistStandDef
1	1	Urban (motorized)	4	☐	1.64	Wiedemann 74	2.00	3.00	Free lane selection	☑	Middle of lane	☐	☐	3.28	0.66
2	2	Right-side rule (motorized)	2	☐	1.64	Wiedemann 99	2.00	3.00	Slow lane rule	☑	Middle of lane	☐	☐	3.28	0.66
3	4	Footpath (no interaction)	2	☐	1.64	No interaction	2.00	3.00	Free lane selection	☑	Any	☐	☐	3.28	0.66
4	5	Cycle-Track (free overtaking)	2	☐	1.64	Wiedemann 99	2.00	3.00	Free lane selection	☑	Right	☑	☑	0.98	0.33
5	11	Freeway (free lane selection)	2	☐	1.64	Wiedemann 99	2.00	3.00	Free lane selection	☑	Middle of lane	☐	☐	3.28	0.66
6	101	AV_cautious (CoEXist)	2	☐	1.64	Wiedemann 99	2.00	3.00	Free lane selection	☑	Middle of lane	☐	☐	3.28	0.66
7	102	AV_normal (CoEXist)	2	☐	1.64	Wiedemann 99	2.00	3.00	Free lane selection	☑	Middle of lane	☐	☐	3.28	0.66
8	103	AV_allknowing (CoEXist)	10	☐	1.64	Wiedemann 99	2.00	3.00	Free lane selection	☑	Middle of lane	☐	☐	3.28	0.66
9	104	Urban (motorized)	4	☐	1.64	Wiedemann 74	2.00	3.00	Free lane selection	☑	Middle of lane	☐	☐	3.28	0.66
10	106	Freeway (free lane selection)	2	☐	1.64	Wiedemann 99	2.00	3.00	Free lane selection	☑	Middle of lane	☐	☐	3.28	0.66

Figure 3.6 - Assigning driving logic to connected vehicles for connected vehicle lanes (Source: Vissim 11)

3.7 Market Penetration Rate

The percentage of CVs in the network is represented by the MPR%. One of the goals of this study is estimating the potential MPR% of CVs when evaluating multiple lane configurations in a CV environment. The latest report on evaluating connected and automated vehicles on freeways and dedicating lanes by NCHRP (Project number: 20-102(08)) [81] showed that network efficiency improved with CVs. The report also showed that dedicated CV lanes have a significant impact on the network with a low MPR%. Moreover, MPR% increases when the CVs are allowed to use all lanes in the network (i.e., GPLs, MLs, and CVLs). Hence, the level of service of GPLs increases with the increase of the capacity, and the result is an improvement in the system performance [81].

In this study, different MPRs were taken into consideration in the experimental design (e.g., 10%, 20%, 30%, etc.). A previous studies, the full market penetration of CVs might not be accomplished in the near future. Therefore, traffic flow will likely be composed of a mixture of conventional vehicles and CVs [51].

3.8 Desired Speed Distribution

The desired speed distribution (DSD) is the distribution of speed when the vehicles' speed is not affected by other vehicles or network obstacles [82]. The DSD has to be inputted in Vissim for different types of vehicles (i.e., PCs, CVs, carpools, and HGVs). The off-peak speed values were employed for generating the DSD in Vissim. It is worth mentioning that the off-peak period was chosen because of the low possibility for a vehicle to be constrained by other vehicles. Thus, in the off-peak period, vehicles were more likely to travel at their desired speed.

In the case of PCs, CVs or carpools, their speed distributions were the same and were divided into four groups. The groups were determined by the speed percentile for the RITIS speed data. First, the speed data was sorted according to the 50th percentile. Subsequently, four groups were defined, and the DSDs in each group had similar 50th percentile speeds. Among the four groups, two groups were dedicated to GPLs and the other two were dedicated to MLs.

The DSDs of the HGVs were inferred from the speed distributions of PCs, CVs and carpools. Johnson and Murray [83] concluded that the average speed difference between cars and trucks was 8.1 miles per hour. The HGV percentage is 5%. Suppose x is the speed of PCs, CVs or carpools, then the speed for HGV is equal to (x-8.1), the average speed is y, which is provided by RITIS, and

$$\mathrm{Y} = 0.95 \times \mathrm{PC} + 0.05 \times (\mathrm{PC} - 8.1) \tag{3.2}$$

From the equation, the speed of the PC, CVs or carpools was about (y+0.5), and the truck speed was about (y-7.6). By shifting the total desired speed distribution by 0.5 mph to the right, PC speed distributions can be gained. Also, by shifting the total DSD for all vehicles by 7.6 mph to the left, HGV speed distributions can be gained.

3.9 Dynamic Toll Pricing

The Vissim software applies a logit model to calculate the probability of a driver deciding to use the MLs. The utility function and the logit model equation are as follows:

$$U_{toll} = \beta_{time} \times Time\ gain - \beta_{cost} \times Toll\ rate + Base\ Utility \tag{3.3}$$

$$P_{toll} = 1 - \frac{1}{1+e^{\alpha \times U_{toll}}} \tag{3.4}$$

The base utility depends on the vehicle class and zero as the default value of the software. The time coefficient (β_{time}) and the cost coefficient (β_{cost}) were calculated from the value of time (VOT). The ratio of the cost coefficient and the time coefficient (β_{time}) was utilized to define the VOT as follows:

$$VOT = \frac{\beta_{time}}{\beta_{cost}}\ (\$/hr) \tag{3.5}$$

In this study, the VOT was assumed to be $8.67 per hr based on the result of a multinomial logit model conducted by Jin et al. [**Error! Reference source not found.**]. The time coefficient was assumed to be one min, and the cost coefficient was 0.14 ($8.67/60) for all types of vehicles that use the MLs. The negative sign of the cost coefficient implies an increase in the MLs utility with the decrease of the tolls.

The toll price is mainly affected by two components. First, the time saved by using the MLs, which varied from 0 to 8.50 min. Second, the speed in the MLs, which was between 30 mph and 73.50 mph. The dynamic toll prices varied between a minimum value of $0.50 and a maximum value of $10.50.

3.10 Scenarios Setup

In order to study the effect of CVs and CVLs, four different cases were studied. The base condition (Case 0) included the I-95 corridor with one access zone (one ingress and one egress) in the middle of the corridor. In this case, three types of vehicles were considered: PCs, HGVs, and carpools. It is worth mentioning that CVs are not considered in the base case (Case 0). Figure 3.7 displays Case 0 with no CVs in the network.

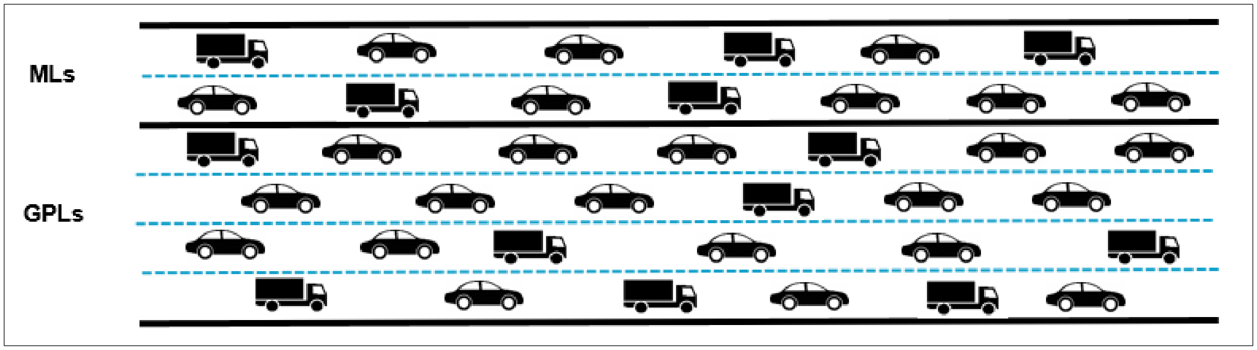


Figure 3.7 - The base case (Case 0) with no connected vehicles in the network

In Case 1, four types of vehicles were studied: PCs, HGVs, carpools, and CVs. In this case, CVs are only allowed in the MLs and have the choice to use any of the MLs. Figure 3.8 provides Case 1 with the configuration of the different types of vehicles in the network.

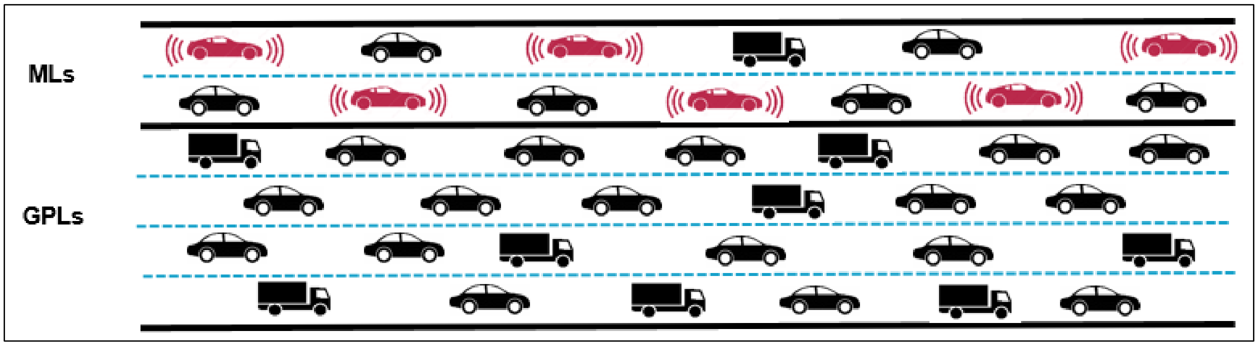


Figure 3.8 - Case 1 with connected vehicles in the managed lanes

Regarding Case 2, four types of vehicles were used in this case, similarly to the previous case. In Case 2, a dedicated CVs lane was studied in the left side of the network Therefore, CVs can use either the CVLs or the MLs. Figure 3.9 presents the configuration of the different types of vehicles in Case 2.

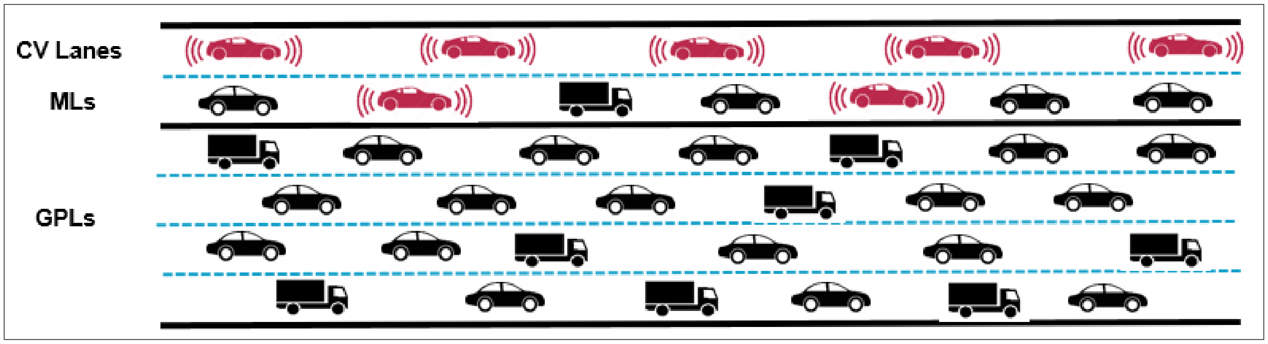


Figure 3.9 - Case 2 with connected vehicles in either managed lanes or connected vehicle lanes

Case 3 also includes four types of vehicles (i.e., PCs, HGVs, carpools, and CVs). Dedicated CVLs were also studied in this case on the left side of the network. In this case, CVs were only allowed to use the CVLs, as shown in Figure 3.10.

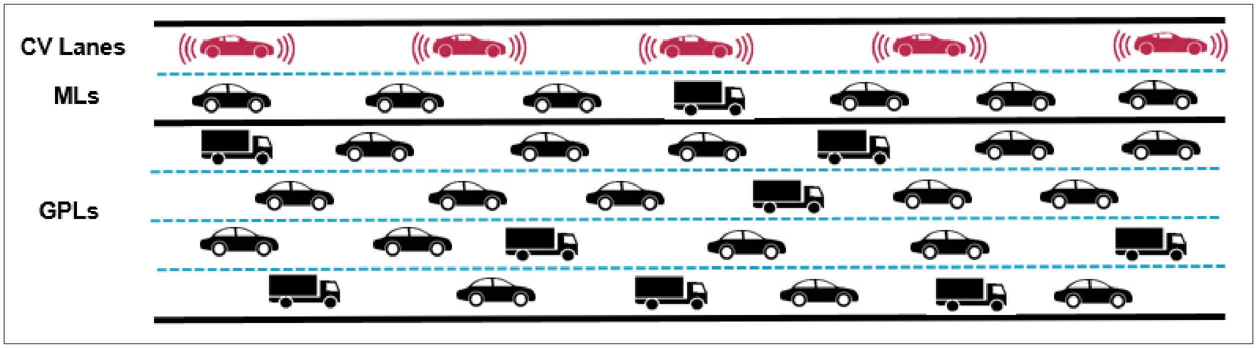


Figure 3.10 - Case 3 with connected vehicles in the connected vehicle lanes only

Case 4 is similar to Case 1 in that it converts one GPL to an ML in order to increase the capacity of the MLs. In this case, CVs were only allowed in the MLs and had the choice to use any of the MLs. Figure 3.11 provides Case 4 with the configuration of the different types of vehicles in the network.

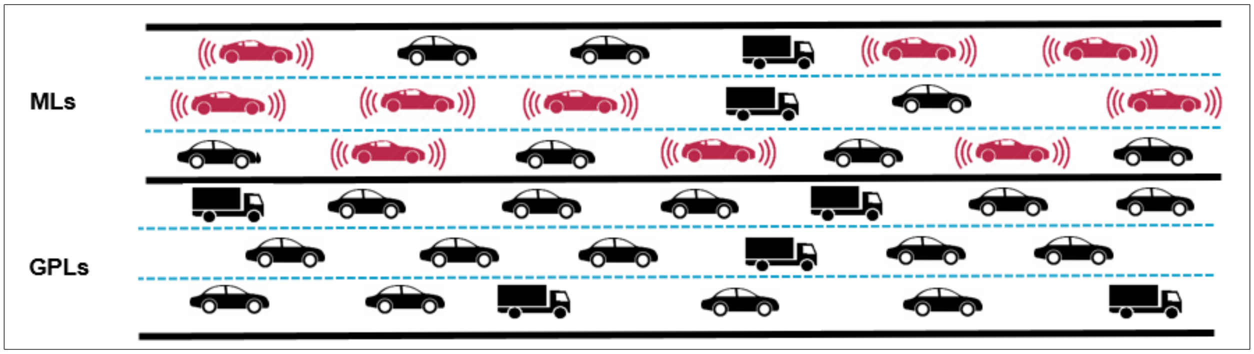


Figure 3.11 - Case 4 with CVs in managed lanes and converting one general-purpose lane to a managed lane

Similar to the previous cases, Case 5 considered four different types of vehicles. In Case 5, CVs had the choice to use any of the lanes in the network: CVLs, MLs, or GPLs. Figure 3.12 shows the configuration of the different vehicle types in Case 5.

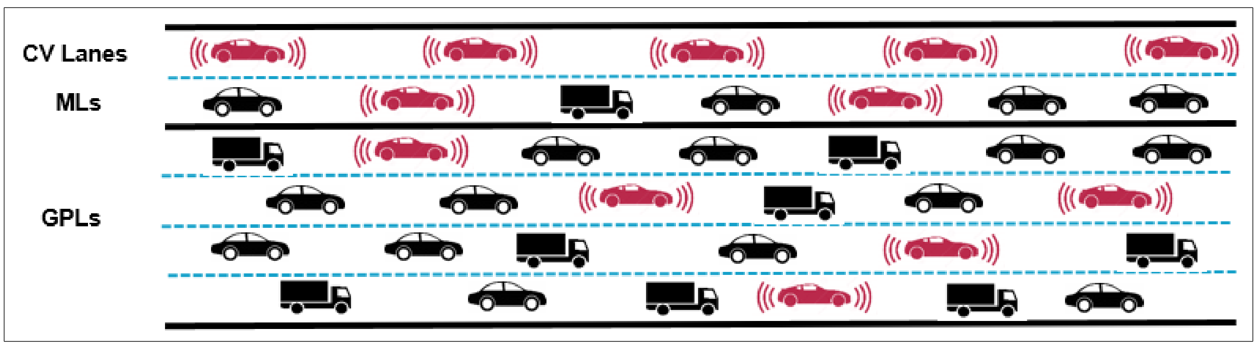


Figure 3.12 - Case 5 with connected vehicles in all lanes (general-purpose, managed, and connected vehicle lanes)

Ninety scenarios, including the base case for peak and off-peak conditions, were tested in this study with different CV lane configurations in the MLs network (i.e., Case 1, Case 2, Case 3, Case 4, Case 5) in both peak and off-peak conditions. Various MPR% were also considered in the scenario designs (e.g., 10%, 20%, 30%, etc.). Table 3.3 presents the 90 studied scenarios. For each scenario, ten random runs with different random seeds were applied. It is worth noting that in Cases 1, 2, and 3, the maximum studied MPR% was 40%; when the MPR% is over 40%, the MLs have reached their capacity. In Case 4, the configurations of lanes were changed in order to increase the capacity of the network. Hence, in Cases 4 and 5, the studied MPR% reached 100%. Similarly, in Case 5, the studied MPR% reached 100% because CVs were allowed to use any of the lanes in the network.

Table 3.3 - List of scenarios

Case	Traffic Condition	Market Penetration Rate (%)									
Case 0	Peak					0					
(Base Condition)	Off-peak					0					
Case 1	Peak	5	10	15	20	25	30	35	40		
(CVs in MLs with no CVLs)	Off-peak	5	10	15	20	25	30	35	40		
Case 2	Peak	5	10	15	20	25	30	35	40		
(CVs in CVLs and MLs)	Off-peak	5	10	15	20	25	30	35	40		
Case 3	Peak	5	10	15	20	25	30	35	40		
(CVs in CVLs only)	Off-peak	5	10	15	20	25	30	35	40		
Case 4 (Converting one GPLs to MLs)	Peak	10	20	30	40	50	60	70	80	90	100
	Off-peak	10	20	30	40	50	60	70	80	90	100
Case 5	Peak	10	20	30	40	50	60	70	80	90	100
(CVs in all lanes)	Off-peak	10	20	30	40	50	60	70	80	90	100

3.11 Safety Analysis

3.11.1 Conflict Frequency

The SSAM was adopted to determine the potential conflict frequency, which is associated with the number of crashes in the field [85]. The main objective of SSAM could be to either evaluate the safety performance of the current roadway designs or to be used as a new strategy for monitoring theoretical roadway designs before implementation [86]. Three types of conflicts can be extracted from SSAM: rear-end, lane change, and crossing conflicts. Two types of conflicts were used in this paper: rear-end and lane-change conflicts. As provided by SSAM, the rear-end conflicts were considered when the conflict angle was between 0 and 30 degrees, while the lane-change conflicts were defined as when the conflict angle was between 30 and 80 degrees. The crossing conflicts were excluded from this study, since the percentage of crossing conflicts was less than 1%, and crossing crashes are less likely to happen on freeways.

The vehicle trajectory files (.trj file) from vissim were imported into SSAM to obtain detailed information about the conflicts. Time-to-collision (TTC) is one of the surrogate safety measures that could be employed to indicate safety conditions. The concept of TTC was first introduced by Hayward [**Error! Reference source not found.**], referring to the time that remains until a collision between the leading and following vehicles will occur if the speed difference is maintained. A TTC of zero implies “virtual” crashes that might lead to the inaccuracy of the simulation models [86]. Consequently, the cases in which the TTC=0 (crash) were excluded before implementing further analysis. According to FHWA [85], TTC is the minimum time-to-collision, which is calculated based on the speed and location of vehicles. The FHWA report recommended a maximum critical value for TTC as 1.5 s. It was stated that conflicts with TTC values larger than 1.5 s are not recognized as a severe condition. As the TTC value increased, the conflict risk was found to decline [86]. Additionally, the FHWA report suggested a minimum TTC value of 0.1 s. Several studies used the same threshold (0.1 s to 1.5 s) as severe conflicts [70, **Error! Reference source not found.**, **Error! Reference source not found.**]. In this study, a TTC threshold between 0.1 s and 1.5 s was used.

For the base case with no CVs, it was found that, for peak conditions, 77.87% were rear-end conflicts and 22.15% were lane change conflicts. It was also found that in off-peak conditions, 65.57% of conflicts were rear-end and 34.43% were lane change conflicts, as shown in Figure 3.13.

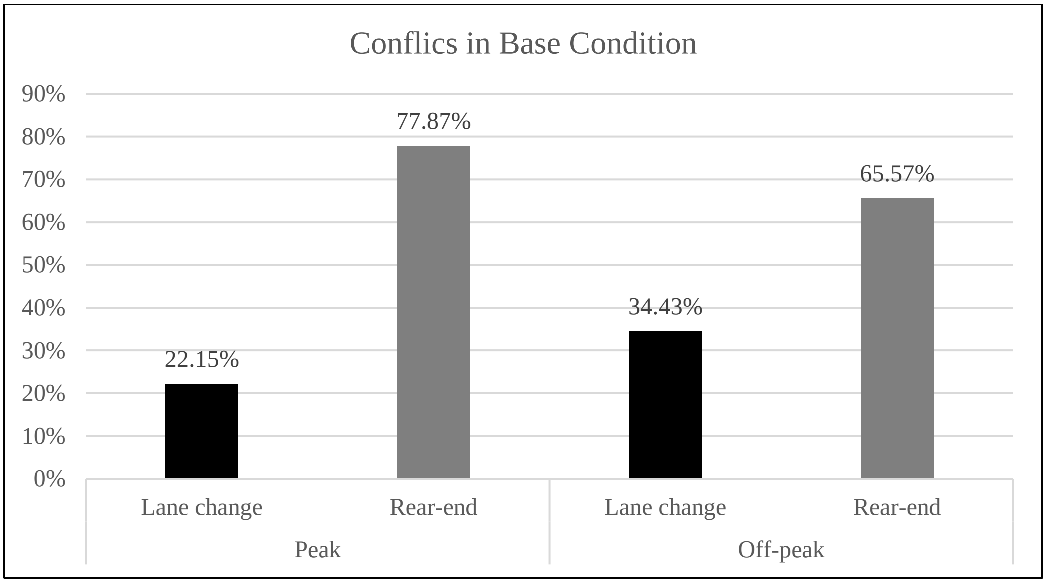


Figure 3.13 - Conflict frequency for peak and off-peak conditions in the base case

The descriptive statistics of the conflict frequency for all studied cases are shown in Table 3.4 for both peak and off-peak periods. The results of the table indicated that Cases 4 and 5 had the lowest conflict frequency among all cases. Meanwhile, Case 3 showed the highest conflict frequency. An ANOVA test was carried out to compare the conflict frequency in various CV lane design cases, MPR%, and traffic conditions. The results showed that there was a significant difference in conflicts between cases (F-value=12.86, p-value<0.0001). The results also showed significant differece in conflicts between different MPR% (F-value=35.09, p-value=0.0003). Additionally, the results showed that conflicts (F-value=51.87, p-value<0.0001) were higher in the peak conditions than the off-peak conditions.

Table 3.4 - Descriptive statistics of conflict frequency for all studied cases

Case	Traffic Condition	Mean	Standard Deviation	Minimum	Maximum
Base	Peak	1687.7	-	1687.7	1687.7
	Off-peak	408	-	408	408
Case 1	Peak	6258.39	12546.35	556.1	36721.1
	Off-peak	266.35	72.06	190.7	390.86
Case 2	Peak	9090.06	17501.07	716.78	51704.8
	Off-peak	360.92	129.59	199.80	560.33
Case 3	Peak	26479.1	27241.1	2155	72846.1
	Off-peak	1104.68	938.02	369.4	2846.1
Case 4	Peak	3490.8	4936.44	490	15472
	Off-peak	298.8	135.567	112	573
Case 5	Peak	1064.9	503.81	487	2102
	Off-peak	256.5	98.32	156	420

In Case 1 (which allows CVs to use any of the MLs), the fewest conflicts occurred when the MPR% was 20% for peak conditions and 30% for off-peak conditions. Figure 3.14 shows the conflict counts for Case 1.

