Final Report

MANAGING THE IMPACTS OF DIFFERENT CV/AV PENETRATION RATES ON RECURRENT FREEWAY CONGESTION FROM THE PERSPECTIVE OF TRAFFIC MANAGEMENT: A Case Study of MD-100

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16. Abstract In the near future, responsible highway agencies will need to effectively coordinate emerging AV flows while contending with daily recurrent congestion. This study presents a systematic procedure for understanding how AV flows impact traffic under different AV behavioral mechanisms (i.e., car-following and lane-changing), penetration rates, and volume levels. Using a congested segment of the MD-100 highway to illustrate the proposed procedure, our research results indicate that the presence of AV flows, depending on their adopted behavioral mechanisms, significantly impact (either positively or negatively) the overall traffic conditions. These impacts, varying with AV penetration rate and volumes, will be experienced indiscriminately by AV and non-AV vehicles. The study has further conducted extensive simulation experiments using the MD-100 network under various AV penetration rates and behavioral mechanisms by modeling the range of the behavioral mechanisms likely adopted by the AV-flows with 135 sets of car-following and lane changing parameters. The collected measures of effectiveness (MOEs) from the experimental results clearly show that at each AV penetration level, there exists a set of optimal behavioral mechanisms for the AV flows to coordinate with non-AV flows to best use roadway capacity and minimize congestion. Since such behavioral mechanisms vary with the AV penetration rate and the congestion level on different segments of the freeway, it justifies the need for a responsible highway agency to develop effective guidelines so that they can coordinate with the AV flows via the V2I infrastructure.

17. Key Words: autonomous vehicles, automated driving, traffic flow management, heterogeneous traffic.	**18. Distribution Statement**

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INTRODUCTION

Transportation technologies, primarily relating to autonomous vehicles (AV), have evolved rapidly during the last decade and promise to significantly impact how we commute daily. Automobile companies – including BMW, Tesla, Audi, GM, and Ford – plan to introduce autonomous vehicles to public roads in the United States by the middle or end of the next decade *(1,2,3,4,5)*. To support the advancement of AV technologies, federal agencies have sponsored multiple pieces of legislation during the past five years *(6,7)*. With the support from both the public and private sectors, it is inevitable that within the next decade AVs will constitute a significant percentage of traffic flows on U.S. highways.

Current AV technologies such as ACC (Adaptive Cruise Control) and LKAS (Lane Keep Assist System) transfer control of the longitudinal behavior of the vehicle from the driver to the vehicle sensors. The International Organization for Standardization (ISO) recommends the manufacturers of ACC-equipped vehicles offer drivers a pre-defined desired time-gap setting ranging between 0.8 and 2.2 seconds *(8)*. Drivers may choose to assign time-gap settings, depending on their driving preference, the freeway traffic conditions, and confidence in the automation system. In doing so, the driver may choose settings without the benefit of the entire highway system in mind. Conceivably, the prevalence and fast penetration of vehicles equipped with autonomous capabilities will significantly impact the dynamic properties of traffic flows and congestion patterns. Highway agencies will be challenged with how to minimize the potential negative impacts of such AV flows on the traffic conditions and ensure the best use of the available roadway capacity.

Over the past few years, researchers have delved into understanding the impacts of different ACC control strategies and their interaction with human-driven vehicles at different penetration levels. For example, Kesting et al. simulated a one-lane highway *(9)* to test a proposed jam-avoiding driving strategy based on the Intelligent Driver Model (IDM), and observed that at 10% ACC vehicle flow rate the cumulative delay reduced by 50%. Tientrakool et al. *(10)* showed that when all vehicles in the system have ACC capabilities, the capacity increased by 43%. Some other studies also report that the introduction of ACC vehicles to the traffic flow can avoid delays *(11)* in bottleneck areas and reduce congestion and jams *(12).* Kerner *(13)* found that ACC vehicles suppress long moving jam and thus promote stability. On the downside, however, he also found that in some cases ACC vehicles could induce congestion at bottlenecks.