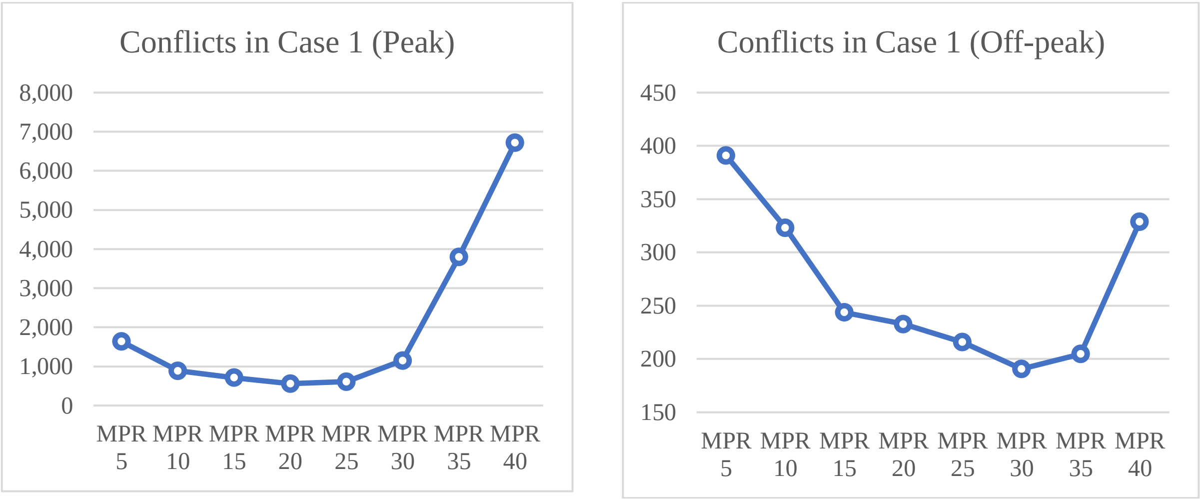


Figure 3.14 - Conflict frequency for peak and off-peak condition in Case 1

Similarly, the lowest conflict frequency happened in Case 2 (which allows CVs to use either dedicated CV lanes or MLs) when the MPR% was 25% for peak conditions and 30% for off-peak conditions. Also, the results showed that traffic conflicts increase dramatically after an MPR of 40%. Figure 3.15 shows the conflict counts for Case 2.

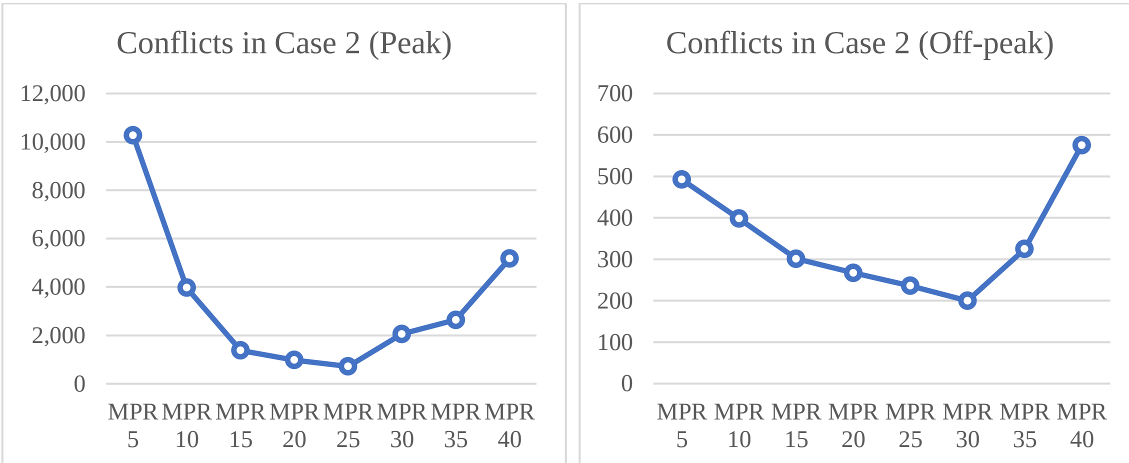


Figure 3.15 - Conflict frequency for peak and off-peak conditions in Cases 2

It was also revealed that Case 3 (which allows CVs to use only dedicated CVLs) has the highest conflict frequency among all other cases, as shown in Figure 3.16. The lowest conflicts happened when the MPR was 15% for peak conditions and 20% for off-peak conditions.

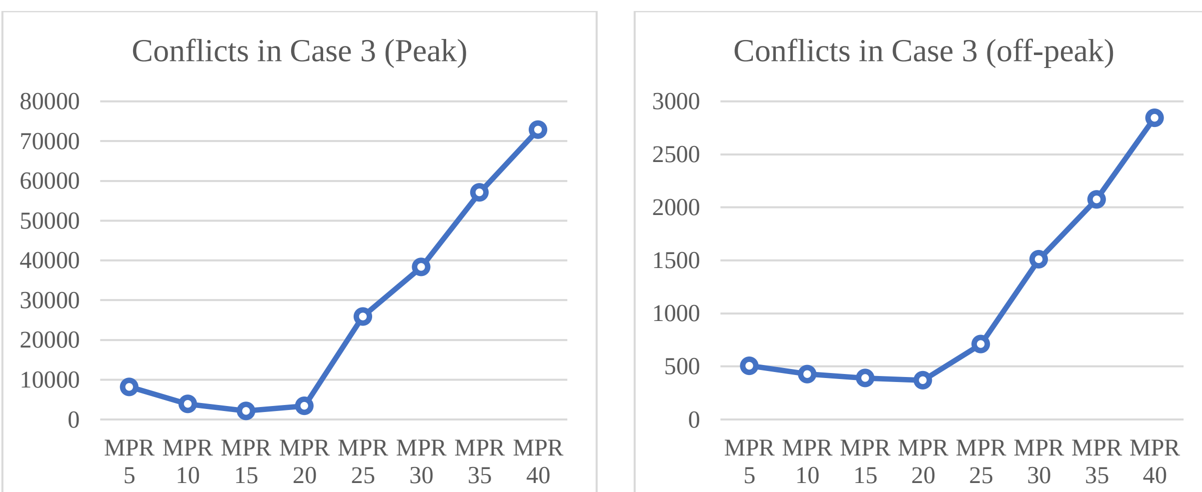


Figure 3.16 - Conflict frequency for peak and off-peak conditions in Case 3

For Case 4 (which is similar to Case 1 in that it converts one GPL to an ML), it was found that in peak conditions, the lowest conflicts occurred at an MPR of 50%. It is worth mentioning that the conflicts were reduced when the MPR was between 40% and 60%. In off-peak conditions, the lowest conflicts occurred at an MPR of 60%. The conflict frequency was the lowest when the MPR was between 50% and 70%. Figure 3.17 shows the distribution of conflict frequency in Case 4.

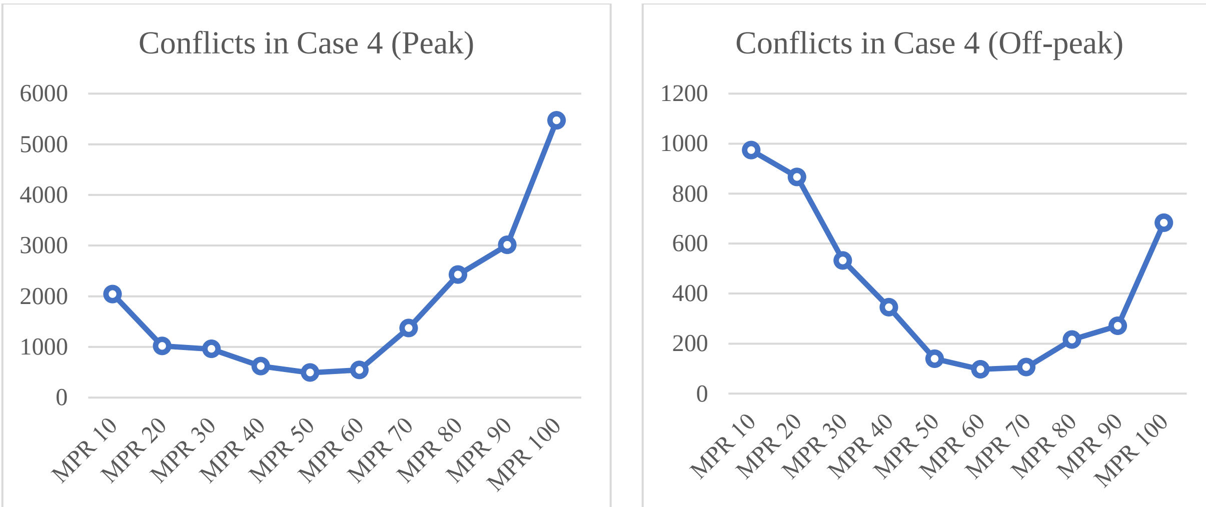


Figure 3.17 - Conflict frequency for peak and off-peak conditions in Case 4

Figure 3.18 shows the distribution of conflict frequency for each MPR% for Case 5 (which allows CVs to use any of the CVLs, MLs, or GPLs) for both peak and off-peak conditions. Looking at the figure, it is apparent that the conflict frequency decreased with the increase of MPR%. In peak conditions, the lowest conflict frequency occurred when the MPR was 100%. The highest conflicts appeared when the MPR was 10%. In off-peak conditions, it is worth noting that the conflict distribution followed the same trend as the peak conditions. The lowest conflict frequency occurred at an MPR of 100%. Hence, a higher MPR% could be recommended in Case 5.

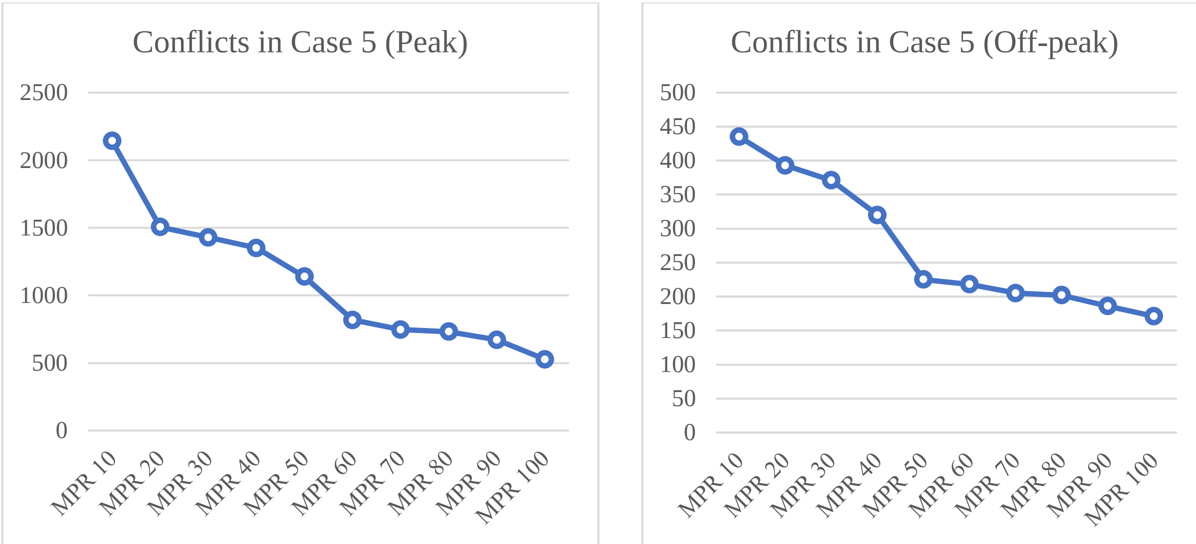


Figure 3.18 - Conflict frequency for peak and off-peak conditions in Case 5

3.11.2 Conflict Reduction

Conflict reduction was calculated based on the difference between the traffic conflicts of any case of CVs (i.e., Case 1, Case 2, Case 3, Case 4, Case 5) and the conflicts of the base case with no CVs, as shown in the following equation.

$$\text{Conflict Reduction} = \frac{Conflicts\ in\ base\ case - Conflicts\ in\ cases\ of\ CVs}{Conflicts\ in\ base\ case} \quad (3.6)$$

For Case 1 (which allows CVs to use any of the MLs), the results of adding CVs to the MLs network revealed that the maximum conflict reduction (compared to the case of no CVs) occurred at an MPR of 20% during peak conditions. The conflict reduction reached 66.87%, more than any other cases. Regarding off-peak conditions, the maximum conflict reduction was 53.23%, and it happened when the MPR was 30%. For Case 2 (which allows CVs to use either dedicated CVLs or MLs), it was found that the maximum conflict reduction (57.53%) occurred when the MPR was 25% during peak condition. On the other hand, in off-peak conditions, it was found that at an MPR of 30%, the maximum conflict reduction occurred, which was 51.03%. For Case 3 (which allows CVs to use only dedicated CVLs), it was found that there was no conflict reduction in the case of peak condition. The safest MPR was 15%, which had an increase of conflicts by 21.68%. However, in the off-peak condition, there was a conflict reduction of 9.46% at the safest MPR, which was 20%. Figure 3.19 and Figure 3.20 show the conflict reduction (value more than zero) and conflict increase (value less than zero) for Cases 1, 2, and 3 for peak and off-peak conditions, respectively.

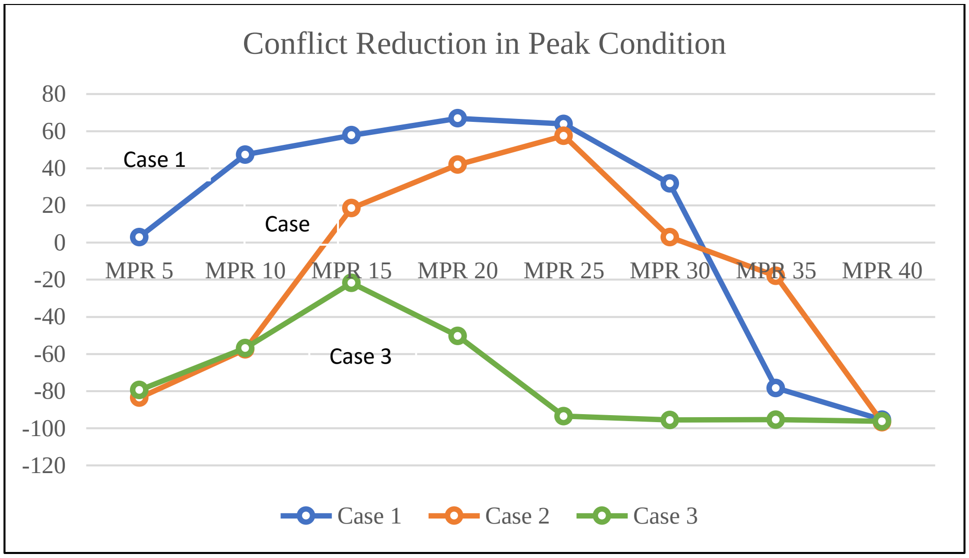


Figure 3.19 - Conflict reduction for peak conditions in Cases 1, 2, and 3

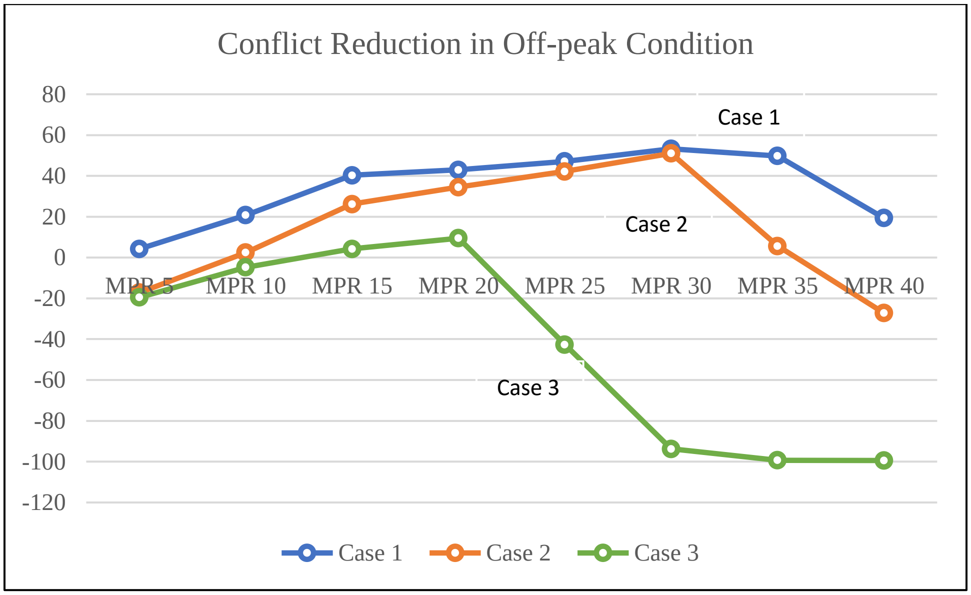


Figure 3.20 - Conflict reduction for off-peak conditions in Cases 1, 2, and 3

According to the conflict reduction results for Case 4 (which is similar to Case 1 in that it converts one GPL to an ML), it was found that the maximum conflict reduction occurred when the MPR was between 40% and 60% for the peak condition. The maximum conflict reduction occurred at an MPR of 50% with a value of 69.67%. The conflict reduction decreased when the MPR reached 80% or more. For off-peak conditions, it is worth mentioning that the lowest conflict reduction occurred when the MPR was between 50% and 70%. The maximum reduction occurred when the MPR was 60% with a value of 60.29%. Figure 3.21 shows the conflict reduction for Case 4.

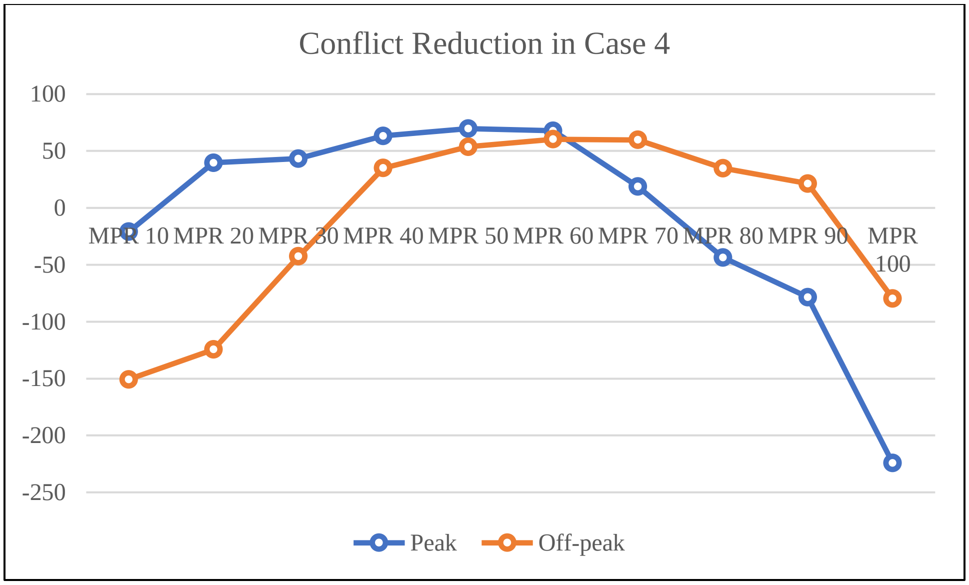


Figure 3.21 - Conflict reduction for peak and off-peak condition in Case 4

Figure 3.22 shows the conflict reduction (compared to the base case with no CVs) for Case 5 (which allows CVs to use any of CVLs, MLs, or GPLs) in all studied MPR%. In peak conditions, it was found that the maximum conflict reduction occurred at a higher MPR%. There was a positive association between higher MPR% and conflict reduction. The highest conflict reduction occurred at an MPR of 100% with a conflict reduction of 72.21%. With an MPR between 60% and 100%, the conflict reduction could reach between 52% and 70%. Also, the conflict reduction could reach 10% to 20% when the MPR was at 20% to 40%. It was also noted that at an MPR of 10%, there was no conflict reduction in the network. It is also worth noting that the off-peak conditions followed the same conflict reduction distribution as the peak conditions. Therefore, a higher MPR% could be recommended for improving the network safety in Case 5. The highest conflict reduction was reached at an MPR of 100% with a reduction of 62.74% in off-peak conditions.

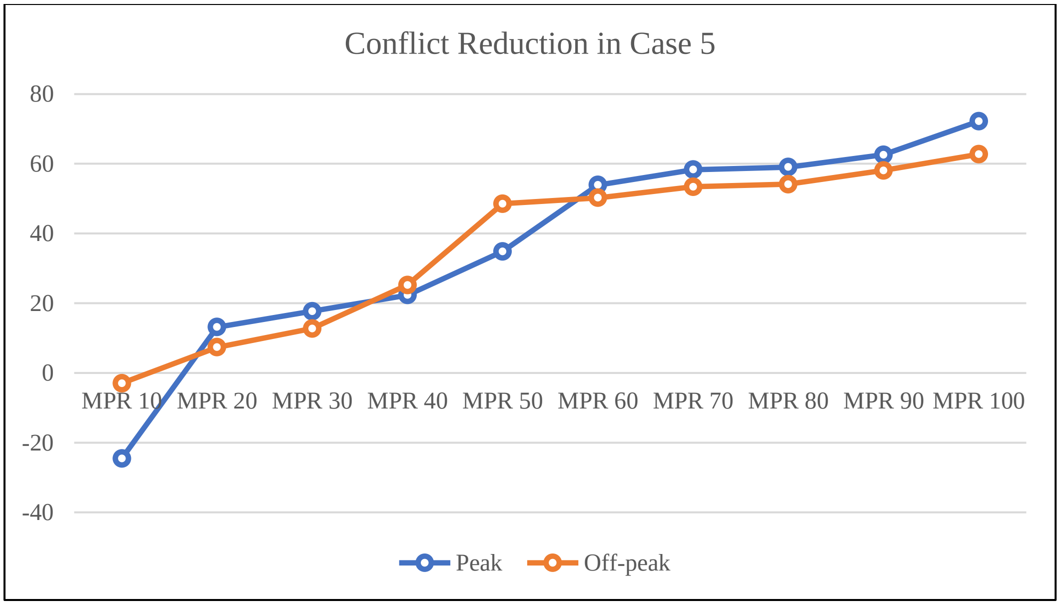


Figure 3.22 - Conflict reduction for peak and off-peak condition in Case 5

3.11.3 Statistical Modeling

The negative binomial (NB) was used in an attempt to quantify the effect of contributing factors on conflict frequencies in the MLs network. The conflict frequency was considered as the dependent variable. The lane configuration cases, MPRs, and traffic conditions served as the independent variables. The model formulation takes the following form:

$$\lambda = \exp(\beta_0 + \beta_z X + \varepsilon) \tag{3.7}$$

where λ is the response variable (conflict frequency); β_0 is the intercept; X represents the different scenarios in all of the cases; β_z represents the corresponding coefficients to be estimated; z represents the different scenarios of various cases and MPR%; and ε is the gamma-distributed error term with a mean equal to 1 and variance α (i.e., over-dispersion parameter). The results of the models are shown in Table 3.5. In the model, the base case with no CVs in the network was set as the baseline.

The results of the NB model confirmed the results of the Tobit model. According to the NB model results, it can be inferred that, for Case 1 (CVs can use any of the MLs), an MPR of 20% and 25% had a significantly lower conflict frequency than the base condition. Specifically, an MPR of 25% is the safest option compared to all other MPRs in Case 1. On the other hand, an MPR of 35% or higher was not recommended since it had a significantly higher conflict frequency than the base case. Moreover, it is apparent from the table that an MPR of 25% was the safest option for Case 2 (CVs can use either MLs or CVLs), with the lowest conflict frequency among all studied rates. A range of 25% to 30% could be recommended as the safest MPR in Case 2 with the lowest conflict frequencies. Furthermore, an inspection of the results in the previous table revealed that an MPR% of Case 3 (CVs only allowed in CVLs) had the highest conflict frequency among all other studied rates. Hence, Case 3 was not recommended in this study. It is also apparent from the table that an MPR of 25% and higher had significantly higher conflicts than the base condition.

Interestingly, for Case 4, (same as Case 1 in that it converts one GPL to an ML), it was found that an MPR between 40% and 60% had a significantly lower conflict frequency than the base case. Specifically, an MPR of 50% had the lowest conflict frequency with the lowest estimate among all rates. For Case 5 (CVs can use any lane in the network), it was found that the maximum conflict reduction occurred at a higher MPR%. There was a significant positive association between a higher MPR% and the reduction of conflict frequency. Specifically, an MPR between 60% and 100% had a significantly lower conflict frequency than the base case. An MPR of 100% had the lowest conflict frequency with the lowest estimate among all rates. Also, it can be concluded that an MPR between 60% and 100% is recommended, since it generated the lowest number of conflicts in the network in Case 5. Furthermore, it is apparent from the traffic conditions that peak conditions had significantly higher conflicts than off-peak conditions.

Table 3.5 - Negative binomial model for conflict frequency

Parameter	Estimate	P-value	Parameter	Estimate	P-value	Parameter	Estimate	P-value
Intercept	9.492	<.0001	Case 2 MPR 35%	0.024	0.960	Case 4 MPR 60%	-1.018	0.034
Case 1 MPR 5%	-0.038	0.937	Case 2 MPR 40%	2.568	<0.0001	Case 4 MPR 70%	-0.576	0.228
Case 1 MPR 10%	-0.378	0.428	Case 3 MPR 5%	0.989	0.038	Case 4 MPR 80%	0.122	0.799
Case 1 MPR 15%	-0.642	0.179	Case 3 MPR 10%	0.442	0.354	Case 4 MPR 90%	0.929	0.052
Case 1 MPR 20%	-0.854	0.074	Case 3 MPR 15%	0.082	0.864	Case 4 MPR 100%	1.540	0.001
Case 1 MPR 25%	-0.828	0.083	Case 3 MPR 20%	0.299	0.531	Case 5 MPR 10%	0.194	0.685
Case 1 MPR 30%	-0.592	0.215	Case 3 MPR 25%	1.289	0.007	Case 5 MPR 20%	-0.068	0.888
Case 1 MPR 35%	0.795	0.097	Case 3 MPR 30%	2.423	<0.0001	Case 5 MPR 30%	-0.123	0.796
Case 1 MPR 40%	2.215	<0.0001	Case 3 MPR 35%	2.806	<0.0001	Case 5 MPR 40%	-0.235	0.622
Case 2 MPR 5%	1.149	0.016	Case 3 MPR 40%	3.064	<0.0001	Case 5 MPR 50%	-0.564	0.238
Case 2 MPR 10%	0.423	0.375	Case 4 MPR 10%	0.688	0.149	Case 5 MPR 60%	-0.791	0.098
Case 2 MPR 15%	-0.263	0.581	Case 4 MPR 20%	0.464	0.332	Case 5 MPR 70%	-0.829	0.083
Case 2 MPR 20%	-0.471	0.324	Case 4 MPR 30%	0.080	0.868	Case 5 MPR 80%	-0.848	0.076
Case 2 MPR 25%	-0.838	0.080	Case 4 MPR 40%	-0.808	0.091	Case 5 MPR 90%	-0.916	0.056
Case 2 MPR 30%	-0.795	0.097	Case 4 MPR 50%	-0.932	0.052	Case 5 MPR 100%	-1.085	0.024
Base Condition					Reference			
Peak (v.s. off- peak)	1.659	<0.0001						
Over-dispersion	0.194	<0.0001						
R-Square					0.354			

3.11.4 Operational Analysis

The traffic operation measurements were analyzed to assess the operational effects of adding CVs and CVLs on freeway facilities with MLs. The evaluation measures for traffic operation included the average travel speed and average delay.

3.11.5 Average Speed

Average travel speed was one of the measurements of effectiveness used to evaluate the performance of the network and to compare the average travel speeds between different cases in the system. The descriptive statistics of the average speed for all studied case are shown in

Table 3.6 for both peak and off-peak periods. The results of the table indicated that Cases 5 and 6 had the highest average speed among all cases. Case 3 showed the lowest average travel speed. An ANOVA test was carried out to compare the average speed in various CVL design cases, MPR%, and traffic conditions. The results showed that there was a significant difference in average speed between cases (F-value=21.45, P-value<0.0001). The results also showed significant differences in average speed between different MPR% (F-value=8.71, P-value<0.0001). Additionally, the results showed that speeds (F-value=84.79, P-value<0.0001) were lower in the peak conditions than in the off-peak conditions.

Table 3.6 - Descriptive statistics of average speed in all studied cases

Case	Traffic Condition	Mean	Standard Deviation	Minimum	Maximum
Base	Peak	58.286	-	58.286	58.286
	Off-peak	59.924	-	59.924	59.924
Case 1	Peak	59.621	3.709	53.681	63.701
	Off-peak	62.479	2.609	58.515	65.049
Case 2	Peak	58.680	1.994	55.795	61.187
	Off-peak	63.029	2.826	57.244	66.127
Case 3	Peak	54.027	2.667	50.719	57.799
	Off-peak	58.665	3.269	53.622	62.127
Case 4	Peak	59.408	4.231	52.144	64.286
	Off-peak	62.726	1.921	59.343	65.123
Case 5	Peak	59.940	2.582	56.519	64.021
	Off-peak	63.353	2.311	60.030	66.408

In Case 1, compared to all studied market penetration rates, the average speed peaked when the MPR was 25% in peak conditions. The lowest speed occurred when the MPR was lower than 10%. In off-peak conditions, the highest average speed occurred when the MPR was 30%. Figure 3.23 provides the distribution of average speed in Case 1 for all studied MPR%.

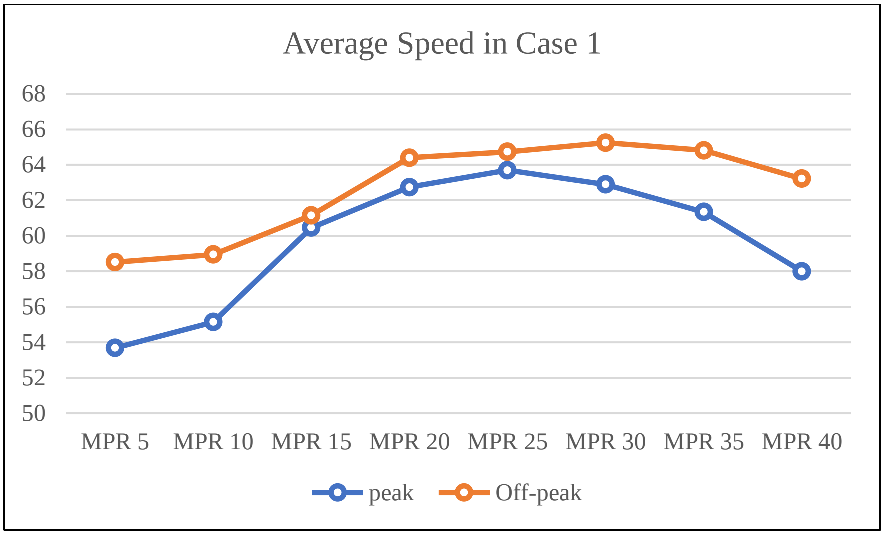


Figure 3.23 - Average speed for different MPR% in Case 1

The results of the speed distribution in Case 2 for different MPR% set out that average speed peaked when the MPR was 25% in peak conditions. Interestingly, in off-peak conditions, there was a clear trend of increasing the average speed with the increase of MPR until the MPR of 25%. Then, speeds decrease in the network with the increase of MPR%. The lowest speed occurred when the MPR was less than 25%. Figure 3.24 displays the average speed distribution for peak and off-peak conditions in Case 2.

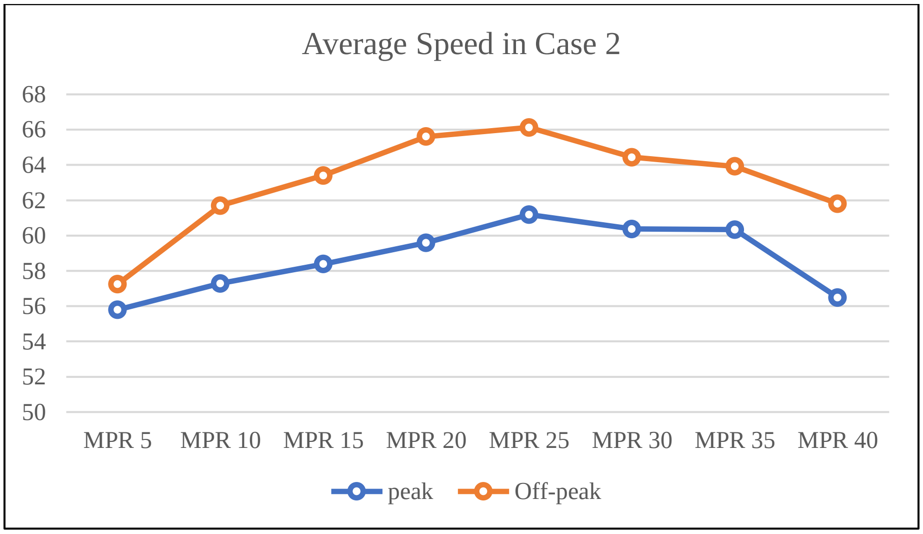


Figure 3.24 - Average speed for peak and off-peak conditions in Case 2

The distribution for average speed for different MPR% in Case 3 is presented in Figure 3.25. What stands out in this figure is that, compared to all studied MPRs, the average speed peaked when the MPR was

15% in peak conditions. In off-peak conditions, the highest average speed occurred when the MPR was 30%. The figure also highlighted that the lowest speeds occurred when the MPR was higher than 30%.

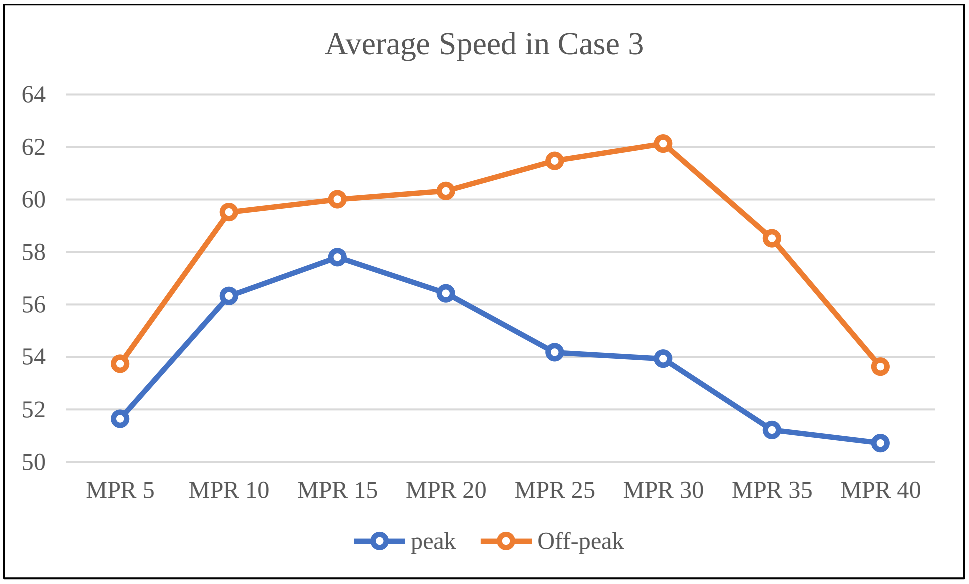


Figure 3.25 - Average speed for peak and off-peak conditions in Case 3

The distribution for average speed for different MPR% in Case 4 is provided in Figure 3.26. What stands out in this figure is that, compared to all studied MPRs, the average speed peaked when the MPR was 50% in peak conditions. The figure also highlighted that the lowest speeds occurred when the MPR was higher than 80%. In off-peak conditions, the highest average speed occurred when the MPR was 70%.

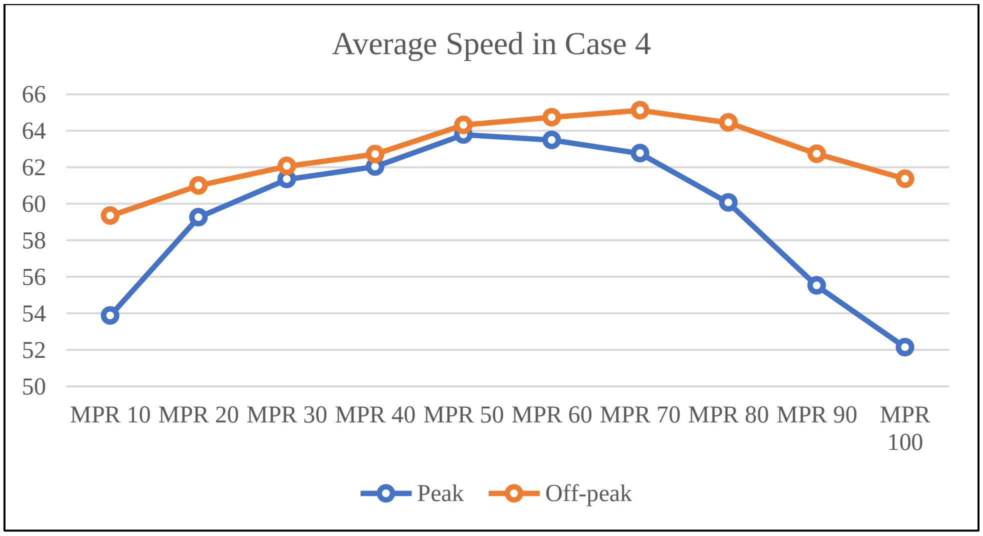


Figure 3.26 - Average speed for peak and off-peak conditions in Case 4

Figure 3.27 provides the speeds in Case 5 for all studied MPR% in both peak and off-peak conditions. Compared to all studied market penetration rates, the average speed peaked with higher MPR% in peak conditions. The highest speeds occurred when the MPR was 100%. Similarly, in off-peak conditions, the highest average speed occurred with higher MPR%.

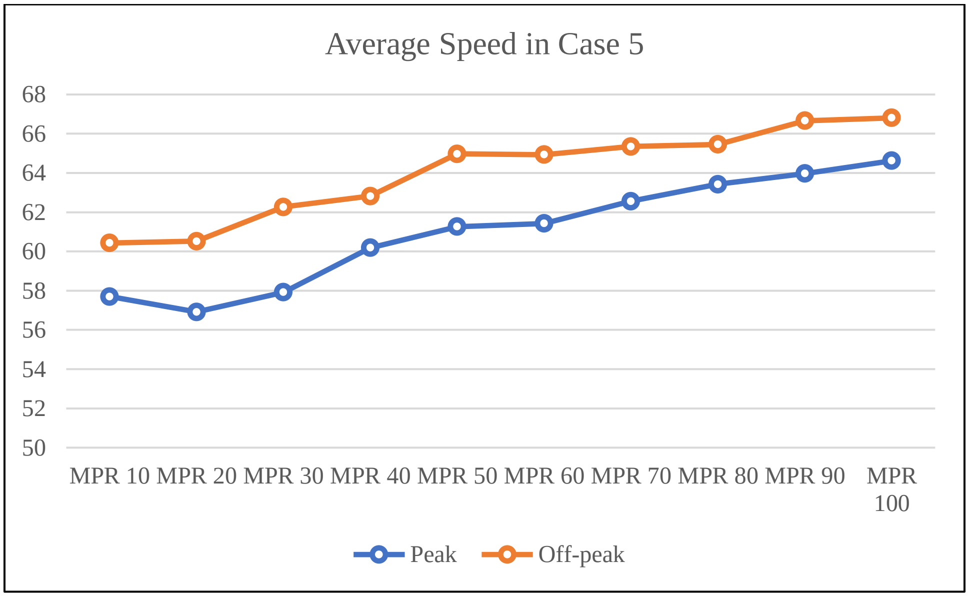


Figure 3.27 - Average speed for peak and off-peak conditions in Case 5

Further analysis was implemented to investigate the speed increase in different scenarios. The speed increase was calculated based on the difference between the average speeds of the different studied cases and the base case as shown in the following equation:

$$\textbf{Speed Increase} = \frac{\textit{Average Speed in case of CVs} - \textit{Average Speed in base case}}{\textit{Average Speed in base case}} \tag{3.8}$$

For Case 1 (which allowed CVs to use any of the MLs), the results of adding CVs to the MLs network revealed that the maximum speed increase (compared to the base case with no CVs) occurred at an MPR of 25% during peak conditions. The speed increase reached 8.51% more than any other cases. Regarding off-peak conditions, the maximum speed increase was 7.87% and it happened when the MPR was 25%. For Case 2 (which allows CVs to use either dedicated CV lanes or MLs), it was found that the maximum speed increase (7.74%) occurred when the MPR was 25% during peak condition. On the other hand, in off-peak conditions, it was found that at an MPR of 25%, the maximum speed increase occurred at 9.38%. For Case 3 (which allows CVs to use only dedicated CVLs), it was found that there was no speed increase in the case of peak condition. However, in the off-peak condition, there was a speed increase of 3.54% at the optimal MPR, which was 30%. Figure 3.28 and Figure 3.29 show the speed increase for Cases 1, 2, and 3 for peak and off-peak conditions, respectively.

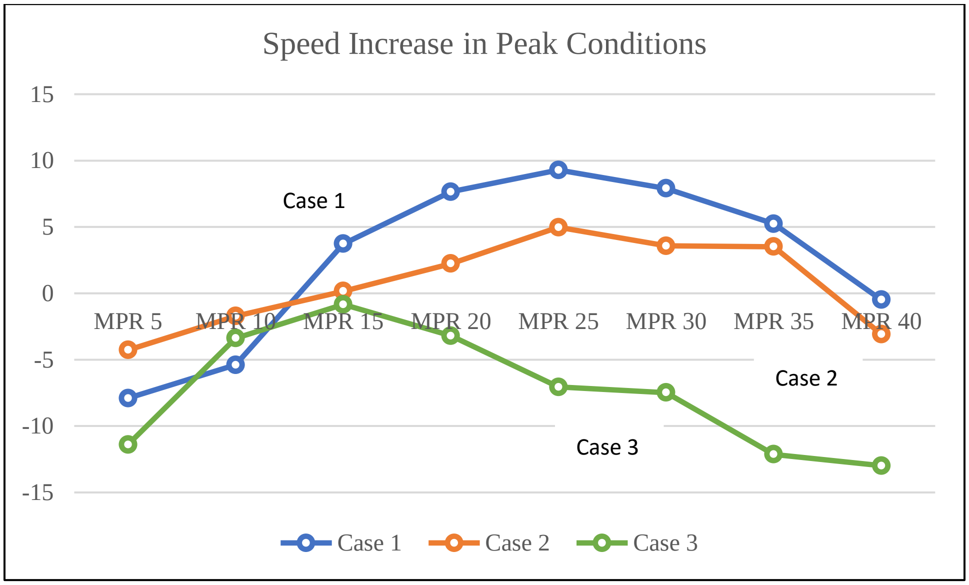


Figure 3.28 - Speed increase for peak condition in Cases 1, 2, and 3

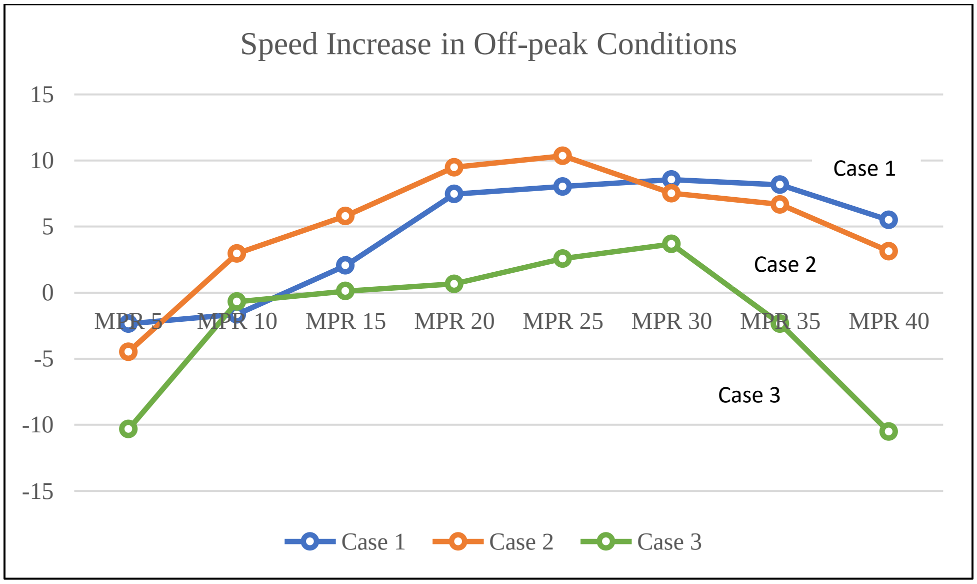


Figure 3.29 - Speed increase for off-peak condition in Cases 1, 2, and 3

Figure 3.30 represents the speed increase for peak and off-peak conditions in Case 4. As can be seen from the figure, in Case 4, the highest speed increase occurred when the MPR was 50% in peak conditions with a 12.45% increase compared to the base condition. The results also revealed that the speed increase deteriorated after an MPR of 70%. In off-peak conditions, the highest speed increase occurred when the MPR was 70% with an 11.05% speed increase.

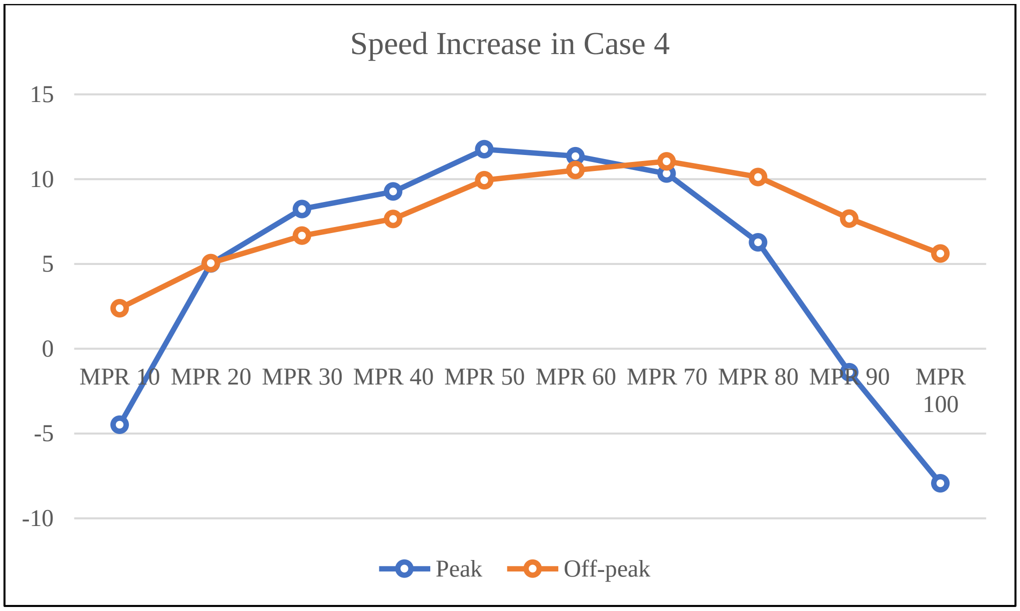


Figure 3.30 - Speed increase for peak and off-peak conditions in Case 4

Figure 3.31 shows the speed increase (compared to the base case with no CVs) for Case 5 (which allows CVs to use any of the CVLs, MLs, or GPLs) in all studied MPR%. In peak conditions, it was found that the maximum speed increase occurred at higher MPR%. There was a positive association between higher MPR% and the speed increase. The highest speed increase occurred at an MPR of 100% with a speed increase of 12.89%. With MPR between 70% and 90%, the speed increase could reach between 10.03% and 12.1%. It is worth noting that the off-peak conditions followed the same speed increase distribution as the peak conditions. Therefore, a higher MPR% could be recommended for improving the network safety in Case 5. The highest speed increase was reached in off-peak conditions at an MPR of 100% with an increase of 13.29%.