The impacts of ACC on multilane highways have also been investigated with simulation in the literature. For example, Marsden et al. *(14)* carried out detailed simulation-based tests using a FLOSIM microscopic model and demonstrated that the average journey time increased at higher levels of ACC vehicle flows. Similar outputs were observed in studies carried out by Arem et al. *(15)* and Minderhound *(16)*. They attributed the increase in average travel time to the sharp deceleration, caused when non-ACC vehicles moved into the lane of ACC-equipped vehicles, thereby resulting in the manual takeover of the ACC vehicle's controls. On the contrary, Kesting et al. *(17)* observed that ACC-equipped vehicles could significantly reduce travel time, even at lower market penetration levels. They used a microscopic modeling approach, based on the IDM model and lane-changing decisions with the MOBIL (Minimizing Overall Braking Induced by Lane Changes) algorithm *(18)*. Simulation results showed that at the market penetration rate of 25%, the traffic congestion in their simulated network was eliminated.

To show the impacts of a mixed fleet containing both vehicles with CACC (Connected Adaptive Cruise Control) capabilities and human-driven ones, Arnaout and Bowling *(19)* simulated a four-lane highway using a microscopic traffic simulator and reported that the impacts of CACC on the flow rate were significantly different when the penetration levels were higher than 40%. Zhu and Ukkusuri *(20)* analyzed the mobility benefits of connected vehicles with different demand and penetration levels and showed a 20% reduction in travel time at 100% AV penetration rate. VanderWerf et al. *(21)* in their study of CACC systems observed that the roadway capacity increases quadratically with the increase in market penetration of vehicles equipped with CACC systems.

Note that, despite the emergence of a large body of studies associated with AV properties, most of the work is focused on the impacts of the different car-following logic of AVs. Few studies have looked at the compounded impacts of different AV car-following and lane-changing parameter settings from the perspective of freeway operations efficiency; that is, how can the travel time and throughput on a freeway corridor under different volumes and AV penetration rates be improved with the optimal but dynamic behavioral mechanisms for AV flows? On freeway segments experiencing congestion, responsible highway agencies can convey such optimal time-varying behavioral mechanisms for AVs to convert their potential negative impacts, if adopting improper behavioral settings, to a state that benefits both AV and non-AV flows.

This study attempts to address the following questions often raised by highway operating agencies: (1) The impacts of various behavior mechanisms governing AVs (car-following and lane-changing behavior) on a target highway segment under different penetration rates, and (2) How to identify the set of behavioral mechanisms for AVs that can avoid causing undesirable negative impacts, and further best interact with non-AV flows to maximize the operational efficiency of a target highway.

Conceivably, precise answers to these two issues may vary among different highway corridors and different states due to the discrepancies in both the behaviors of driving populations and other environmental as well as geometric factors. Hence, this study has presented a methodology via a case study of MD-100 that allows the responsible agencies to assess the impacts of varying AV penetration rates on the traffic conditions of a target freeway. Based on the results, the study has also developed operational guidelines for interacting with the emerging AV flows when their impacts on the operational efficiency of a highway corridor emerge as a critical issue.