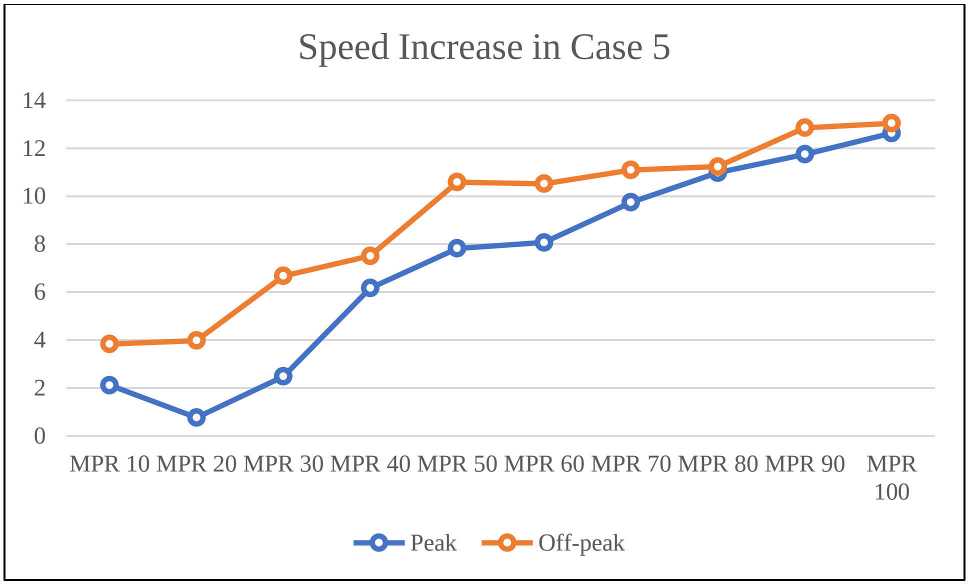


Figure 3.31 - Speed increase for peak and off-peak conditions in Case 5

3.11.6 Statistical Modeling

The Tobit model was used in this study since it is a regression model that can model a continuous dependent variable that can be censored to a lower threshold, an upper threshold, or both. The Tobit model was developed to determine the best scenario with an optimal MPR% among all studied scenarios. In the model, different scenario variables of various lane configuration cases and MPR% of CVs were included. In addition, traffic conditions (peak, off-peak) were considered. The statistical analysis software SAS 9.4 was used for generating the model results. Table 9 provides the model results.

Table 3.7 - Tobit model for average speed

Parameter	Estimate	P-value	Parameter	Estimate	P-value	Parameter	Estimate	P-value
Intercept	61.061	<.0001	Case 2 MPR 35%	1.273	0.247	Case 4 MPR 60%	4.762*	<0.0001
Case 1 MPR 5%	-3.256*	0.0003	Case 2 MPR 40%	-0.207	0.850	Case 4 MPR 70%	4.588*	<0.0001
Case 1 MPR 10%	-1.310	0.233	Case 3 MPR 5%	-6.663*	<0.0001	Case 4 MPR 80%	2.901*	0.007
Case 1 MPR 15%	1.455	0.186	Case 3 MPR 10%	-1.439	0.190	Case 4 MPR 90%	-0.229	0.832
Case 1 MPR 20%	3.716*	0.001	Case 3 MPR 15%	-0.456	0.678	Case 4 MPR 100%	-2.601*	0.016
Case 1 MPR 25%	4.862*	<0.0001	Case 3 MPR 20%	-0.981	0.372	Case 5 MPR 10%	-0.689	0.531
Case 1 MPR 30%	4.617*	<0.0001	Case 3 MPR 25%	-2.033*	0.0346	Case 5 MPR 20%	-1.034	0.346
Case 1 MPR 35%	1.473	0.180	Case 3 MPR 30%	-3.127*	0.0012	Case 5 MPR 30%	0.337	0.759
Case 1 MPR 40%	0.755	0.492	Case 3 MPR 35%	-4.488*	<0.0001	Case 5 MPR 40%	1.250	0.255
Case 2 MPR 5%	-2.835*	0.010	Case 3 MPR 40%	-7.184*	<0.0001	Case 5 MPR 50%	1.516	0.168
Case 2 MPR 10%	0.139	0.900	Case 4 MPR 10%	-2.746*	0.011	Case 5 MPR 60%	2.574*	0.019
Case 2 MPR 15%	1.536	0.162	Case 4 MPR 20%	0.778	0.471	Case 5 MPR 70%	3.701*	0.001
Case 2 MPR 20%	3.395*	0.002	Case 4 MPR 30%	1.545	0.151	Case 5 MPR 80%	4.184*	0.0001
Case 2 MPR 25%	4.302*	<0.0001	Case 4 MPR 40%	3.026*	0.005	Case 5 MPR 90%	5.366*	<0.0001
Case 2 MPR 30%	3.046*	0.006	Case 4 MPR 50%	4.697*	<0.0001	Case 5 MPR 100%	5.860*	<0.0001
Base Condition				Reference				
Peak (v.s. off- peak)	-3.393	<.0001						
α	1.127	<.0001						
R-Square				0.443				

The Tobit model results revealed that, in Case 1 (CVs can use any of the MLs), an MPR of 25% had significantly higher speed than the base case with no CVs in the network. Closer inspection of the results revealed that an MPR of 25% had the second highest speed among all studied MPR%, with a significantly higher speed than the base case. On the other side, an MPR of 10% or lower was not recommended, since it had lower speed than other studied MPR%. As the results shows, an MPR of 20%-30% was recommended as the optimal MPR% in Case 1, since it had significantly higher speed than the base condition. Moreover, it is apparent from the table that, for Case 2 (CVs can use either MLs or CVLs), an MPR of 25% was the best option with the highest speed among all studied rates. A range of 20% to 30% could be recommended as the optimal MPR% in Case 2 with the highest speeds. It is also apparent from the table that an MPR of 5% had lower speeds than all other MPR%. Furthermore, an inspection of the results in the previous table revealed that Case 3 (CVs only allowed in CVLs) was not recommended. Case 3 had lower speeds than the base case for all studied MPR%. There was a significantly lower speed, compared to the base case, when the MPR was 25% or higher. Likewise, an MPR of 5% showed significantly lower speed than the base case.

For Case 4 (same as Case 1 in that it converted one GPL to an ML), it was found that an MPR between 40% and 80% had significantly higher speed than the base case. Specifically, an MPR of 50% had the highest speed, with the lowest estimate among all rates. Also, it can be concluded that an MPR between 40% and 80% is recommended, since it generated the highest speed in the network for Case 4. Interestingly, for Case 5 (CVs can use any lane in the network), it was found that the maximum speed increase occurred at higher MPR%. There was a significantly positive association between higher MPR% and the increase of speed. Specifically, an MPR between 60% and 100% had a significantly higher speed than the base case. An MPR of 100% had the speed with the highest estimate among all rates. Also, it can be concluded that an MPR% between 60% and 100% is recommended, since it generated the highest speed in the network. Furthermore, it is apparent from the traffic conditions that peak conditions had significantly lower speed than off-peak conditions.

3.11.7 Average Delay

The average delay of all vehicles can be measured by subtracting the theoretical travel time from the actual travel time. The theoretical travel time is the free flow travel time. The descriptive statistics of the average delay for all studied cases are shown in Table 3.8 for both peak and off-peak periods. The results of the table indicated that Cases 4 had the lowest average delay among all cases. Case 3 showed the highest delays. An ANOVA test was carried out to compare the average delay in various CVL design cases, MPR%, and traffic conditions. The results showed that there was a significant difference in average delay between the studied cases (F-value=47.16, p-value<0.0001). The results also showed significant differeces in average delay between different MPR% (F-value=11.87, p-value<0.0001). Additionally, the results showed that delays (F-value=178.86, p-value<0.0001) were higher in the peak conditions than in the off-peak conditions.

Table 3.8 - Descriptive statistics for average delay in all studied cases

Case	Traffic Condition	Mean	Standard Deviation	Minimum	Maximum
Base	Peak	21.555	-	21.555	21.555
	Off-peak	17.125	-	17.125	17.125
Case 1	Peak	22.806	4.421	18.810	30.304
	Off-peak	17.195	1.591	15.736	20.460
Case 2	Peak	22.447	2.744	19.265	27.646
	Off-peak	18.610	2.222	16.381	22.919
Case 3	Peak	30.172	5.725	22.940	38.210
	Off-peak	21.522	2.113	18.981	24.919
Case 4	Peak	22.748	4.336	18.005	30.081
	Off-peak	16.809	2.493	13.864	21.048
Case 5	Peak	21.608	3.174	18.687	28.347
	Off-peak	15.923	1.721	13.278	18.687

Figure 3.32 shows the average delay for Case 1 for both peak and off-peak conditions. In peak conditions, it can be noted from the figure that the lowest average delay occurred when the MPR was 20%. Also, the figure showed that average delay increased after an MPR of 30%. For off-peak conditions, it was noted that the lowest average delay happened when the MPR was between 10% and 25%. Subsequently, the average delay increased after an MPR of 30%.

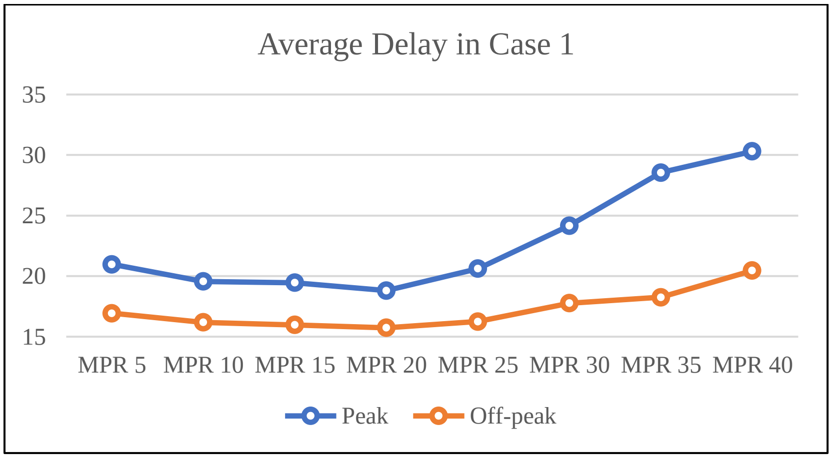


Figure 3.32 - Average delay for peak and off-peak conditions in Case 1

Figure 3.33 shows the average delay for Case 2 for both peak and off-peak conditions. In peak conditions, it can be noted from the figure that the lowest average delay occurred when the MPR was 30%. The average delay increased after an MPR of 30%. For off-peak conditions, it was noted that the lowest average delay occurred when the MPR was 25%. Subsequently, the average delay increased after an MPR of 25%.

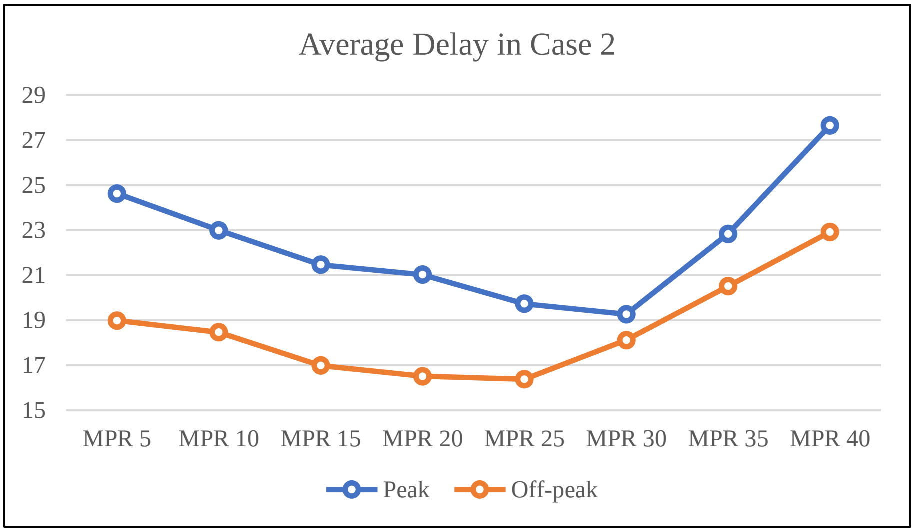


Figure 3.33 - Average delay for peak and off-peak conditions in Case 2

The results of the delay in Case 3 for different MPR% set out that, in peak conditions, the lowest average delay occurred when the MPR was 20%. Subsequently, the average delay increased after an MPR of 25%. For off-peak conditions, it was noted that the lowest average delay happened when the MPR was 25%. The average delay increased after an MPR of 25%. The average delay for various MPR% in Case 3 is displayed in Figure 3.34 for both peak and off-peak conditions.

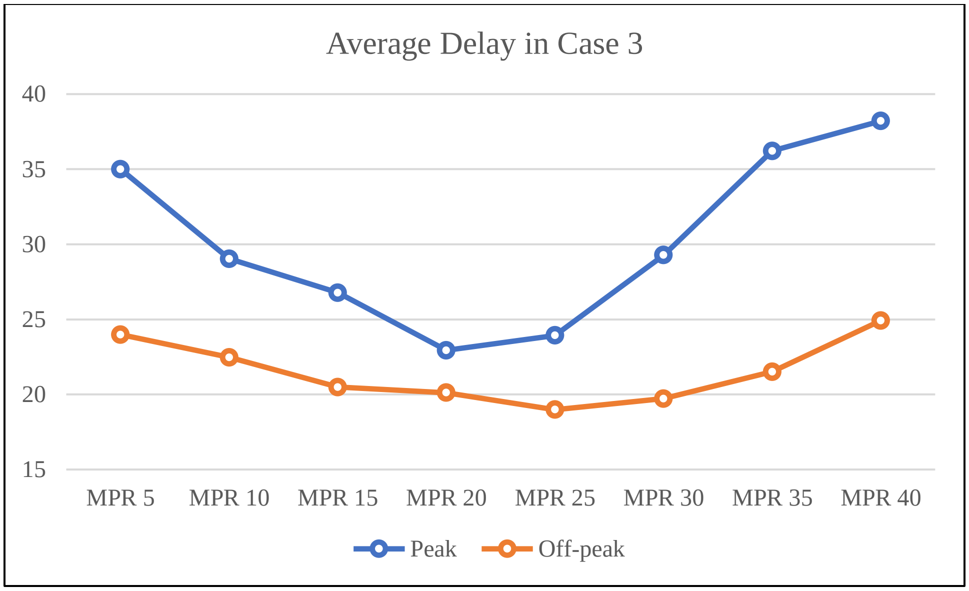


Figure 3.34 - Average delay for peak and off-peak conditions in Case 3

The results of the delay in Case 4 for different MPR% set out that, in peak conditions, the lowest average delay occurred when the MPR was 50%. Subsequently, the average delay increased after an MPR of 70%. For off-peak conditions, it was noted that the lowest average delay happened when the MPR was 60%. The average delay for various MPR% in Case 4 is displayed in Figure 3.35 for both peak and off-peak conditions.

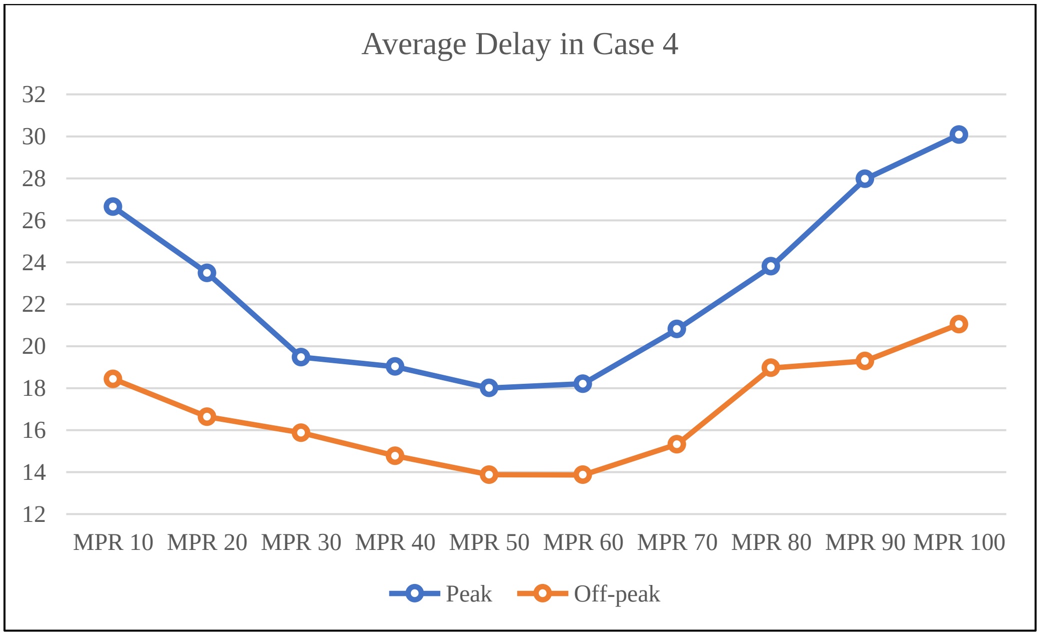


Figure 3.35 - Average delay for peak and off-peak conditions in Case 4

Figure 3.36 shows the average delay for Case 5 for both peak and off-peak conditions. In peak conditions, it can be noted from the figure that the lowest average delay occurred at higher values of MPR%. The lowest delay occurred when the MPR was 100%. It can also be seen in the figure that lower MPR (e.g., 10%, 20%) had higher delay. For off-peak conditions, it was noted that the lowest average delay occurred when the MPR was 100%.

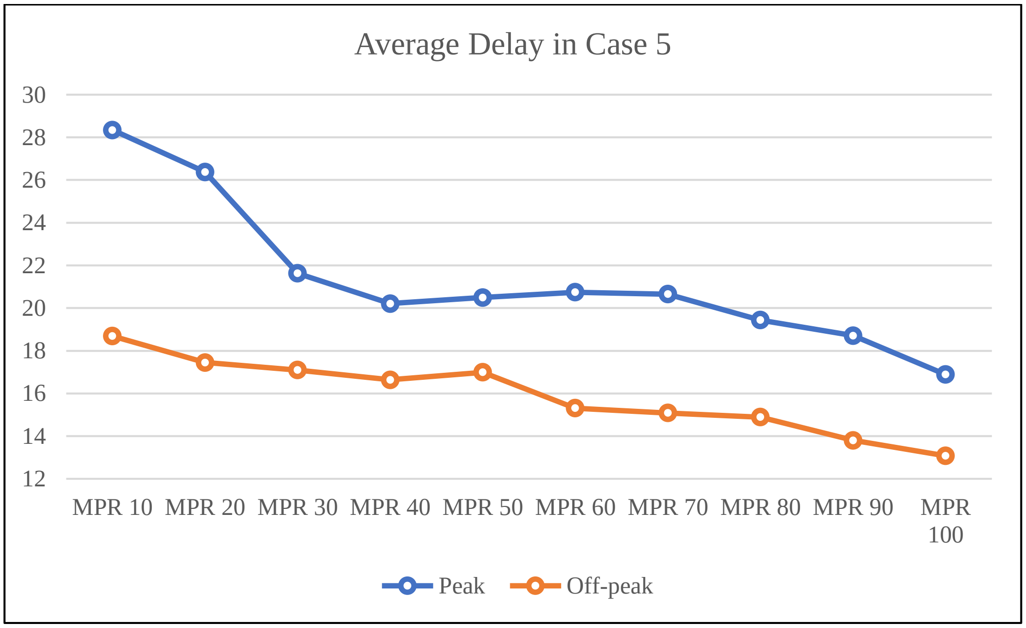


Figure 3.36 - Average delay for peak and off-peak conditions in Case 5

3.11.8 Delay Reduction

Delay reduction was calculated based on the delay in the base case and the delay in the studied cases. The delay reduction was calculated as follows:

$$\text{Delay Reduction} = \frac{Average\ Delay\ in\ base\ case - Average\ Delay\ in\ cases\ of\ CVs}{Average\ Delay\ in\ base\ case} \tag{3.9}$$

For Case 1 (which allows CVs to use any of the MLs), the results of adding CVs to the MLs network revealed that the maximum delay reduction (compared to the case of no CVs) occurred at an MPR of 20% during peak conditions. The delay reduction reached 16.61% more than any other cases. Regarding off-peak conditions, the maximum delay reduction was 13.18% and it occurred when the MPR was 20%. For Case 2 (which allows CVs to use either dedicated CVLs or MLs), it was found that the maximum delay reduction (15.47%) occurred when the MPR was 30% during peak condition. On the other hand, in off-peak conditions, it was found that for an MPR of 25%, the maximum delay reduction occurred at 9.62%. For Case 3 (which allows CVs to use only dedicated CV lanes), it was found that there was no delay reduction in the case of peak condition. The optimal MPR was 20%, which had an increase of delay by 1.71%. Similarly, in the off-peak condition, there was a delay increase of 10.24% at the optimal MPR of 25%. Figure 3.37 and Figure 3.38 show the delay reduction (value more than zero) and delay increase (value less than zero) for Cases 1, 2, and 3 for peak and off-peak conditions, respectively.

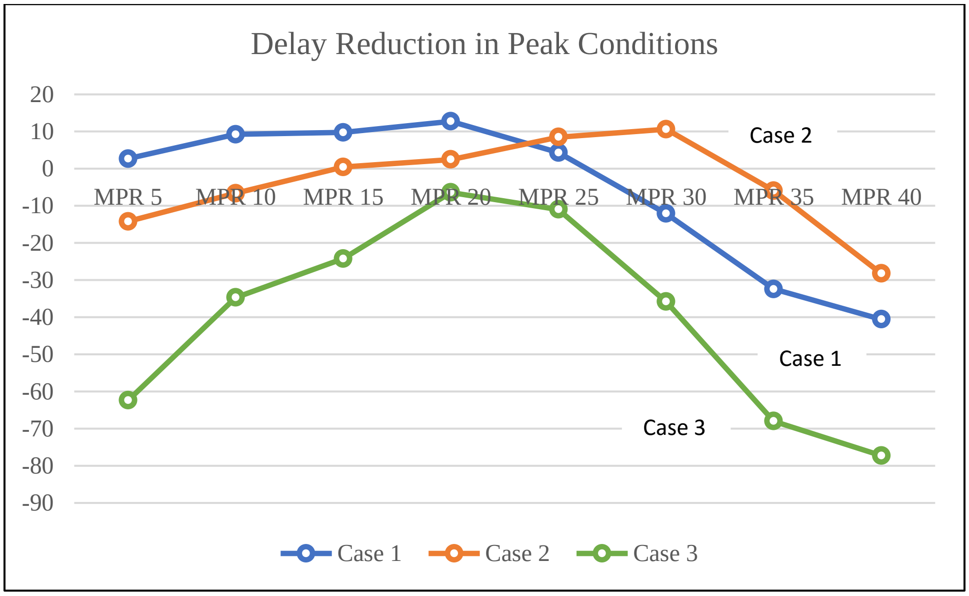


Figure 3.37 - Average delay reduction in peak conditions

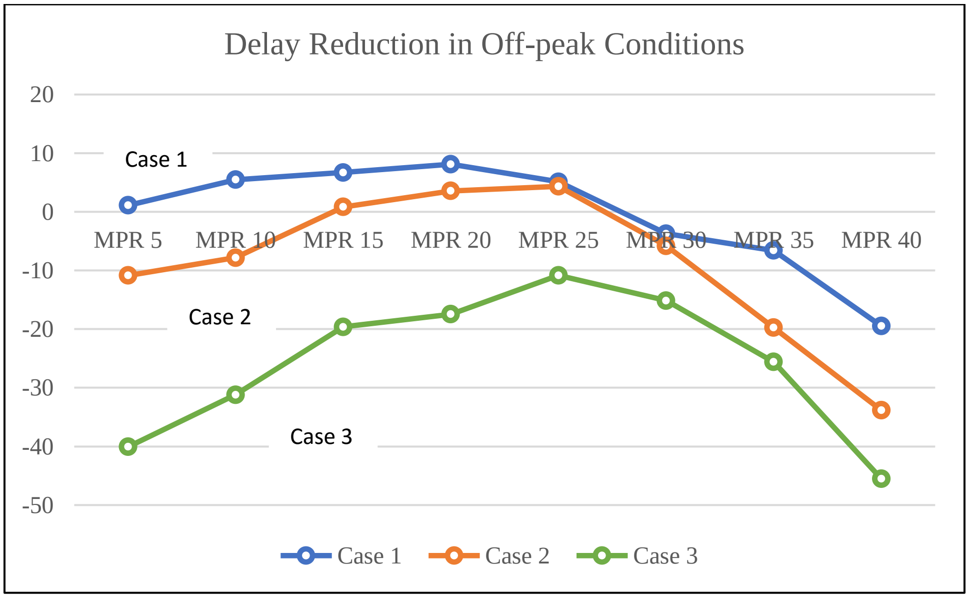


Figure 3.38 - Delay reduction in off-peak conditions

Figure 3.39 represents the delay reduction for peak and off-peak conditions in Case 4. As can be seen from the figure, the highest delay reduction occurred when the MPR was 50% in peak conditions with a 16.5% increase compared to the base condition. The results also revealed that the delay reduction deteriorated after an MPR of 80%. In off-peak conditions, the highest delay reduction occurred when the MPR was 60% with a 19% delay reduction.

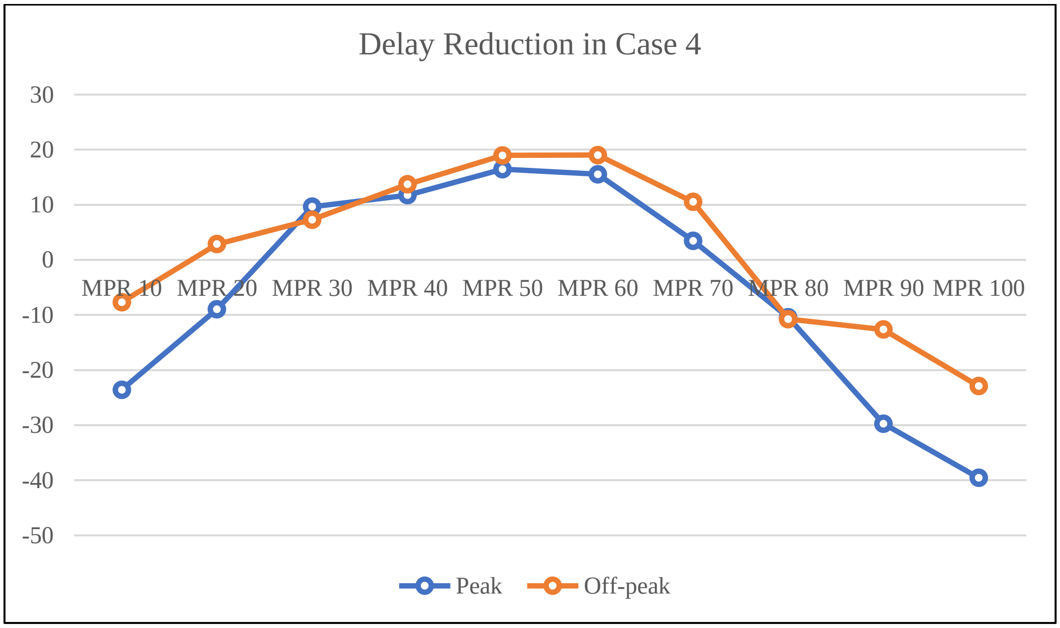


Figure 3.39 - Delay reduction in Case 4

Figure 3.40 shows the delay reduction (compared to the base case with no CVs) for Case 5 (which allows CVs to use any of CVLs, MLs, or GPLs) in all studied MPR%. In peak conditions, it was found that the maximum delay reduction occurred at higher MPR%. There was a positive association between higher MPR% and the delay reduction. The highest delay reduction occurred at an MPR of 100% with a delay reduction of 21.65%. With MPR between 80% and 100%, the delay reduction could reach between 9.8% and 13.3%. It was also noted that at an MPR of 30% or lower, there was no delay reduction in the network. It is worth noting that the off-peak conditions followed the same delay reduction distribution as the peak conditions. Therefore, higher MPR% could be recommended for improving the network safety in Case 5. The highest delay reduction was reached at an MPR of 100% with a reduction of 23.64%.

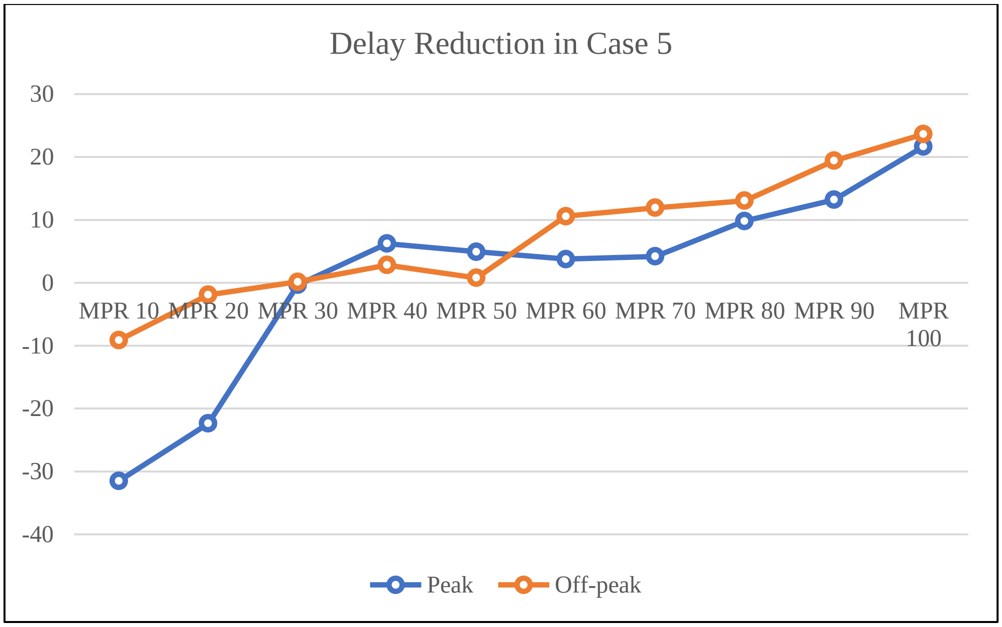


Figure 3.40 - Delay reduction in Case 5

3.11.9 Statistical Modeling

Similar to the average speed analysis, a Tobit model was developed to determine the best scenario with the optimal MPR% among all studied scenarios. The model formulation is similar to the model in the conflict frequency section. The results of the Tobit model are shown in Table 3.9.

Table 3.9 - Tobit model for delay

Parameter	Estimate	P-value	Parameter	Estimate	P-value	Parameter	Estimate	P-value
Intercept	16.696	<.0001	Case 2 MPR 35%	1.832	0.203	Case 4 MPR 60%	-3.305	0.022
Case 1 MPR 5%	-0.384	0.790	Case 2 MPR 40%	5.442	0.0002	Case 4 MPR 70%	-1.274	0.377
Case 1 MPR 10%	-1.466	0.309	Case 3 MPR 5%	10.155	<.0001	Case 4 MPR 80%	2.043	0.156
Case 1 MPR 15%	-1.625	0.259	Case 3 MPR 10%	6.411	<.0001	Case 4 MPR 90%	4.287	0.003
Case 1 MPR 20%	-2.667	0.064	Case 3 MPR 15%	2.140	0.137	Case 4 MPR 100%	6.225	<.0001
Case 1 MPR 25%	-2.952	0.040	Case 3 MPR 20%	1.638	0.256	Case 5 MPR 10%	3.177	0.027
Case 1 MPR 30%	-0.024	0.986	Case 3 MPR 25%	2.113	0.143	Case 5 MPR 20%	1.574	0.275
Case 1 MPR 35%	3.061	0.034	Case 3 MPR 30%	5.156	0.0003	Case 5 MPR 30%	-0.978	0.497
Case 1 MPR 40%	5.042	0.001	Case 3 MPR 35%	9.520	<.0001	Case 5 MPR 40%	-1.613	0.263
Case 2 MPR 5%	1.963	0.173	Case 3 MPR 40%	12.224	<.0001	Case 5 MPR 50%	-2.148	0.136
Case 2 MPR 10%	0.888	0.538	Case 4 MPR 10%	3.198	0.026	Case 5 MPR 60%	-2.512	0.081
Case 2 MPR 15%	-0.616	0.669	Case 4 MPR 20%	0.719	0.618	Case 5 MPR 70%	-2.774	0.054
Case 2 MPR 20%	-2.220	0.123	Case 4 MPR 30%	-1.665	0.248	Case 5 MPR 80%	-3.176	0.028
Case 2 MPR 25%	-2.786	0.053	Case 4 MPR 40%	-2.441	0.090	Case 5 MPR 90%	-3.685	0.011
Case 2 MPR 30%	-2.698	0.061	Case 4 MPR 50%	-3.399	0.018	Case 5 MPR 100%	-4.358	0.003
Base Condition					Reference			
Peak (v.s. off- peak)	5.287	<0.0001						
α	1.4401	<0.0001						
R-Square					0.394			

The results of the Tobit model results revealed that, in Case 1, an MPR of 20% is considered the optimal option for Case 1 (CVs can use any of the MLs), with the lowest delay compared to all other MPRs. Closer inspection of the results revealed that an MPR of 25% had the second lowest delay compared to the other studied MPR%. On the other hand, an MPR of 35% or higher was not recommended, since it had a significantly higher delay than the base case. What emerged from the results reported here was that an MPR of 20%-25% is the most optimal MPR% for Case 1. Furthermore, it is be inferred from the results that for Case 2 (CVs can use either MLs or CVLs), an MPR of 25% was the optimal option with the lowest delay among all studied rates. A range of 25% to 30% can be recommended as the optimal MPR% in Case 2 with the lowest delay. It is also apparent from the table that an MPR of 40% and higher had a significantly higher delay than the baseline. For Case 3 (CVs only allowed in CVLs), an inspection of the results revealed that an MPR of 25% had the least delay among all other rates. The results also revealed that an MPR of 30% or higher had a significantly higher delay than the base condition. Likewise, a significant higher delay occurred when the MPR was 10% or lower. As mentioned before, limiting CVs to use only CVLs is not recommended since it generated higher delay than other cases.

According to the model results, for Case 4 (same as Case 1 in that it converted one GPL to an ML), it was found that an MPR between 40% and 60% had a significantly lower delay than the base case. Specifically, an MPR of 50% had the lowest delay with the lowest estimate among all rates. Also, it can be concluded that an MPR between 40% and 60% is recommended, since it generated the lowest delay in the network in Case 4. For Case 5 (CVs can use any lane in the network), it was found that the maximum delay reduction occurred at higher MPR%. There was a significantly positive association between higher MPR% and the reduction of delay. Specifically, an MPR between 60% and 100% had significantly lower delay than the base case. An MPR of 100% had the delay with the lowest estimate among all rates. Also, it can be concluded that an MPR% between 60% and 100% is recommended, since it generated the lowest delay in the network in Case 5. Furthermore, it is apparent from the traffic conditions that peak conditions had significantly higher delays than off-peak conditions. Therefore, more attention should be paid to peak conditions.

3.12 Summary and Conclusion

This part of the study was undertaken for investigating the safety and operational effect of adding CVs and CVLs to the MLs network with the intention of maximizing system-wide efficiency. Microscopic traffic simulation techniques were developed and applied, including a 9-mi corridor of MLs on Interstate (I-95) in South Florida. Several tasks were determined to achieve the goal of Chapter 3. The networks of the MLs with CVs and CV lanes for different cases were built. In all networks, CVs followed the normal driving logic provided by PTV Vissim 11. In normal logics, vehicles have the capability of measuring speeds of and gaps with the surrounding vehicles with its sensors. The parameters for car following and lane changing models in Vissim 11 were calibrated and validated using real-world CVs data in a project named CoEXist conducted by PTV. The base case (Case 0) represented the current design of the MLs network with one access zone in the middle of the network (one entrance and one exit). The first case (Case 1) included adding CVs to the MLs. In this case, CVs were not allowed to use GPLs except for the CVs that exited the MLs to use the off-ramps. The second case (Case 2) allowed CVs to use either MLs or CVLs. In this case, CVLs were one lane at the left side of the network. In Case 3, CVs were only allowed in the dedicated CVLs. Case 4 included allowing CVs on any of the MLs, by increasing the capacity of MLs by converting one lane of the GPLs to an ML. In this case, CVs were only allowed in the MLs and had the choice to use any of the MLs. In Case 5, CVs could use any of the lanes in the network. For each case, several MPRs were applied and investigated to determine the optimal MPR% for different designs. For each scenario, ten random runs with different random seeds were applied. The comparison between the different cases of MLs designs with the presence of CVs and CVLs with different MPRs were generated for different traffic conditions, including peak and off-peak conditions.

The safety and operational analysis of the CVs and CVLs configurations in MLs were successfully demonstrated. Regarding the MPR, Table 12 shows the optimal MPR% for each case based on three measures of performance: conflict reduction, speed increase, and delay reduction compared to the base case with no CVs. The best scenarios in Case 1 occurred when the MPR was between 20% and 25% for peak conditions with a conflict reduction of 65%. Similarly, for off-peak conditions, the best scenarios happened when the MPR was between 20% and 30% with a conflict reduction of 53%. For Case 2, the maximum conflict reduction, speed increase, and delay reduction happened when the MPR was between 25% and 30%. For off-peak conditions, the best scenarios occurred when the MPR was between 25% and 30%. Moreover, Case 3 (CVs can only use CVLs) was not recommended since it showed lower conflict reduction than other studied cases.

For Case 4 (which is similar to Case 1 in that it converts one GPL to an ML), it was found that the maximum conflict reduction occurred when the MPR was between 40% and 60% for the peak condition. The maximum conflict reduction occurred at an MPR of 50% with a reduction of 70%. For off-peak conditions, it is worth mentioning that the lowest conflict reduction occurred when the MPR was between 50% and 70%. The maximum reduction occurred when the MPR was 60% with 60.29%.

For Case 5 (which allows CVs to use any of CVLs, MLs, or GPLs), it was found that the maximum conflict reduction occurred at a higher MPR%. There was a positive association between higher MPR% and the conflict reduction. With MPR between 60% and 100%, the conflict reduction could reach between 50% and 70%. Also, the conflict reduction could reach 10% to 20% when the MPR was 20% to 40%. It was also noted that at an MPR of 10%, there was no conflict reduction in the network. It is worth noting that the off-peak conditions followed the same conflict reduction distribution as the peak conditions. Hence, a higher MPR% could be recommended for improving the network safety in Case 5. The highest conflict reduction was reached at an MPR of 100% with a reduction of 72.21% and 62.75% for peak and off-peak conditions, respectively.

Table 3.10 - Optimal market penetration rates for different cases

Traffic Condition	Case	Conflict Reduction		Speed Increase		Delay Reduction	
		Optimal MPR%	Reduction%	Optimal MPR%	Increase%	Optimal MPR%	Reduction%
Peak	Case 1	20%	66.87%	25%	8.51%	20%	12.73%
	Case 2	25%	57.53%	25%	4.74%	30%	10.62%
	Case 3	15%	No Reduction	15%	No Increase	20%	No Reduction
	Case 4	50%	69.67%	50%	11.75%	50%	16.47%
	Case 5	100%	72.21%	100%	12.89%	100%	21.65%
Off-peak	Case 1	30%	53.23%	30%	7.87%	20%	8.11%
	Case 2	30%	51.03%	25%	9.38%	25%	4.34%
	Case 3	20%	9.46%	30%	3.54%	25%	No Reduction
	Case 4	60%	60.29%	60%	11.05%	70%	19.04%
	Case 5	100%	62.75%	100%	13.29%	100%	23.64%

Furthermore, based on the Tobit and NB models, Case 5 (allowing CVs in MLs and GPLs) proved to be the superior case with regard to the safety and operations of the lane configuration in a CVs environment. In this case, the recommended MPR was shown to be between 60% and 100%, based on the modeling results of conflict frequency, speed, and delay. If CVs were only allowed in the MLs, Case 1 (CVs can use any of the MLs) would be the best case. In this case, the optimal MPR was determined to be between 15% and 25%. It is worth noting that Case 2 (CVs can use either MLs or CVLs) could also be considered, since there was no significant difference between Case 1 and Case 2. In this case, the recommended MPR was between 20% and 25%. Moreover, it is worth mentioning that an MPR higher than 40% and lower than 10% is not recommended for Cases 1, 2, and 3 since it might result in a significantly high number of conflicts along the network. Case 3 (CVs can only use CVLs) was not recommended since it showed significantly higher conflict frequency, higher delays, and lower speeds than other studied cases.

One of the most prominent findings from this study was that the safety and operation of the network improved by converting one GPL to an ML (Case 4). In this case, it was found that an MPR between 40% and 60% had significantly lower conflict frequency, higher speeds, and lower delays than the base case. Specifically, an MPR of 60% had the lowest conflict frequency, lowest delays, and highest speed among all studied rates. Lastly, it was found that the off-peak periods had better safety and operational performance (e.g., lower conflict frequency, less delay, higher speed) in comparison to the peak periods. Lastly, it was found that the off-peak periods had better safety and operational performance (e.g., lower conflict frequency, less delay, higher speed) in comparison to the peak periods. For future studies, more attention should be allotted to the peak conditions.

It is expected that the outcomes from this study could be used as guidance to establish effective safety and operational plans for MLs in a CV environment. The findings of this study have several important implications for future practice or policy. It is recommended that both lane configuration and MPR should be considered when designing MLs in a CVs environment. The study provides recommendations to transportation agencies for improving the mobility and the efficiency of MLs.

Taken together, the findings of this study have important practical implications for future practice. Table 13 shows the suggestions for CVL design for different MPR%. The results highlighted that an MPR of 10% or lower had no significant improvement over the base case with no CVs. Therefore, an MPR lower than 10% is not recommended in an MLs network. The findings suggested that an MPR between 10% and 30% is recommended when CVs are only allowed in MLs (Case 1 or Case 2). By converting one lane of the GPLs to an ML (Case 4), the MPR could be increased to 60%. Lastly, the findings suggested that an MPR of 100% could be achieved by allowing the CVs to use all the lanes in the network (Case 5). In this case, the conflict reduction could reach 72% for an MPR of 100% and could achieve 61% for an MPR between 60% and 90%.

Table 3.11 – Connected vehicles lane design recommendations for different MPR%

MPR%	CV Lane Design Recommendations
0-10%	Not recommended
10%-30%	Case 1: CVs can use any lane of the MLs or Case 2: CVs can use MLs or CVLs
40%-60%	Case 4: Converting one lane of GPLs to MLs
60%-100%	Case 5: CVs can use any lane in the network (GPLs, MLs, CVLs)

4 Impact of Dedicated Lanes for Connected Vehicle Platooning on Expressways

Connected vehicles technology has recently drawn increasing attention from governments, vehicle manufacturers, and researchers. However, the full market penetration of CVs might not be accomplished in the near term, so traffic flow will likely be composed of a mixture of conventional vehicles and CVs. In this context, the study of CV MPR is worthwhile in the CV transition period. The overarching goal of this chapter is to evaluate the longitudinal safety of CV platoons by comparing the implementation of managed-lane CV platoons and all-lanes CV platoons (with the same MPR) to the non-CV scenario. This study applied the CV concept on a congested expressway (SR408) in Florida to improve traffic safety. The IDM, along with the platooning concept, was used to regulate the driving behavior of CV platoons with an assumption that the CVs would follow this behavior in the real world. A high-level control algorithm of CVs in an ML was proposed in order to form platoons with three joining strategies: rear join, front join, and cut-in join. Five surrogate safety measures, standard deviation of speed, time exposed time-to-collision (TET), time integrated time-to-collision (TIT), time exposed rear-end crash risk index (TERCRI), and sideswipe crash risk (SSCR) were utilized as indicators for safety evaluation. The results showed that both CV approaches (i.e., managed-lane CV platoons, and all-lanes CV platoons) significantly improved the longitudinal safety in the studied expressway compared to the non-CV scenario. In terms of surrogate safety measures, the managed-lane CV platoons significantly outperformed the all-lanes CV platoons with the same MPR. Different TTC thresholds were also tested and showed similar results on traffic safety. Results of this study provide useful insight for the management of CV MPR as managed-lane CV platoons.

4.1 Background

The development of information and communication technologies has facilitated CV technologies, in which vehicles communicate with other vehicles (V2V), roadway infrastructure (V2I), and pedestrians (V2P) in real-time. Connected vehicles are regarded as one of the most promising methods to improve traffic safety. According to NHTSA, at a full V2V adoption, CV technology will annually prevent 439,000 to 615,000 crashes [47]. However, as stated earlier, the full MPR of CV will not be accomplished in the near term [47], so traffic flow will be a mixture of conventional vehicles and CVs. Some studies have found that the efficiency of CV technologies is heavily decided by the CV MPR [90, 44, 52, **Error! Reference source not found.**]. Thus, in the CV transition period, studying the MPR on the safety impact of CV technology is needed.

Vehicle platooning with CV technology is another key element of the future transportation systems that can help us enhance traffic operations and safety simultaneously. Recent research [45] proposed a stochastic model to evaluate the collision probability for heterogeneous vehicle platooning, which can deal with inter-vehicle distance distribution. The results showed great potential in decreasing chain collisions and alleviating the severity of chain collisions in the platoon at the same time. Platoon-based driving may significantly improve traffic safety and efficiency because a platoon has closer headways and lower speed variations than found in traditional traffic flow. Although the platoon-based cooperative driving system has been widely studied, there have not been enough studies that allocate managed-lane CV platoons, which are highly related to CV MPR. The safety benefits of managed-lane CV platoons are expected to be positive because of the dissociation of conventional vehicles and CVs in the same lane. Most of the research in CV technology has been related to the implementation of CV in all lanes of the entire roadway with different MPRs, and no researcher has analyzed managed-lane CV platoons. Figure 4.1 illustrates the managed-lane CV concept along with the regular vehicle lanes.

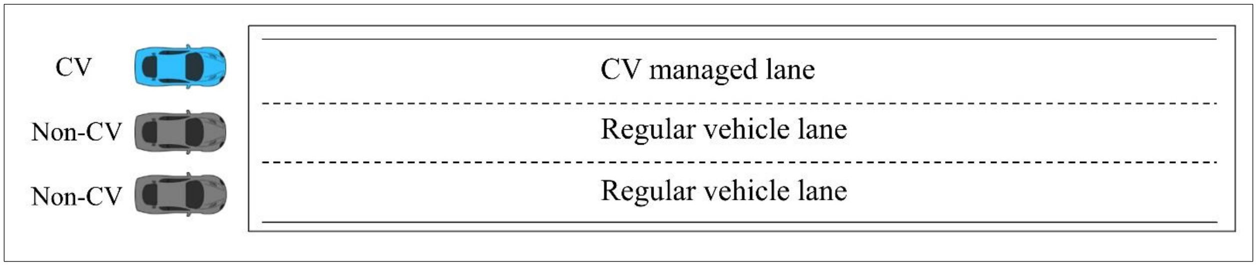


Figure 4.1 - Illustration of CV managed lane and regular vehicle lane

The overarching goal of this study was to evaluate the longitudinal safety evaluation of managed-lane CV platoons on a congested expressway. To have better understanding of managed-lane CV effectiveness, this study selected a congested expressway, SR408, which has 17 weaving segments. The simulation experiments were designed to include deployment of both managed-lane and all-lanes CV platoons in this expressway. Then, a driving behavior model for CVs and the platooning concept were used with an assumption that the CVs would follow this driving behavior in the real world. Five surrogate safety measures, standard deviation of speed, TET, TIT, TERCRI, and SSCR, were utilized as indicators for safety evaluation. Sensitivity analyses were also conducted for the different TTC thresholds. Results of this study provide useful information for expressway safety when CVs are applied as a managed-lane concept for the management of CV MPR in the near future.