METHODOLOGY FOR IMPACT ASSESSMENT AND GUIDELINE DEVELOPMENT

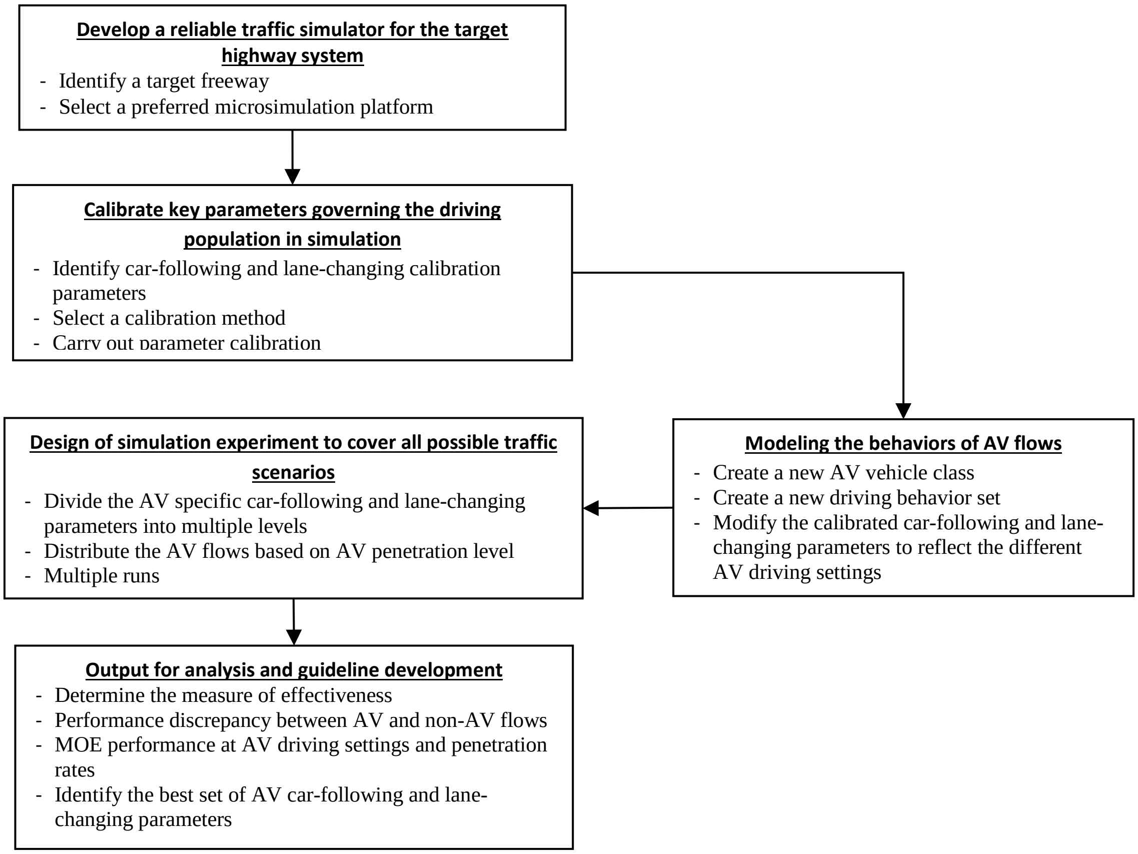


FIGURE 1: Methodology flowchart

Figure 1 illustrates the key steps involved in the methodology development and their outputs. Additional descriptions of primary activities to be done in each step are presented in sequence below:

Step-1: Develop a reliable traffic simulator for the target highway system

The first step is to develop a simulation platform for the target highway system that enables the responsible highway agency to explore the impacts of the AV flow's driving behaviors on the traffic conditions and formation of congestion under different AV market penetration rates. Like platforms used in traffic system control, such a simulation platform shall be microscopic in nature in that it can faithfully reflect the key geometric features, environmental factors, and behavior of the driving population on the recurring traffic conditions.

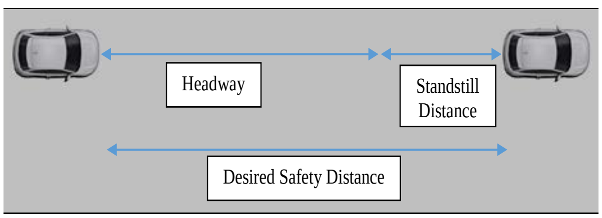
Step-2: Calibrate key parameters governing the driving population in simulation

To ensure the fidelity of the developed simulator, one of the most critical steps is to calibrate the behavioral-related parameters embedded in the simulator's car-following and lane-changing models with field data. There are a variety of calibration methods, such as genetic algorithm (GA), available in the literature *(22,23)*. Only after the simulator-produced speed, flow rate, and occupancy on the target freeway system (including mainline, ramps, and weaving segment) are statistically indifferent from those measured from detectors, can one conclude that the behavior of the driving populations are consistent with those performing daily commutes, and the simulator is ready for control and strategy development.

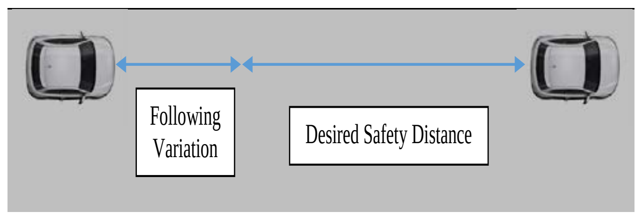
Step-3: Modeling the behaviors of AV flows

The focus of this step is to model the behavioral mechanisms governing AV flows, and use such mechanisms to simulate their interaction with non-AV flows under varying traffic scenarios. Note that AVs are expected to be able to maintain a range of time-gaps. This is observed in ACC-equipped vehicles being sold today, in which the driver can change the time-gap settings to reflect their preferences. Invariably the change in the time-gap settings is accommodated through pre-defined levels set by the vehicle manufacturer. This is reflected by a range of time-gaps that drivers select while driving ACC and CACC vehicles. Results from field tests *(24)* show that mean time-gap setting for ACC system is 1.54 (±0.41) seconds and for CACC equipped vehicles is 0.71 (±0.41) seconds. As this is an evolving technology, similar standards and ranges can also be expected for the lane-changing parameters of AVs.