4.2 Data Preparation

A congested expressway, the Holland East-West Expressway (SR408) in Orlando, Florida, was selected as a testbed for this study. The testbed was a 22-mile section of SR408 with 17 weaving segments from West Colonial Drive, Orlando, to Challenger Parkway, Orlando. This expressway is monitored by a microwave vehicle detection system (MVDS), which indicates the basic traffic characteristics of the selected road segment, and almost all ramps have an MVDS detector. MVDS. The study area and MVDS detectors are shown in Figure 4.2.

Figure 4.2 - The study area showing MVDS detectors

The collected traffic dataset contains seven important variables, including volume, speed, and lane occupancy for each lane at 1-minute intervals, and also categorizes vehicles into four types according to their length: (1) vehicles 0 to 3 meters in length, (2) vehicles 3 to 7.5 meters in length, (3) vehicles 7.5 to 16.5 meters in length, and (4) vehicles over 16.5 meters in length. In this study, vehicles were classified into two categories: PC and HGV. A vehicle was considered a PC if its length was equal to or less than 7.5 meters (Type 1 and Type 2). The traffic data were collected from MVDS detectors installed in the above-mentioned areas (Figure 4.2).

4.3 Vissim Simulation Model and Calibration

A well calibrated and validated Vissim network replicating the field condition is a prerequisite of microsimulation-based study. Simulations were conducted in PTV Vissim, version 9.0. The testbed was an approximately 22-mile section of SR 408. The traffic information on the simulation network, including traffic volume aggregated into 5-minute intervals, PC and HGV percentages, and desired speed distribution, were obtained from the MVDS detectors. The simulation time was set from 6:30 A.M. to 9:30 A.M in Vissim. After excluding the first 30 minutes of Vissim warm-up time and the last 30 minutes of cool-down time, 180 minutes of Vissim data was used for calibration and validation. The GEH statistic was used to compare the field volumes with simulation volumes; it is a modified Chi-square statistic that takes into account both the absolute difference and the percentage difference between the modeled and the observed flows. The definition of GEH is as follows:

$$GEH = \sqrt{\frac{2\times(M_{obs}(n)-M_{sim}(n))^2}{(M_{obs}(n)+M_{sim}(n)}} \quad (4.1)$$

where $M_{obs}(n)$ is the observed volume from field detectors and $M_{sim}(n)$ is the simulated volume obtained from the simulation network. The simulated volume would precisely reflect the field volume if more than 85% of the measurement locations' GEH values were less than 5 [70, 73]. It is worth mentioning that, for GEH < 5, flows can be considered a good fit; for 5 < GEH < 10, flow may require further investigation; and for 10 < GEH, flow cannot be considered a good fit. To validate the simulation network, average speeds from the field and simulation have been utilized. Mean, minimum, and maximum values of the average speeds from in-field detectors were calculated. As for speed, the absolute speed difference between simulated speeds and field speeds should be within 5 mph for more than 85% of the checkpoints [**Error! Reference source not found.**]. The simulated traffic volumes and speeds were aggregated to 5-minute intervals and then compared with the corresponding field traffic data. Ten simulation runs with different random seeds' worth of results showed that 93.23% of observed GEHs were less than 5, and 92.92% of the aggregated speeds in the simulation were within 5 mph of field speeds. The results above proved that the traffic calibration and validation satisfy the requirements and indicate that the network was consistent with that of the field traffic conditions.

Traffic safety deteriorated significantly in weaving segments compared to non-weaving segments, which increased crash risk in weaving segments [15-18]. As a result, there was a need to revalidate the weaving segment VISSIM network with respect to both traffic and safety. To simplify the validation process, a sensitivity analysis was conducted on Vissim driver behavior parameters in simulation models to reflect the weaving segments condition. Based on the literature review, six parameters were chosen for Vissim calibration and validation for weaving segments [**Error! Reference source not found.**, 30, 31, **Error! Reference source not found.**]: DLCD (desired lane change distance), CC0 (standstill distance), CC1 (headway time), CC2 (following variation), waiting time per diffusion, and safety distance reduction factor. For each parameter, a range of values (9 values), which includes the default, was determined based on previous study and engineering judgment [**Error! Reference source not found.**]. A total of 490 simulation runs [(1 base-models + 6×8 car-following parameters) times 10 random seeds] were conducted. Toward this end, the standard deviation of speed was selected in order to compare the field and simulated values with a two-sample t-test at the 5% significance level. For sensitivity analysis, standard deviation of speed was calculated in 5 minutes of each run and compared with the corresponding field standard deviation of speed in 5 minutes by a two-sample t-test. For each value of parameters, the results of the t-test with 10 different random seeds proved that the distribution of the field and the simulated standard deviation of speeds were identical. The sensitivity analysis results revealed three parameters that are vital to reflect the safety in weaving segment: DLCD, CC1, and safety distance reduction factor. The default values of DLCD, CC1, and safety distance reduction factor in VISSIM were 200 m, 0.9 s, and 0.60, respectively, whereas the calibrated values were found to be 400 m, 0.8 s, and 0.50, respectively.

4.4 Methodologies

An overview of whole methodology is provided in Figure 4.3. The CV platoon was deployed in the simulation experiments in managed-lane CV platoons and all-lanes CV platoons with the same MPR of

40%. For the ML simulation experiment, CV platoons were dedicated only in the inner lane (close to the median), and all other lanes were implemented as regular vehicles. While the simulation experiment for all lanes, CV platoons were implemented in all lanes of the expressway along with regular vehicles. The main difference between the base scenario and the all-lanes CV platoons was the car following behavior. However, all-lanes CV platoons also considered the platooning concept compared to the base scenario. A car following model is a prerequisite to regulate the driving behavior of CVs in microsimulation. In the base scenario, the car following model used was Wiedemann 99, which is the default car following model in Vissim. Connected vehicles are expected to have the capability of sending/receiving information to/from other vehicles and infrastructure-based equipment. In this study, we considered only the V2V communication using a DSRC of 300 meters (1000 feet). With reliable connectivity in the V2V communications networks, each vehicle would receive information about other vehicles in this network. Considering the flow of information in a V2V communications network, drivers are certain about other drivers' behavior. Moreover, they are aware of the driving environment, road condition, and weather condition downstream of their current location. Therefore, a deterministic acceleration modeling framework is suitable for modeling this environment. Some previous research used the IDM, which was proposed by Treiber et al. [**Error! Reference source not found.**] in order to model this CV environment [**Error! Reference source not found.**, **Error! Reference source not found.**, 52]. While capturing different congestion dynamics, this model provides greater realism than most of the other deterministic acceleration modeling frameworks. However, only the car following behavior was not enough to model the CV platoons. The platooning technique was also applied by implementing three joining schemes for CVs: rear, front, and cut-in joins (see next section for details). The IDM and the platooning concept were used to regulate the driving behavior of CV platoons with an assumption that the CVs would follow this behavior in the real world. All CV behavior and the control algorithm of the CV platoons will be described in the next section. The outputs of the CV platoons' behavior model were microscopic simulation traffic data, such as position, speed, occupancy, time interval, vehicle length, and acceleration. Based on surrogate safety measures, a relation can be established between these microscopic data and longitudinal safety.

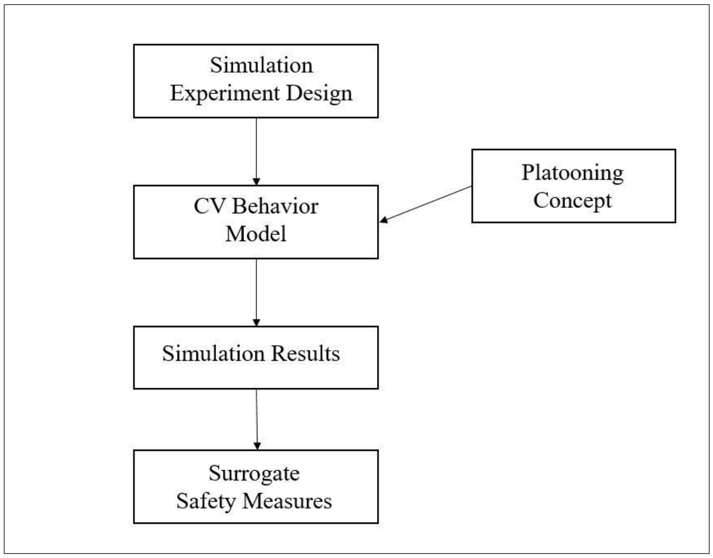


Figure 4.3 - A flowchart of the entire methodology

4.4.1 CV with platooning behavior model

A car following model is a prerequisite to regulate the driving behavior of CVs in microsimulation. The IDM, introduced by Treiber et al. [**Error! Reference source not found.**], is a non-linear car following model for which the acceleration ($\dot{v}_{IDM}$) is calculated by the speed differences (Δv) and the dynamic desired gap distance (s^*). Most researchers used IDM as a machine driving platform in order to simulate their own driving behavior such as adaptive cruise control (ACC) and cooperative adaptive cruise control (CACC) in microsimulation [**Error! Reference source not found.-Error! Reference source not found.**]. The acceleration ($\dot{v}_{IDM}$) is expressed in equations 4.2 and 4.3.

$$\dot{v}_{IDM}(t+t_a) = \max\left\{b_m, a_m\left[1-\left(\frac{v}{v_o}\right)^{\delta}-\left(\frac{s^*}{s}\right)^2\right]\right\} \tag{4.2}$$

$$s^* = s_0 + max\left[0, vT + \frac{v\Delta v}{2\sqrt{a_m b}}\right] \tag{4.3}$$

where t_a = the perception-reaction time, b_m = the maximum deceleration, a_m = the maximum acceleration, v = the speed of the following vehicle, v_0 = the desired speed, δ = the acceleration exponent, s = the gap distance between two vehicles, s_0 = the minimum gap distance at standstill, T = the safe time headway, and b = the desired deceleration

The parameters of the IDM model should be calibrated based on the empirical data of CVs, which are unavailable. Hence, the parameter calibrations are currently intractable. Nevertheless, all the model parameters of this IDM model were potentially determined according to previous studies [**Error!**

Reference source not found., **Error! Reference source not found.**-**Error! Reference source not found.**], which were basically modeled with ACC. Other research also used the same parameters value in order to simulate the CV environment [**Error! Reference source not found.**, 52]. The parameters of the CV behavior model are presented below in Table 4.1.

Table 4.1 - Model parameter settings

Model Parameters	Connected Vehicle
Desired speed, v_0	120 km/h
Acceleration exponent, δ	4
Maximum acceleration, a_m	1 m/s^2
Desired deceleration, b	2 m/s^2
Minimum gap distance at standstill, s_0	2 m
Safe time headway, T	0.6 s
Maximum deceleration, b_m	2.8 m/s^2
Time delay, t_a	1.5 s

Additionally, CVs were implemented as a platooning concept (CVPL) in this study. In this study, three joining schemes for CVs, rear, front, and cut-in joins, were implemented to maintain the platoon. For the managed-lane CV platoon scenario, platoons form in the managed lane dedicated to CVs, while in the all-lanes CV platoon scenario, platoons form in any lane of the designated roadway. The joining scheme of CVs in manage-lane CV and all lanes CV scenarios are presented in Figure 4.4 and Figure 4.5, respectively, to maintain a platoon. The rear join leads a new CV from the regular vehicle lane following the last vehicle of a CV group in a managed lane driving along the most adjacent lane of the joining vehicle (Figure 4.4). For the all-lanes CV scenario, the rear join leads a new CV following the last vehicle of a CV group in any lane driving along the most adjacent lane of the joining vehicle (Figure 4.5) Thus, the joining process is similar between the managed-lane CV platoons and the all-lanes CV platoons. The only difference is that platooning occurs at the designated ML in the managed-lane CV platoons, while in the simulation experiment for all lanes, CV platoons were implemented in all the lanes of the expressway along with regular vehicles. The front join performs the same process as the rear join to allow a new CV from the regular vehicle lane to join an existing CV group in a CV managed lane, except that it leads the joining vehicle to the front of the first vehicle in the CV group. The cut-in join method is implemented by cooperatively adjusting the maneuvers of the joining vehicle from the regular lane and a CV of the managed lane in the group. As shown in Figure 4.4, once the joining vehicle identifies a target CV group in the CV managed lane, it approaches the group and determines a proper position in which to be inserted based on current driving information such as speed, position, etc. Then the deceleration rate of a CV in the target group is adjusted to create a safe gap for the joining vehicle while the leading vehicle maintains its current speed. If the safe gap is satisfied for the lane change behavior of the joining vehicle, which is governed by Vissim's lane changing model, the joining vehicle begins to change the lane.

We developed high-level control algorithm architecture for managed-lane and all-lanes CV platoons as shown in Figure 4.6 and Figure 4.7, respectively. The all-lanes CV platoon scenario is almost the same as the managed-lane CV platoon scenario. The same car following model (IDM) and platooning concept were used in both scenarios to simulate the behavior of CVs. The only difference is that CVs were allowed to occupy all lanes of the roadway in the all-lanes CV platoon scenario. Moreover, platooning can form in any lane of the roadway in the all-lanes CV platoon. For the managed-lane CV platoon scenario, CVs were allowed only in the designated managed lane of the roadway. The platoons were also formed in the managed lane only. It is worth mentioning that the algorithm continuously adjusted the acceleration or deceleration rates using the above-mentioned IDM equation between the leading and subject vehicles using a DSRC system of 300 meters (1000 feet). The main assumption is that all the CV vehicles will follow the control algorithm in the real world.

The driving behavior model of CV platoons for both approaches (i.e., managed-lane CV platoons and all-lanes CV platoons) were implemented as Dynamic Link Library (DLL) plug-in, which overrides the Vissim default driving behavior. The DLL was written in C++, which offers Vissim an option to replace the internal driving behavior and create the V2V communication system. Note that the car following and lane changing behaviors of non-CVs were determined by Vissim's default driving behavior model.

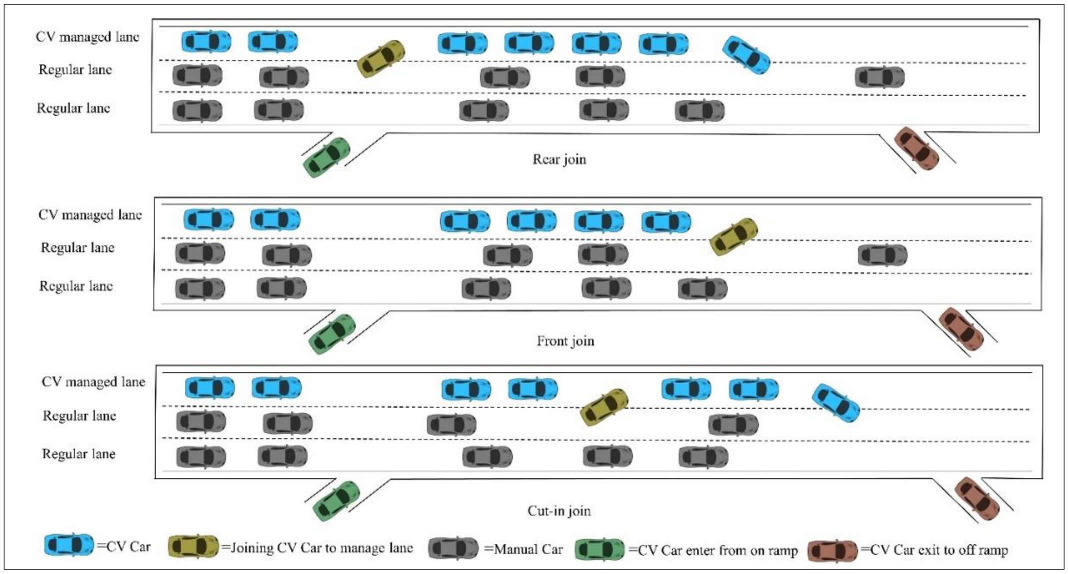


Figure 4.4 - Illustration of CV join to maintain a platoon in managed-lane CV scenario

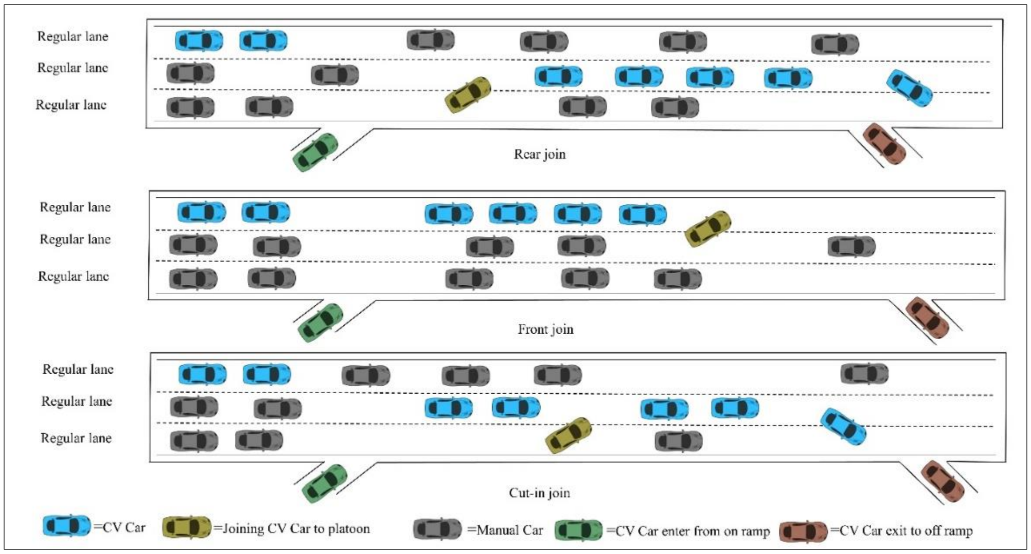


Figure 4.5 - Illustration of CV join to maintain a platoon in all-lanes CV scenario

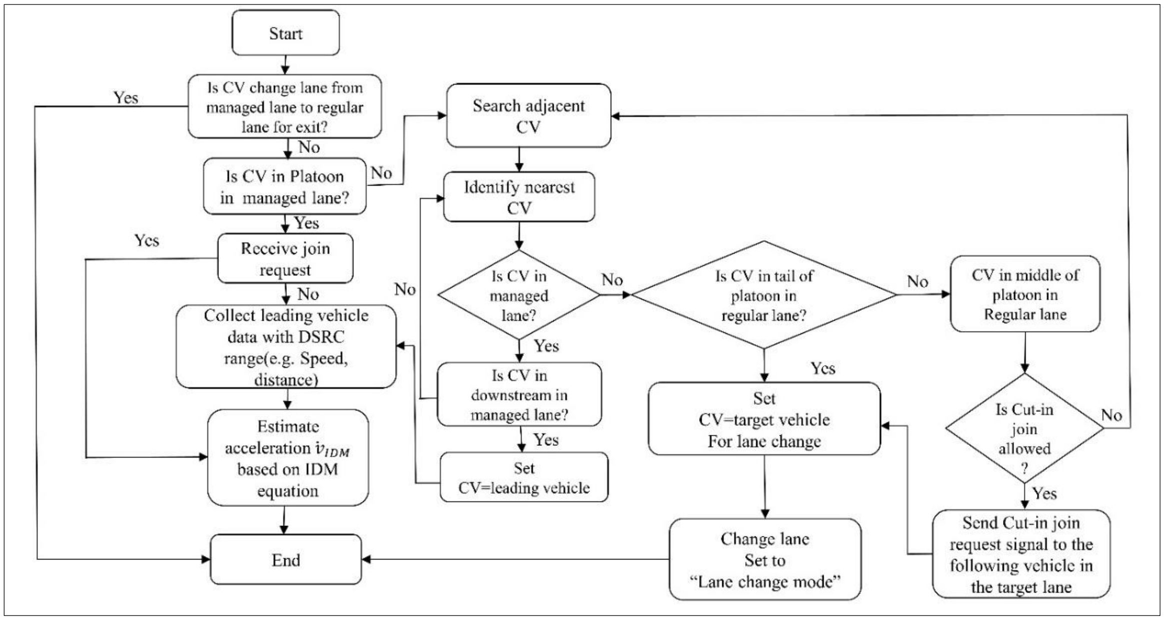


Figure 4.6 - Control algorithm of CVs to maintain a platoon in the managed-lane CV scenario

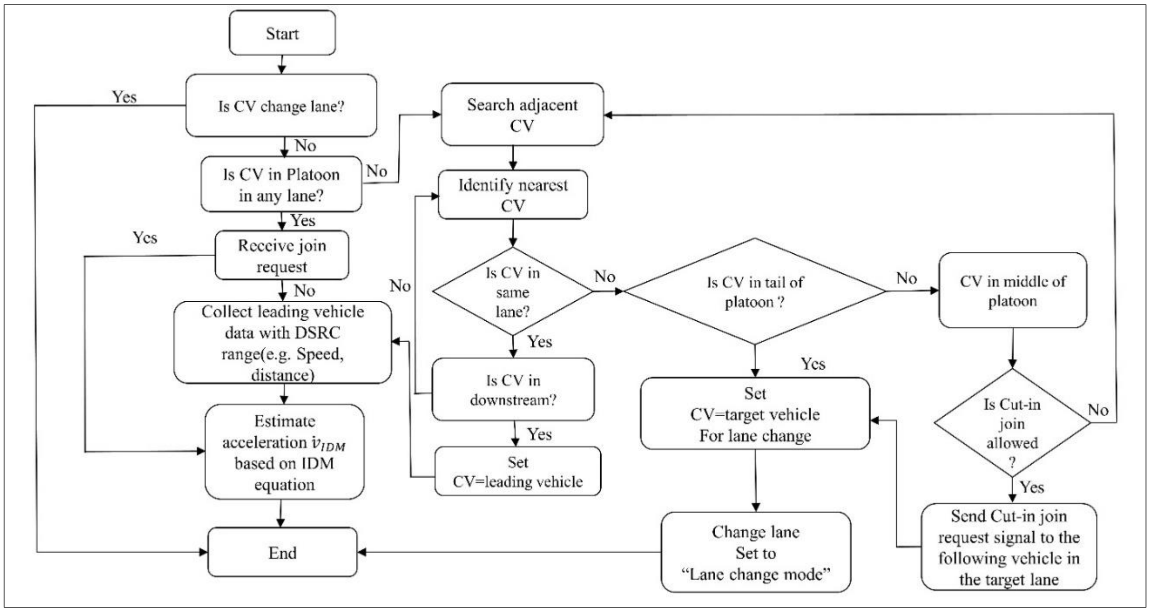


Figure 4.7 - Control algorithm of CVs to maintain a platoon in the all lanes CV scenario.

The comparison among these three scenarios (base, all-lanes CV platoons, and managed-lane CV platoons) are presented in Table 4.2.

Table 4.2 - Comparisons among the three scenarios (base, all-lanes CV, managed-lane CV).

Attributes	Base Scenario	All-lanes CV platoon Scenario	Managed-lane CV platoon scenario
Car following model	Wiedemann 99 (Vissim Default)	IDM model (Equation 1)	IDM model (Equation 1)
Parameters	Vissim default	Presented in Table 4.1	Presented in Table 4.1
Communication	No communication	V2V	V2V
Control method (Platooning)	No platooning	Platooning (**Figure** 4.5 and Figure 4.7)	Platooning (**Figure** 4.4 and Figure 4.6)

4.4.2 CV with platooning behavior model

Traffic crashes are rare events that involve numerous human factors along with the road environment and vehicle factors. A surrogate safety assessment technique should be adopted to measure safety, as microsimulation software cannot be directly used to measure crashes or traffic safety. So, the surrogate measures of safety are widely used as proxy indicators to evaluate the crash risk in microsimulation. A number of previous studies used surrogate measures such as speed variance, TTC, post-encroachment time, and rear-end crash risk index [**Error! Reference source not found.**-**Error! Reference source not found.**]. In this study, five surrogate measures of safety were considered to evaluate the traffic safety. Standard deviation of speed was considered one of the surrogate measures of safety. Two surrogate measures of safety, derived from TTC and denoted as TET and TIT, are utilized to establish the relation between microscopic traffic data and longitudinal safety of CVs.