To reflect these changes in a simulation platform, one can modify the parameters defining car-following and lane-changing, shown in Figure 2, to reflect aggressive, calibrated (the observed behavior for the target freeway) and moderate vehicle operation settings.

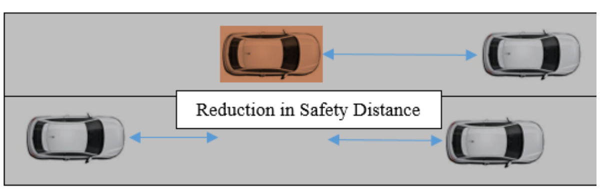


<u>Desired Safety Distance</u>: Distance defined by standstill distance and headway maintained between the front bumper and the rear bumper of the preceding AV. Under aggressive settings, AVs will be able to accommodate shorter safety distances than their human counterparts.

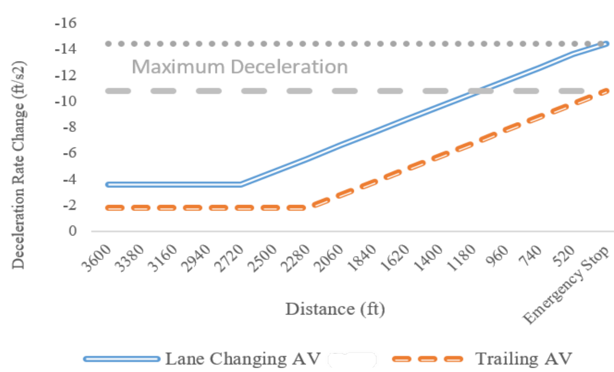


<u>Following Variation</u>: Distance beyond the desired safety distance before the AV moves closer to the preceding AV. Under aggressive settings, AVs will allow a shorter distance before it intentionally moves closer to the preceding vehicle to maintain the desired safety distance.

(a) AV car-following parameters



<u>Safety Distance Reduction</u>: Reduction in the safety distance when an AV attempts to change lanes. Under aggressive settings, AVs will allow a greater reduction in the safety distance during the lane changes.



<u>Deceleration Rate during Lane Change</u>: Deceleration rate of the lane-changing AV and the trailing AV during a necessary lane change. Under aggressive settings, AVs will decelerate at a higher rate during the mandatory lane-changing behavior.

(b) AV lane-changing parameters

FIGURE 2: AV-specific car-following and lane-changing parameters

Within the simulation platform the following tasks need to be carried out:

- Create a new driving behavior set in the simulation platform that reflects the behavior of AVs (note: the new behavior set should reflect the calibrated car-following and lane-changing parameters as human-driven vehicles). These parameters are later modified, independently from the parameters in the non-AV driving behavior set, to reflect different AV driving settings.
- Create a new vehicle class to represent AVs and connect them to the AV driving behavior set.
- Identify the range of values for the parameters described in Figure 2, and accordingly define upper bound and lower bound limits while maintaining the calibrated parameter value as the reference point (i.e., if the calibrated headway is two seconds, then the upper and lower bounds could be defined by a 50% increase or decrease).
- Specify different levels of AV-specific driving parameters, (i.e., aggressive, calibrated, and moderate) by their upper and lower bound limits.

With the above modeling work, the simulator can reflect the different possible behaviors of the AV flows defined through an AV occupant's selection of the AV's embedded car-following and lane-changing mechanisms.

Step 4: Design of simulation experiments to cover all possible traffic scenarios

The purpose of this step is to simulate those traffic scenarios most likely to be seen on the target freeway segment in the presence of AV flows, under different AV penetration rates. The simulation experiment will involve the following process:

- Divide both the car-following and lane-changing parameters of the AV flows into multiple levels (i.e., Aggressive-2, Aggressive-1, calibrated, moderate-1, and moderate-2), where the parameters for calibrated AV flows are the same as those for non-AV vehicles (i.e., calibrated settings).
- Maintain the car-following and lane-changing parameter values of the human-driven vehicles constant at the calibrated values.
- Distribute the volume between AV and non-AV vehicles for AV penetration rates ranging from 0% to 100% at 10% increments.
- Simulate the sets of car-following and lane-changing behaviors of AVs, based on the number of levels defined for each parameter.
- Replicate five times for each set of driving behaviors of AVs with different random seeds to account for randomness.
-

Step-5: Output for analysis and guideline development

The experimental analysis of all simulated scenarios will focus on the following issues:

- The performance discrepancy between AV and non-AV flows with respect to travel time on different highway segments.
- MOE performance as a result of different AV driving settings at various AV market penetration rates and on different highway segments.
- The set of car-following and lane-changing parameters that can yield the best performance with respect to each of the selected MOEs in each experimental traffic scenario.

Note that the MOEs for the above issues include: travel time, throughput and queue lengths, where travel time and throughput are computed separately for AV and non-AV flow. Also, the MOEs are determined by location (i.e., ramps, mainline segment, bottleneck area). With the above output, the traffic operators will have sufficient information to make decisions regarding the proper AV control mechanism and relay the recommended settings to the vehicles during the congested period. Similarly, when the detectors in the field indicate the occurrence of an incident, responsible agencies can summon the AVs upstream from the incident to re-program and operate using the prescribed driving settings.

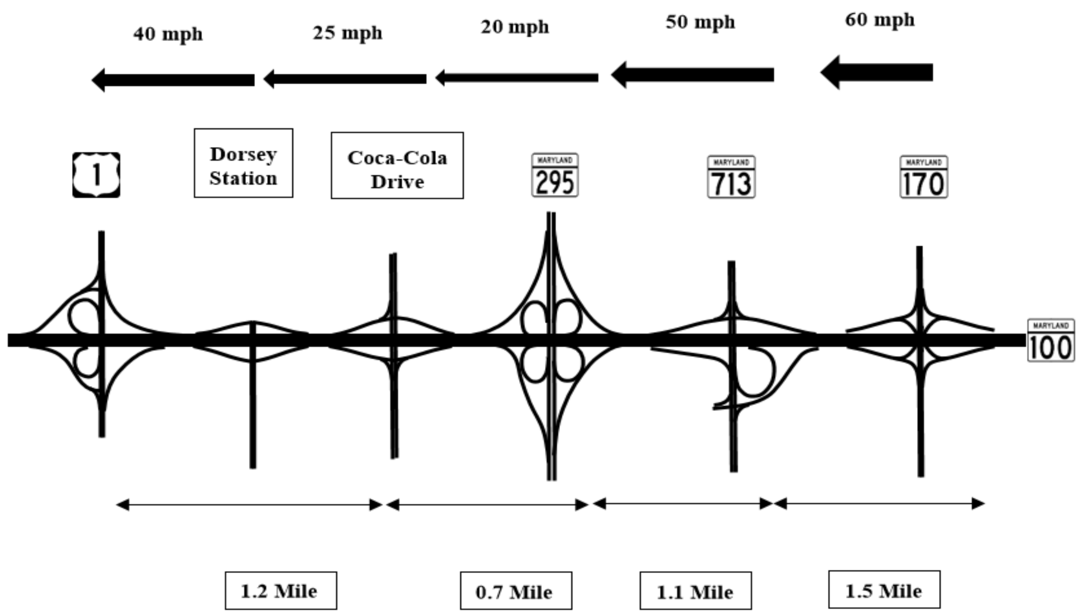
A CASE STUDY FOR ILLUSTRATING THE APPLICATION PROCESS

This case study serves as an example to illustrate the potential applications of the methodology.