TTC represents the time required for two successive vehicles, occupying the same lane, to collide if they continue at their present speed when vehicle n moves faster than the preceding vehicle (n-1). The TTC notion can be expressed as equation 4.4:

$$\boldsymbol{TTC_n(t)} = \begin{cases} \frac{\boldsymbol{x_{n-1}(t) - x_n(t) - L_{n-1}}}{\boldsymbol{v_n(t) - v_{n-1}(t)}}, & \boldsymbol{if\ v_n(t) > v_{n-1}(t)} \\ \infty, & \boldsymbol{if\ v_n(t) \le v_{n-1}(t)} \end{cases} \tag{4.4}$$

where $TTC_n(t)$ = the TTC value of vehicle *n* at time t, x = the positions of vehicles, v= the velocities of vehicles, and L_{n-1}= Length of preceding vehicles.

Furthermore, two types of TTC are usually utilized in traffic safety analysis: TTC1 and TTC2. TTC1 assumes the preceding vehicle maintains its speed, while TTC2 describes situations when the preceding vehicle stops suddenly, which is also called TTC at braking [**Error! Reference source not found.**]. During the simulation, traffic data was collected at eighteen detectors in the VISSIM network. However, few small TTC1 was observed during the simulation. Thus, TTC at braking (TTC2) is employed in this study to evaluate traffic safety in different situations. In this study, the definition of the TTC at braking (TTC_{brake}) is as follows [**Error! Reference source not found.**

$$\boldsymbol{TTC_{brake}(t)} = \frac{\boldsymbol{x_{n-1}(t) - x_n(t) - L_{n-1}}}{\boldsymbol{v_n(t)}} \tag{4.5}$$

The smaller TTC_{brake} value indicates the larger risk at a certain time instant. The TET and TIT, two aggregate indictors developed by Minderhoud and Bovy [**Error! Reference source not found.**], are potentially used in this study as surrogate safety measures. The TET refers to the total time spent under dangerous traffic conditions, determined by a TTC_{brake} value below the threshold value of TTC (TTC*).

$$TET\ (t) = \sum_{n=1}^{N} \delta_t \times \Delta t, \quad \delta_t = \begin{cases} 1, & 0 < TTC_{brake}(t) \le TTC^* \\ 0, & otherwise \end{cases} \tag{4.6}$$

$$TET = \sum_{t=1}^{Time} TET(t) \tag{4.7}$$

where t = the time ID, n = the vehicle ID, N = the total number of vehicles, δ = the switching variable, Δt = the time step, which was 0.1 s in simulation, Time = the simulation period, and TTC^* = the threshold of TTC. The TTC* is used to differentiate unsafe car following conditions from those considered safe. According to previous studies, the value of TTC* varies from 1 to 3 s [48, **Error! Reference source not found.**, **Error! Reference source not found.**].

The TIT notion refers to the entity of the TTC_{brake} lower than the threshold. A reciprocal transformation was made considering that a lower TTC means a higher collision risk:

$$\boldsymbol{TIT(t)} = \sum_{n=1}^{N}\left[\frac{1}{TTC_{brake}(t)} - \frac{1}{TTC^*}\right].\boldsymbol{\Delta t}, 0 < \boldsymbol{TTC_{brake}(t)} \leq \boldsymbol{TTC^*} \qquad (4.8)$$

$$\boldsymbol{TIT} = \sum_{t=1}^{Time}\boldsymbol{TIT(t)} \qquad (4.9)$$

Additionally, rear end crashes are the most common type of crashes in any roadway. A rear-end crash may occur if the leading vehicle stops suddenly and the following vehicle does not decelerate in time. So, maintaining an insufficient safety distance between the leading and following vehicles is the primary cause of rear-end crashes. To avoid rear-end crashes, the stopping distance of the following vehicle should be smaller than that of the leading vehicle. A rear-end crash risk index (RCRI) was proposed by Oh et al. [**Error! Reference source not found.**], in which the dangerous condition can be mathematically expressed as:

$$SD_F > SD_L \qquad (4.10)$$

$$SD_L = v_L \times h + \frac{v_L^2}{2\times a_L} + l_L \qquad (4.11)$$

$$SD_F = v_F \times PRT + \frac{v_F^2}{2\times a_F} \qquad (4.12)$$

where SD_L and SD_F are the stopping distance of the leading and the following vehicles, respectively. l_L is the length of the leading vehicle, v_L is the speed of the leading vehicle, v_F is the speed of the following vehicle, PRT is the perception-reaction time, h is the time headway, a_L is the deceleration rate of the leading vehicle, and a_F is the deceleration rate of the following vehicle. As mentioned earlier, for the Vissim model, we used two types of vehicles, PC and HGV. Therefore, different deceleration rates were employed to estimate the reliable safe distance for the leading and following vehicles. The deceleration rates of PC and HGV were selected as 3.42 m/s^2 and 2.42 m/s^2, respectively, while the Perception-reaction time(PRT) was selected as 1.5 s; these values are generally accepted by the

American Association of State Highway and Transportation Officials (AASHTO) [**Error! Reference source not found.**]. We proposed one surrogate measure of safety, derived from RCRI and denoted as TERCRI.

$$\boldsymbol{TERCRI\ (t) = \sum_{n=1}^{N} RCRI_n(t) \times \Delta t,\quad RCRI_n\ (t) = \begin{cases} 1, & SDF > SDL \\ 0, & Otherwise \end{cases}} \tag{4.13}$$

$$\boldsymbol{TERCRI = \sum_{t=1}^{Time} TERCRI(t)} \tag{4.14}$$

Moreover, rear-end crashes are not the only crash type on expressways. Sideswipe crashes are another type of frequent crashes on expressways. It is worth mentioning that the most common way for a sideswipe crash to occur is during the lane changing maneuver. However, it can also happen in a lane changing maneuver on ramps. Therefore, the lane changing conflict can be a surrogate measure of the SSCR. It is difficult to determine the surrogate measures of sideswipe crashes analytically. Therefore, the SSAM [86], developed by the Federal Highway Administration, was applied to analyze the lane changing conflict, which can be related to the surrogate measures of sideswipe crashes. The experimental Vissim model generated several groups of traffic trajectory data files. The vehicle conflicts' data were stored in these trajectory data files, which contain the conflict locations' coordinates, conflict time, time-to-conflict, and post-encroachment-time, among other measures. Hence, the SSAM was applied to analyze these conflict data in order to compare the SSCR among the three scenarios.

In a nutshell, the standard deviation of speed, TET, TIT, TERCRI, and SSCR were considered as surrogate measures of safety in order to evaluate the longitudinal safety of managed-lane CV platoons.

4.5 Results and Discussions

Five surrogate measures of safety were considered to evaluate the safety performances of managed-lane CV platoons in an expressway. To gain a better understanding, we introduced CV platoons in all lanes and in a managed ane only on the expressway with similar MPR. These two CV scenarios were compared with the base scenario (non-CV scenario) in order to observe the effectiveness of CV platoons. As mentioned earlier, standard deviation of speed, TET, TIT, TERCRI, and SSCR were the five surrogate measures of safety considered in this study. Each scenario (base scenario, all-lanes CV platoons, and managed-lane CV platoons) was simulated 20 times to consider random effects of simulation, and the preliminary results are shown in Figure 4.8. The TTC threshold was considered 2 s for the preliminary analysis, and then a sensitivity analysis was conducted for different TTC thresholds from 1 to 3 s.

As shown in Figure 4.8, the distribution of standard deviation of speed, TET, TIT, TERCRI, and SSCR of each scenario approximately followed the normal distribution because of the random effect of simulation. However, the magnitudes (minimum value, maximum value) were significantly different for each scenario. The values (minimum, maximum) of standard deviation of speed, TET, TIT, TERCRI, and SSCR of the base scenario were found in the ranges of [12, 16], [4400, 4725], [2175, 2475], [2700, 2925], and [1212, 1310], respectively.

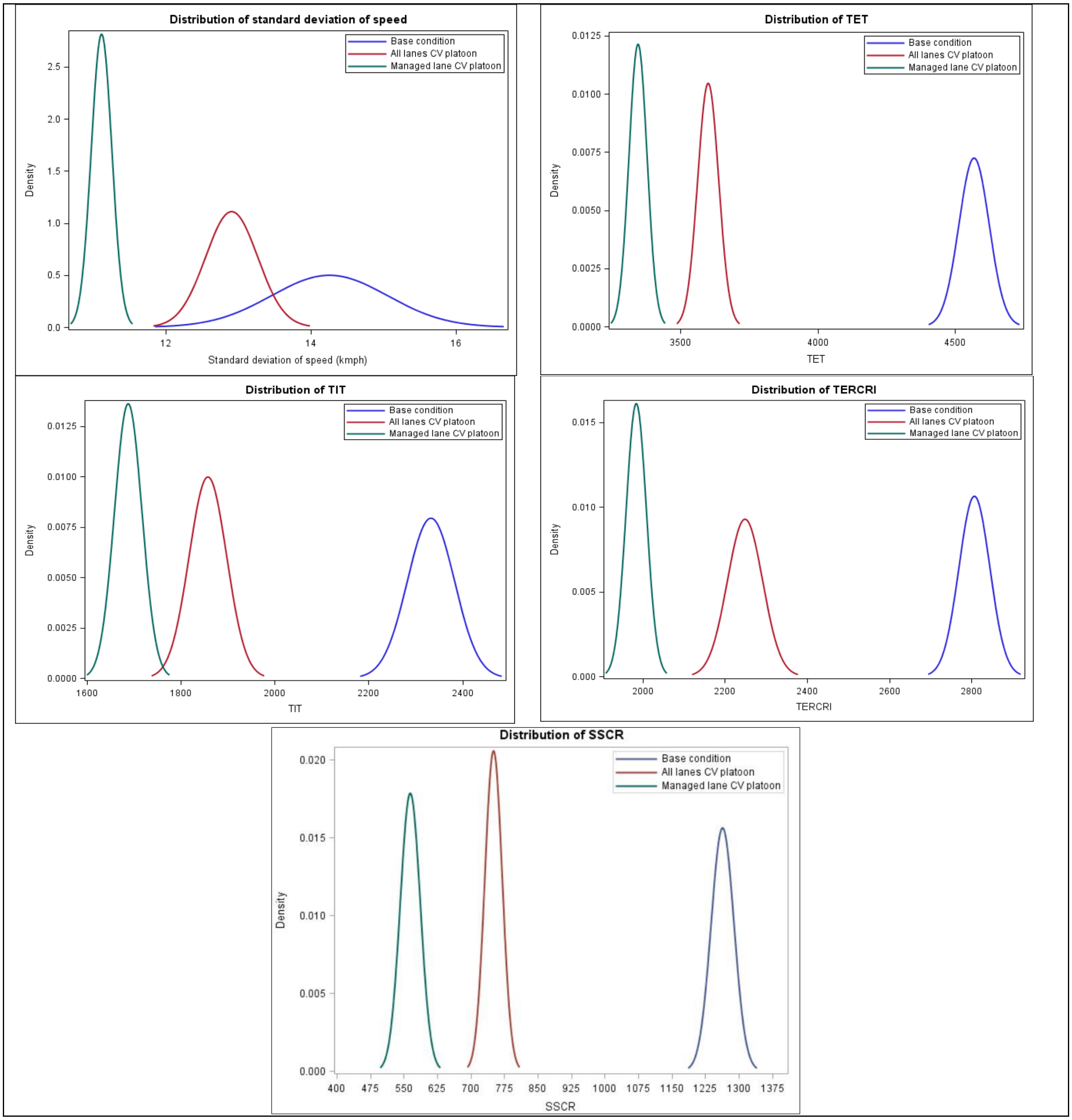


Figure 4.8 - Standard deviation of speed, TET, TIT, TERCRI, and SSCR distribution with different scenarios

While the five indicators (i.e. standard deviation of speed, TET, TIT, TERCRI, and SSCR) of the all-lanes CV platoon scenario were within the range of approximately [12, 14], [3485, 3725], [1725, 1970], [2125, 2375], and [712, 787] respectively and the scenarios for managed-lane CV platoons were within the range of approximately [10.75, 11.5], [3250, 3450], [1600, 1775], [1910, 2060], and [538, 612] respectively. The larger values of each surrogate safety indicator imply the more dangerous situations. Hence, there are higher longitudinal crash risks in the base scenario than in the managed-lane CV and all-lane CV platoons. Among the three scenarios, all five indicators had the lowest values for managed-lane CV platoons, representing a safer situation.

The descriptive statistics of standard deviation of speed, TET, TIT, TERCRI, and SSCR in the three scenarios are presented in Table 4.3. The non-CV scenario has the largest mean value of standard deviation of speed (14.26), TET (4569.45), TIT (2333.05), TERCRI (2807.40), and SSCR (1263.80), followed by the all-lanes CV platoons with 12.91 for standard deviation of speed, 3601.15 for TET, 1857.90 for TIT, 2249.00 for TERCRI, and 751.30 for SSCR, respectively.

Table 4.3 - Summary statistics of standard deviation of speed, TET, TIT, TERCRI, and SSCR.

Scenarios	Measures	Number of Runs	Minimum	Maximum	Mean	Standard Deviation
Base	SD of speed (Km/h)	20	13.04	15.83	14.26	0.80
	TET (s)	20	4482	4692	4569.45	55.10
	TIT (s)	20	2258	2440	2333.05	50.28
	TERCRI (s)	20	2734	2881	2807.40	37.51
	SSCR	20	1212	1310	1263.80	25.56
All lane CV	SD of speed (Km/h)	20	11.98	13.56	12.91	0.36
	TET (s)	20	3512	3675	3601.15	38.16
	TIT (s)	20	1801	1934	1857.90	39.97
	TERCRI (s)	20	2103	2301	2249.00	42.99
	SSCR	20	712	787	751.30	19.41
CV managed lane	SD of speed (Km/h)	20	10.83	11.32	11.12	0.14
	TET (s)	20	3307	3417	3345.60	32.88
	TIT (s)	20	1645	1756	1688.10	29.31
	TERCRI (s)	20	1947	2036	1984.25	24.77
	SSCR	20	538	612	564.95	22.37

*SD of speed=standard deviation of speed

The mean value of five surrogate indicators of managed-lane CV platoons were lowest, with mean standard deviation of speed (11.12), TET (3345.60), TIT (1688.10), TERCRI (1984.25), and SSCR (564.95), respectively. Therefore, the scenario with managed-lane CV platoons has the lowest longitudinal crash risks when compared to the all-lanes CV platoon, while the scenario with the base condition has the highest crash risk.

The one-way ANOVA analyses are presented in Table 4.4 and indicate significant differences among these three scenarios. This illustrates that managed-lane CV platoons significantly outperformed all-lane CV platoons.

Table 4.4 - One-way ANOVA analysis of standard deviation of speed, TET, TIT, TERCRI, and SSCR.

Measures	Attribute	Sum of squares	DF	Mean Squares	F-value	Significance
Standard deviation of Speed (km/h)	Between Groups	99.32	2	49.66	188.33	<0.0001
	Within Groups	15.03	57	0.26		
	Total	114.35	59			
TET (s)	Between Groups	16671463.43	2	8335731.72	4486.73	<0.0001
	Within Groups	105898.30	57	1857.86		
	Total	16777361.73	59			
TIT (s)	Between Groups	4470400.43	2	2235200.22	1345.16	<0.0001
	Within Groups	94714.55	57	1661.66		
	Total	4565114.98	59			
TERCRI (s)	Between Groups	7063193.63	2	3531596.82	2738.25	<0.0001
	Within Groups	73514.55	57	1289.73		
	Total	7136708.18	59			
SSCR	Between Groups	5238492.63	2	2619246.32	5133.24	<0.0001
	Within Groups	29084.35	57	510.25		
	Total	5267576.98	59			

A heat map is presented in Figure 4.9; it shows the effectiveness of managed-lane CV platoons and all-lanes CV platoon compared to the non-CV scenario. Managed-lane CV platoons showed the highest safety improvement in terms of the five surrogate measures of safety presented in the heat map. In the managed-lane CV platoon scenario, the values of standard deviation of speed, TET, TIT, TERCRI, and SSCR were lowest, as shown by the lighter color in heat map.

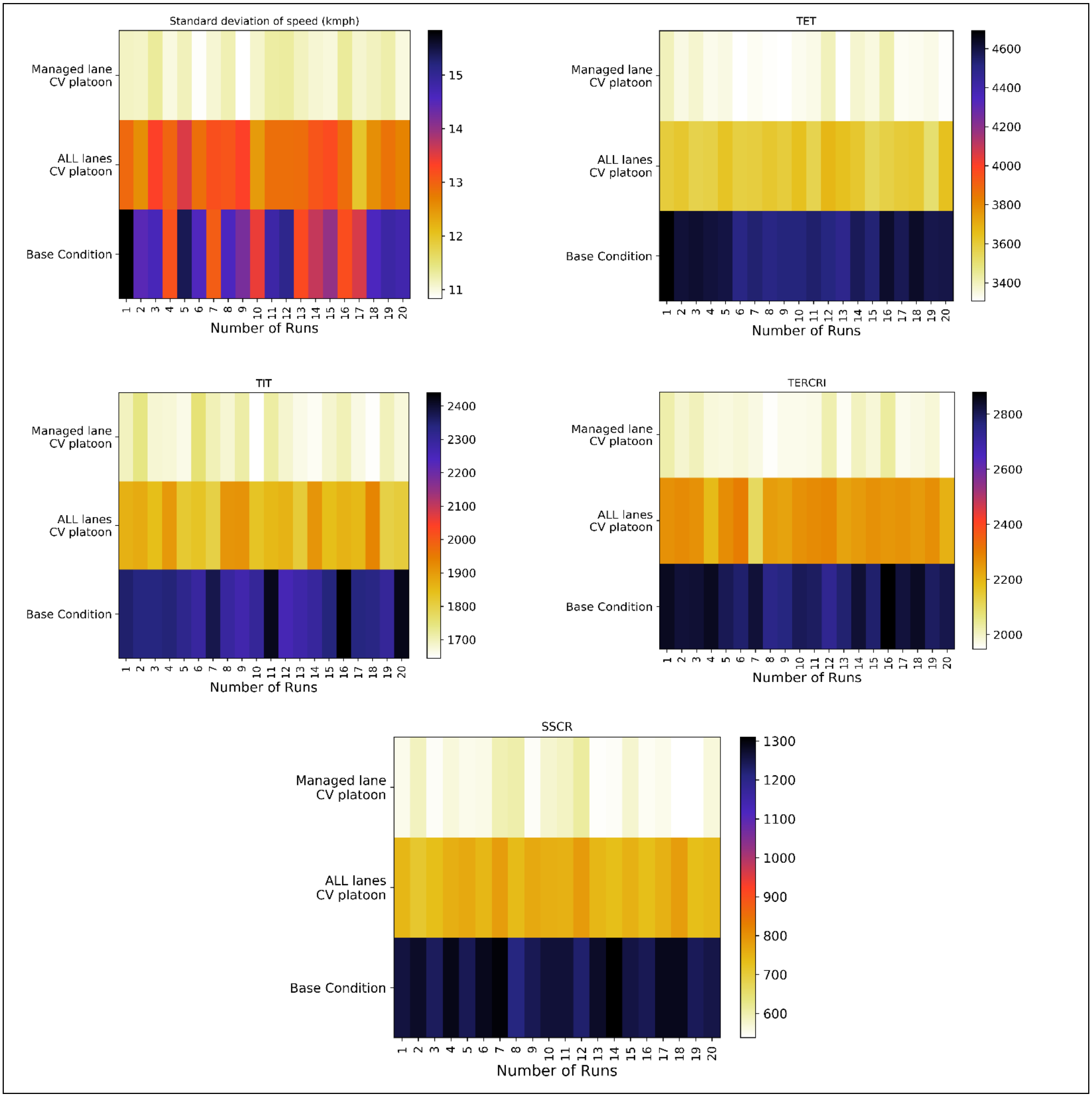


Figure 4.9 - Heat map of surrogate measures of safety

On the other hand, the values of the five surrogate measures of safety were the largest, representing a higher crash risk in the non-CV scenario with the darkest color. In the all-lanes CV platoon scenario, the values of the aforementioned surrogate measures of safety were smaller than the base scenario but larger than the managed-lane CV platoon scenario. From the above discussion, it can be inferred that managed-lane CV platoons clearly outperformed the all-lanes CV platoons in terms of surrogate measures of safety.

The above results of TET and TIT are mainly based on the same parameter setting of TTC threshold of 2 s. Sensitivity analyses of TTC thresholds were also conducted. The various values of TTC threshold do not affect the results of simulations; the five values ranging from 1 to 3 s have almost same results, as shown in Table 4.5. Compared with the base scenario, all the reductions of TIT and TET values remain within 19% to 21% for the all-lanes CV platoons with different values of TTC thresholds. In addition, the TIT and TET values are all reduced within 26% to 28% of the managed-lane CV platoons compared with the base condition.

Table 4.5 - Sensitivity analysis of different values of TTC threshold

TTC* (s)	Scenarios	Base condition		Scenario 1 (All-lanes CV)		Scenario 2 (Managed-lane CV)	
	Measures	TET	TIT	TET	TIT	TET	TIT
1.0	Average value	2238	674	1765	539	1602	497
	Changing proportion	-	-	21%	20%	28%	26%
1.5	Average value	3634	1654	2921	1326	2647	1182
	Changing proportion	-	-	19%	19%	27%	29%
2.0	Average value	4569	2333	3601	1858	3346	1688
	Changing proportion	-	-	21%	20%	27%	28%
2.5	Average value	5290	2824	4222	2251	3820	2045
	Changing proportion	-	-	20%	20%	28%	28%
3.0	Average value	5889	3205	4634	2554	4227	2313
	Changing proportion	-	-	21%	20%	28%	28%

Overall, the deployment of all-lanes and managed-lan CV platoons in the congested expressway studied would significantly decrease the standard deviation of speed, TET, TIT, TERCRI, and SSCR, and thereby might decrease the probability of crashes. However, it is clearly seen that managed- lane CV platoons significantly outperformed all-lanes CV platoons with the same MPR.

4.6 Summary and Conclusion

The primary objective of this study was to evaluate the longitudinal safety of managed-lane CV platoons on expressways based on simulation results. The simulation experiments were designed by deploying managed-lane CV platoons and all-lanes CV platoons on a congested expressway. Then, a vehicle behavior model for a CV platoon was used based on the IDM model, and five surrogate safety measures (standard deviation of speed, TET, TIT, TERCRI, and SSCR) were measured as safety indicators. Sensitivity analyses were also conducted for different TTC thresholds to compare the results among the three scenarios.

The distribution of the five surrogate measures of safety approximately follow the normal distribution because of the stochastic nature of simulation. The values of standard deviation of speed, TET, TIT, TERCRI, and SSCR were largest for the base (non-CV) scenario. The results showed that both CV platoon scenarios improved safety significantly over the non-CV scenario. However, the surrogate safety measures were smaller in managed-lane CV platoons than in all-lanes CV platoons. Hence, the traffic stream with managed-lane CV platoons has lower longitudinal crash risks than all-lanes CV platoons. One-way ANOVA analysis showed significant differences among the three tested scenarios and inferred that managed-lane CV platoons significantly outperformed all-lanes CV platoons. In addition, the results of sensitivity analysis indicated that the TTC threshold ranging from 1 to 3 s has almost the same results. Hence, the different TTC thresholds did not affect the simulation results.

From our analysis, it is evident that managed-lane CV platoons and all-lanes CV platoons significantly improved the longitudinal safety in the studied expressway segments compared to the base condition. In terms of surrogate safety measures, the managed-lane CV platoons significantly outperformed all-lanes CV platoons with the same MPR. The study is not without limitations. In our research effort, we considered several IDM parameters that were implemented in previous studies. The parameters should be calibrated based on the empirical data of CVs, which are unavailable; thus, the parameter calibrations are currently intractable. However, the optimization of these parameters was beyond the scope of this study. It can serve as a good platform for further analysis with a combination of variable speed limit, ramp metering, and CV technology in any congested expressway.

References

1. Perez, B. G., Fuhs, C., Gants, C., Giordano, R., Ungemah, D. H., & Berman, W. (2012). *Priced managed lane guide* (No. FHWA-HOP-13-007). Washington, DC: Federal Highway Administration.
2. Fitzpatrick, K., Brewer, M. A., Chrysler, S., Wood, N., Kuhn, B., Goodin, G., Fuhs, C., Ungemah, D., Perez, B., Dewey, V., Thompson, N., Swenson, C., Henderson, D., & Levinson, H. (2016). *Guidelines for implementing managed lanes* (NCHRP Project 15-49). Washington, DC: Transportation Research Board.
3. Fitzpatrick, K., Brewer, M., Lindheimer, T., Chrysler, S., Avelar, R., Wood, N., ... & Fuhs, C. (2016). *Research supporting the development of guidelines for implementing managed lanes* (NCHRP Project 15-49). Washington, DC: Transportation Research Board.
4. ATKINS. (2013, October 10). *The road less traveled*. Retrieved from http://www.atkinsglobal.com/en-GB/angles/all-angles/the-road-less-travelled
5. Kuhn, B., Texas Transportation Institute, & Federal Highway Administration. (2010). *Efficient use of highway capacity summary: Report to congress.* Washington, DC: Federal Highway Administration.
6. Federal Highway Administration. (2012). *Tolling and pricing program*. Retrieved from http://ops.fhwa.dot.gov/publications/fhwahop13007/pmlg6_0.htm
7. Federal Highway Administration. (2017). The Federal Highway Administration (FHWA): Freeway Management Program.. Retrieved from: https://ops.fhwa.dot.gov/freewaymgmt/index.htm
8. HNTB. (2013). Priced managed lanes in America. Retrieved from: https://www.ibtta.org/sites/default/files/documents/2013/Normandy/Lefrois_Greg_Managed%20Lanes.pdf.
9. Abuzwidah, M., & Abdel-Aty, M. (2018). Crash risk analysis of different designs of toll plazas. *Safety Science*, *107*, 77-84.
10. Abuzwidah, M., & Abdel-Aty, M. (2017). Effects of using high occupancy vehicle lanes on safety performance of freeways. *Proceedings of the Transportation Research Board 96th Annual Meeting*. Washington, DC: Transportation Research Board.
11. Fuhs, C.A. (1990). High-occupancy vehicle facilities: A planning, design, and operation manual. Parsons-Brinckerhoff, New York, 1990.
12. California Department of Transportation. (2011). *Updated managed lane design: Traffic operations policy directive 11-02.* Sacramento, CA: CALTRANS.
13. Jang, K., Chung, K., Ragland, D. R., & Chan, C. Y. (2009). Safety performance of high-occupancy-vehicle facilities: Evaluation of HOV lane configurations in California. *Transportation Research Record, 2099*(1), 132-140.
14. Machumu, K. S., Sando, T., Mtoi, E., & Kitali, A. (2017). Simulation-based comparative performance measures for I-295 express lanes in Jacksonville, Florida (No. 17-06536). Washington, DC: Transportation Research Board.
15. Glad, R.W. (2001). *Weave analysis and performance: The Washington State case study*. Olympia, WA: Washington State Department of Transportation.
16. Golob, T.F., Recker, W.W., & Alvarez, V.M. (2004), Safety aspects of freeway weaving sections. *Transportation Research Part A: Policy and Practice, 38*(1): p. 35-51.

17. Kim, K., & Park, B. (2018). Safety features of freeway weaving segments with a buffer-separated high-occupancy-vehicle (HOV) lane*. International Journal of Injury Control and Safety Promotion, 25*(3), p. 284-292.
18. Pulugurtha, S. S., & Bhatt, J. (2010). Evaluating the role of weaving section characteristics and traffic on crashes in weaving areas. *Traffic Injury Prevention, 11*(1), 104-113.
19. Cirillo, J. A. (1970). The relationship of accidents to length of speed-change lanes and weaving areas on interstate highways. *Highway Research Record, 312.*
20. Bonneson, J. A., & Pratt, M. P. (2008). Procedure for developing accident modification factors from cross-sectional data. *Transportation Research Record, 2083*(1), 40-48.
21. Qi, Y., Liu, J., & Wang, Y. (2014). *Safety performance for freeway weaving segments* (No. SWUTC/14/600451-00045-1). College, Station, TX: Texas A&M Transportation Institute.
22. Burgess, C., Wilbur Smith Associates, The Resource Group, Perteet, EnviroIssues, IBI Group, & Demich Consulting. (2006). *HOT lane buffer and mid-point access: Design review report*. Olympia, WA: Washington State Department of Transportation.
23. Venglar, S., Fenno, D., Goel, S., & Schrader, P. (2002). *Managed lanes: Traffic modeling* (Report No. FHWA/TX-02/4160-4). College Station, TX: Texas Transportation Institute.
24. Machumu, K. S., Sando, T., Mtoi, E., Chimba, D., & Kwigizile, V. (2017). Simulation-based determination of the minimum routing decision distance for managed lanes: Case study of I-295 in Jacksonville, Florida (No. 17-00178). Washington, DC: Transportation Research Board.
25. Haleem, K. M. (2007). Exploring the potential of combining ramp metering and variable speed limit strategies for alleviating real-time crash risk on urban freeways (Master's thesis). University of Central Florida, Orlando, FL.
26. Nilsson, L. (1993). Behavioural research in an advanced driving simulator-experiences of the VTI system. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *37*(9), 612-616.
27. Allen, R., Rosenthal, T., & Cook, M. (2011). A short history of driving simulators. In D. L. Fisher, M. Rizzo, J. K. Caird, & J. D. Lee (Eds.) *Handbook of Driving Simulation for Engineering, Medicine and Psychology* (pp. 2.1-2.16). Boca Raton, FL: CRC Press.
28. Bham, G., Mathur, D., Leu, M., & Vallati, M. (2010). Younger driver's evaluation of vehicle mounted attenuator markings in work zones using a driving simulator. *Transportation Letters, 2*(3), 187-198.
29. Abdel-Aty, M., & Wang, L. (2017). Implementation of variable speed limits to improve safety of congested expressway weaving segments in microsimulation. *Transportation Research Procedia, 27*, 577-584.
30. Koppula, N. (2002). A comparative analysis of weaving areas in HCM, TRANSIMS, CORSIM, VISSIM and INTEGRATION (Doctoral dissertation). Virginia Tech, Blacksburg, VA.
31. Woody, T. (2006). Calibrating freeway simulation models in Vissim (Master's thesis). Retrieved from http://scholar.googleusercontent.com/scholar?q=cache:ukXfUyeKLtsJ:scholar.google.com/&hl=zh-CN&as_sdt=0,10&scioq=Calibrating+freeway+simulation+models+in+Vissim.+University+of+WashingtonSaad,

32. M., Abdel-Aty, M., Lee, J., & Wang, L. (2018). Determining the optimal access design of managed lanes considering dynamic pricing. In 18th International Conference Road Safety on Five Continents (RS5C 2018), Jeju Island, South Korea, May 16-18, 2018.
33. Saad, M., Abdel-Aty, M., Lee, J., & Wang, L. (2018). Safety analysis of access zone design for managed toll lanes on freeways. *Journal of Transportation Engineering, Part A: Systems, 144*(11), 04018067.
34. Cai, Q., Saad, M., Abdel-Aty, M., Yuan, J., & Lee, J. (2018). Safety impact of weaving distance on freeway facilities with managed lanes using both microscopic traffic and driving simulations. *Transportation Research Record, 2672*(39), 130-141.
35. Yuan, J., Abdel-Aty, M., Cai, Q., & Lee, J. (2019). Investigating drivers' mandatory lane change behavior on the weaving section of freeway with managed lanes: a driving simulator study. *Transportation Research Part F: Traffic Psychology and Behaviour, 62*, 11-32.
36. Saad, M., Abdel-Aty, M., Lee, J., & Wang, L. (2018). *Access design safety analysis for managed lanes including accessibility level and weaving length* (No. 18-00860). Washington, DC: Transportation Research Board.
37. Saad, M. (2016). *Analysis of driving behavior at expressway toll plazas using driving simulator* (Master's thesis). University of Central Florida, Orlando, FL.
38. Saad, M., Abdel-Aty, M., & Lee, J. (2019). Analysis of driving behavior at expressway toll plazas. *Transportation Research Part F: Traffic Psychology and Behaviour, 61*, 163-177.
39. Abuzwidah, M., & Abdel-Aty, M. (2015). Safety assessment of the conversion of toll plazas to all-electronic toll collection system. *Accident Analysis & Prevention, 80*, 153-161.
40. Singh, S. (2015, February). *Critical reasons for crashes investigated in the National Motor Vehicle Crash Causation Survey* (Traffic Safety Facts Crash Stats. Report No. DOT HS 812 115). Washington, DC: National Highway Traffic Safety Administration.
41. Yue, L., Abdel-Aty, M., Wu, Y., & Wang, L. (2018). Assessment of the safety benefits of vehicles' advanced driver assistance, connectivity and low level automation systems. *Accident Analysis & Prevention, 117*, 55-64.
42. Fyfe, M., & Sayed, T. (2017). Safety evaluation of connected vehicles for a cumulative travel time adaptive signal control microsimulation using the surrogate safety assessment model (No. 17-01651). Washington, DC: Transportation Research Board.
43. Olia, A., Abdelgawad, H., Abdulhai, B., & Razavi, S. N. (2016). Assessing the potential impacts of connected vehicles: mobility, environmental, and safety perspectives. *Journal of Intelligent Transportation Systems, 20*(3), 229-243.
44. Paikari, E., Tahmasseby, S., & Far, B. (2014). A simulation-based benefit analysis of deploying connected vehicles using dedicated short range communication. *2014 IEEE Intelligent Vehicles Symposium Proceedings*, 980-985.
45. Tian, D., Zhou, J., Wang, Y., Sheng, Z., Xia, H., & Yi, Z. (2016). Modeling chain collisions in vehicular networks with variable penetration rates. *Transportation Research Part C: Emerging Technologies, 69*, 36-59.
46. Rahman, M. S., & Abdel-Aty, M. (2018). Longitudinal safety evaluation of connected vehicles' platooning on expressways. *Accident Analysis & Prevention, 117*, 381-391.
47. National Highway Traffic Safety Administration. (2016). *Vehicle-to-vehicle communication technology for light vehicles: Preliminary regulatory impact analysis* (FMVSS No.150). Washington, DC: National Highway Traffic Safety Administration.

48. Li, Y., Wang, H., Wang, W., Liu, S., & Xiang, Y. (2016). Reducing the risk of rear-end collisions with infrastructure-to-vehicle (I2V) integration of variable speed limit control and adaptive cruise control system. *Traffic Injury Prevention, 17*(6), 597-603.
49. Rahman, M. S., Abdel-Aty, M., Wang, L., & Lee, J. (2018). Understanding the highway safety benefits of different approaches of connected vehicles in reduced visibility conditions. *Transportation Research Record, 2672*(19), 91-101.
50. Mirheli, A., Hajibabai, L., & Hajbabaie, A. (2018). Development of a signal-head-free intersection control logic in a fully connected and autonomous vehicle environment. *Transportation Research Part C: Emerging Technologies, 92*, 412-425.
51. Talebpour, A., Mahmassani, H. S., & Elfar, A. (2017). Investigating the effects of reserved lanes for autonomous vehicles on congestion and travel time reliability. *Transportation Research Record, 2622*(1), 1-12.
52. Talebpour, A., & Mahmassani, H. S. (2016). Influence of connected and autonomous vehicles on traffic flow stability and throughput. *Transportation Research Part C: Emerging Technologies, 71*, 143-163.
53. Talebpour, A., & Mahmassani, H. S. (2015). *Influence of autonomous and connected vehicles on stability of traffic flow* (No. 15-5971). Washington, DC: Transportation Research Board.
54. Morando, M. M., Tian, Q., Truong, L. T., & Vu, H. L. (2018). Studying the safety impact of autonomous vehicles using simulation-based surrogate safety measures. *Journal of Advanced Transportation, 2018*.
55. Kockelman, K., Avery, P., Bansal, P., Boyles, S. D., Bujanovic, P., Choudhary, T., ... & Hutchinson, R. (2016). *Implications of connected and automated vehicles on the safety and operations of roadway networks: A final report* (No. FHWA/TX-16/0-6849-1). Austin, TX: Center for Transportation Research.
56. Fernandes, P., & Nunes, U. (2010). Platooning of autonomous vehicles with intervehicle communications in SUMO traffic simulator. *13th International IEEE Conference on Intelligent Transportation Systems*, 1313-1318.
57. Genders, W., & Razavi, S. N. (2015). Impact of connected vehicle on work zone network safety through dynamic route guidance. *Journal of Computing in Civil Engineering, 30*(2), 04015020.
58. Guériau, M., Billot, R., El Faouzi, N. E., Monteil, J., Armetta, F., & Hassas, S. (2016). How to assess the benefits of connected vehicles? A simulation framework for the design of cooperative traffic management strategies. *Transportation Research Part C: Emerging Technologies, 67*, 266-279.
59. Guler, S. I., Menendez, M., & Meier, L. (2014). Using connected vehicle technology to improve the efficiency of intersections. *Transportation Research Part C: Emerging Technologies, 46*, 121-131.
60. Jin, Q., Wu, G., Boriboonsomsin, K., & Barth, M. (2014). Improving traffic operations using real-time optimal lane selection with connected vehicle technology. *2014 IEEE Intelligent Vehicles Symposium Proceedings*, 70-75.
61. Lee, J., & Park, B. (2012). Development and evaluation of a cooperative vehicle intersection control algorithm under the connected vehicles environment. IEEE Transactions on Intelligent Transportation Systems, 13(1), 81-90.
62. Letter, C., & Elefteriadou, L. (2017). Efficient control of fully automated connected vehicles at freeway merge segments. *Transportation Research Part C: Emerging Technologies, 80*, 190-205.

63. Li, Z., Chitturi, M. V., Zheng, D., Bill, A. R., & Noyce, D. A. (2013). Modeling reservation-based autonomous intersection control in VISSIM. *Transportation Research Record, 2381*(1), 81-90.
64. Qian, X., Gregoire, J., Moutarde, F., & De La Fortelle, A. (2014). Priority-based coordination of autonomous and legacy vehicles at intersection. *Proceedings of the 17th International IEEE Conference on Intelligent Transportation Systems*, 1166-1171.
65. Tajalli, M., & Hajbabaie, A. (2018). *Collision mitigation at signalized intersection using connected vehicles data and technologies* (No. 18-06418). Washington, DC: Transportation Research Board.
66. Wan, N., Vahidi, A., & Luckow, A. (2016). Optimal speed advisory for connected vehicles in arterial roads and the impact on mixed traffic. *Transportation Research Part C: Emerging Technologies, 69*, 548-563.
67. Wu, W., Li, P. K., & Zhang, Y. (2015). Modelling and simulation of vehicle speed guidance in connected vehicle environment. *International Journal of Simulation Modelling, 14*(1), 145-157.
68. Jin, Q., Wu, G., Boriboonsomsin, K., & Barth, M. (2013). Platoon-based multi-agent intersection management for connected vehicle.*16th International IEEE Conference on Intelligent Transportation Systems*, 1462-1467.
69. ATKINS (2016). Research on the Impacts of Connected and Autonomous Vehicles (CAVs) on Traffic Flow. Department for Transport, United Kingdom. Retrieved from: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/530091/impacts-of-connected-and-autonomous-vehicles-on-traffic-flow-summary-report.pdf
70. Wang, L., Abdel-Aty, M., & Lee, J. (2017). Implementation of active traffic management strategies for safety on congested expressway weaving segments. *Transportation Research Record, 2635*(1), 28-35.
71. Shalaby, A., Abdulhai, B., & Lee, J. (2003). Assessment of streetcar transit priority options using microsimulation modelling. *Canadian Journal of Civil Engineering, 30*(6), 1000-1009.
72. Dowling, R., Skabardonis, A., & Alexiadis, V. (2004). *Traffic analysis toolbox volume III: guidelines for applying traffic microsimulation modeling software* (No. FHWA-HRT-04-040). Washington, DC: Federal Highway Administration.
73. Yu, R., & Abdel-Aty, M. (2014). An optimal variable speed limits system to ameliorate traffic safety risk. *Transportation Research Part C: Emerging Technologies, 46*, 235-246.
74. Ekram, A. A., & Rahman, M. S. (2018). Effects of connected and autonomous vehicles on contraflow operations for emergency evacuation: a microsimulation study (No. 18-06791). Washington, DC: Transportation Research Board.
75. Florida Department of Transportation. (2002), *Project traffic forecasting handbook*. Tallahassee, FL: Florida Department of Transportation.
76. American Community Survey (2016), US Census American Community Survey's for Miami-Dade. Retrieved from: https://www.miamidade.gov/business/library/reports/2011-2015-acs-muliti-year-profile.pdf
77. Joseph, R. (2013). Managed lanes case studies-a companion to the preliminary investigation-impacts of increasing vehicle-occupancy requirements on HOV/HOT Lanes. Sacramento, CA: Caltrans Division of Research and Innovation.
78. Sukennik, P. (2018). *Micro-Simulation guide for automated vehicles.* Karlsruhe, Germany: PTV Group. Retrieved from: https://www.h2020-coexist.eu/wp-content/uploads/2018/11/D2.5-Micro-simulation-guide-for-automated-vehicles.pdf

79. Groves, A. (2018), *Preparing the transition to Automated Vehicles.* PTV Group, CoEXist Project. http://www.mva.maryland.gov/safety/MarylandCAV/PTV-Groves.pdf.
80. PTV Group. (2018). *Webinar: What's new in PTV Vissim 11 and PTV Viswalk 11.* Retrieved from https://www.youtube.com/watch?v=yz04_sC9cLo.
81. National Academies of Sciences, Engineering, and Medicine (NASEM), 2018. Dedicating Lanes for Priority or Exclusive Use by Connected and Automated Vehicles. The National Academies Press, Washington, DC. https://doi.org/10.17226/25366.
82. PTV Group. (2015). PTV VISSIM 7 User Manual. Karlsruhe, Germany: PTV Group.
83. Johnson, S., & Murray, D. (2010). Empirical analysis of truck and automobile speeds on rural interstates: Impact of posted speed limits (Report No. 10-0833). Washington, DC: Transportation Research Board.
84. Jin, X., Hossan, M. S., & Asgari, H. (2015). Investigating the value of time and value of reliability for managed lanes (No. BDV29-977-12). Florida. Dept. of Transportation.
85. Shahdah, U., Saccomanno, F., & Persaud, B. (2014). Integrated traffic conflict model for estimating crash modification factors. *Accident Analysis & Prevention, 71*, 228-235.
86. Gettman, D., Pu, L., Sayed, T., & Shelby, S. (2008). *Surrogate safety assessment model and validation: Final report* (Publication No. FHWA-HRT-08051). Washington, DC: Federal Highway Administration.
87. Sayed, T., & Zein, S. (1999). Traffic conflict standards for intersections. *Transportation Planning and Technology, 22*(4), 309-323.
88. Saleem, T., Persaud, B., Shalaby, A., & Ariza, A. (2014). Can microsimulation be used to estimate intersection safety? Case studies using VISSIM and Paramics. Transportation research record, 2432(1), 142-148.
89. Saulino, G., Persaud, B., & Bassani, M. (2015, January). Calibration and application of crash prediction models for safety assessment of roundabouts based on simulated conflicts. In Proceedings of the 94th Transportation Research Board (TRB) Annual Meeting, Washington, DC, USA (pp. 11-15).
90. Lee, J., Park, B., & Yun, I. (2013). Cumulative travel-time responsive real-time intersection control algorithm in the connected vehicle environment. Journal of Transportation Engineering, 139(10), 1020-1029.
91. Yang, K., Guler, S. I., & Menendez, M. (2016). Isolated intersection control for various levels of vehicle technology: Conventional, connected, and automated vehicles. Transportation Research Part C: Emerging Technologies, 72, 109-129.
92. Nezamuddin, N., Jiang, N., Zhang, T., Waller, S. T., & Sun, D. (2011). Traffic operations and safety benefits of active traffic strategies on TXDOT freeways (No. FHWA/TX-12/0-6576-1).
93. Jolovic, D., & Stevanovic, A. (2012). Evaluation of VISSIM and FREEVAL to assess an oversaturated freeway weaving segment. In TRB Annual Meeting (p. 12p).
94. Zhizhou, W., Jian, S., & Xiaoguang, Y. (2005, December). Calibration of VISSIM for shanghai expressway using genetic algorithm. In Proceedings of the Winter Simulation Conference, 2005. (pp. 4-pp). IEEE.
95. Habtemichael, F., & Picado-Santos, L. (2013, January). Sensitivity analysis of VISSIM driver behavior parameters on safety of simulated vehicles and their interaction with operations of simulated traffic. In Transportation Research Board 92ndAnnual Meeting.

96. Treiber, M., Hennecke, A., & Helbing, D. (2000). Congested traffic states in empirical observations and microscopic simulations. Physical review E, 62(2), 1805.
97. Talebpour, A., Mahmassani, H. S., & Bustamante, F. E. (2016). Modeling driver behavior in a connected environment: Integrated microscopic simulation of traffic and mobile wireless telecommunication systems. Transportation Research Record, 2560(1), 75-86.
98. Talebpour, A., Mahmassani, H. S., & Hamdar, S. H. (2015). Modeling lane-changing behavior in a connected environment: A game theory approach. Transportation Research Procedia, 7, 420-440.
99. Kesting, A., Treiber, M., & Helbing, D. (2010). Enhanced intelligent driver model to access the impact of driving strategies on traffic capacity. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 368(1928), 4585-4605.
100. Kesting, A., Treiber, M., Sch nhof, M., & Helbing, D. (2008). Adaptive cruise control design for active congestion avoidance. Transportation research. Part C, Emerging technologies, 16(6), 668-683.
101. Khondaker, B., & Kattan, L. (2015). Variable speed limit: A microscopic analysis in a connected vehicle environment. Transportation Research Part C: Emerging Technologies, 58, 146-159.
102. Li, Y., Li, Z., Wang, H., Wang, W., & Xing, L. (2017). Evaluating the safety impact of adaptive cruise control in traffic oscillations on freeways. Accident Analysis & Prevention, 104, 137-145.
103. Li, Y., Wang, H., Wang, W., Xing, L., Liu, S., & Wei, X. (2017). Evaluation of the impacts of cooperative adaptive cruise control on reducing rear-end collision risks on freeways. Accident Analysis & Prevention, 98, 87-95.
104. Milanés, V., & Shladover, S. E. (2014). Modeling cooperative and autonomous adaptive cruise control dynamic responses using experimental data. Transportation Research Part C: Emerging Technologies, 48, 285-300.
105. Abdel-Aty, M., Haleem, K., Cunningham, R., & Gayah, V. (2009, June). Application of variable speed limits and ramp metering to improve safety and efficiency of freeways. In 2nd International Symposium on Freeway and Tollway Operations (pp. 1-13).
106. Gettman, D., & Head, L. (2003). Surrogate safety measures from traffic simulation models. Transportation Research Record, 1840(1), 104-115.
107. Peng, Y., Abdel-Aty, M., Shi, Q., & Yu, R. (2017). Assessing the impact of reduced visibility on traffic crash risk using microscopic data and surrogate safety measures. Transportation research part C: emerging technologies, 74, 295-305.
108. Hayward, J. C. (1972). Near miss determination through use of a scale of danger.
109. Minderhoud, M. M., & Bovy, P. H. (2001). Extended time-to-collision measures for road traffic safety assessment. Accident Analysis & Prevention, 33(1), 89-97.
110. Li, Z., Li, Y., Liu, P., Wang, W., & Xu, C. (2014). Development of a variable speed limit strategy to reduce secondary collision risks during inclement weathers. Accident Analysis & Prevention, 72, 134-145.
111. Sultan, B., Brackstone, M., & McDonald, M. (2002). Parameter analysis for collision avoidance systems. In 9th World Congress on Intelligent Transport SystemsITS America, ITS Japan, ERTICO (Intelligent Transport Systems and Services-Europe).
112. Oh, C., Park, S., & Ritchie, S. G. (2006). A method for identifying rear-end collision risks using inductive loop detectors. Accident Analysis & Prevention, 38(2), 295-301

113. American Association of State Highway and Transportation Officials (AASHTO) (2004). A Policy on Geometric Design of Highways and Streets. Washington, D.C.