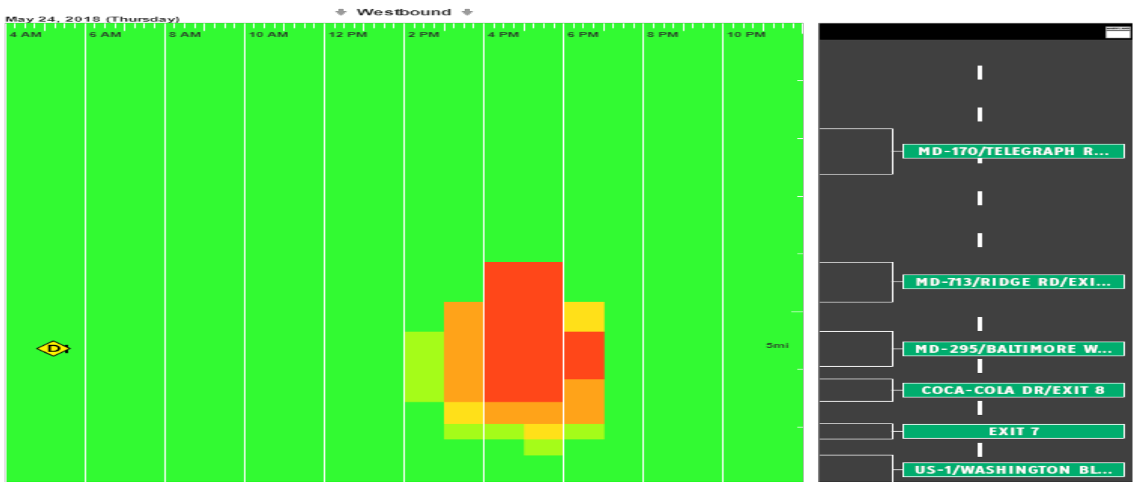
The freeway selected for illustration and case study

MD-100 is a two-lane highway in each direction with a speed limit of 55 mph, connecting Anne Arundel County in the east and Howard County to the west. Figure 3(a) describes the westbound segment of MD-100 between MD-170 and US-1 used in this study.

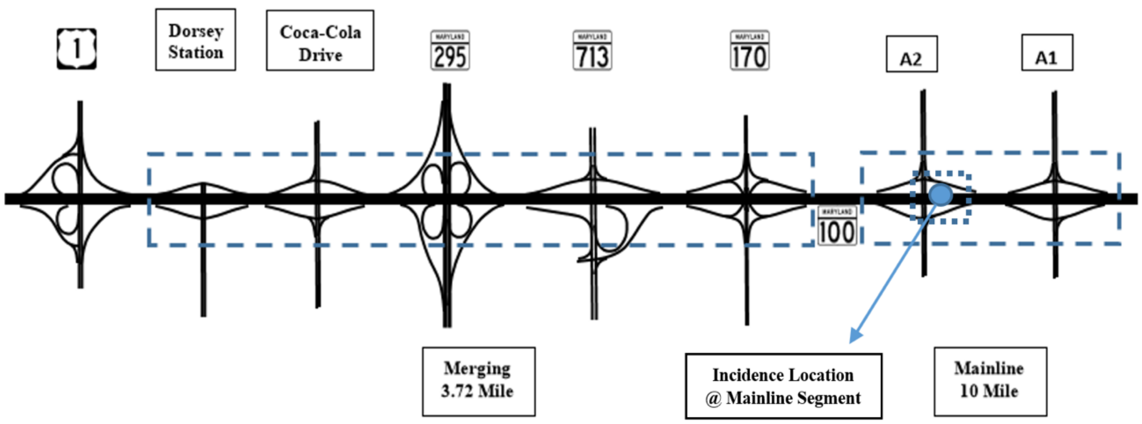
The segment between MD-713 and US-1 experiences recurrent congestion between 3 pm and 5 pm and its average flow speed decreases from 60 mph to 20 mph within three miles. As shown in Figure 3(b), recurrent congestion at the on-ramp for Coca-Cola Drive usually extends over 1.75 miles to the MD-713 on-ramp, and even longer during inclement weather conditions.



(a) Spatial distribution of traffic-flow speeds



(b) Congestion pattern on a typical weekday



(c) Freeway network segmentation

FIGURE 3: Geometric features and spatial distribution of speeds on MD-100 WB

Simulation software

VISSIM 5.40, a microscopic traffic simulator, was used in this study as there still does not exist a commonly available AV traffic simulator. The parameter calibration was carried out using a total of four hours of data, including volume and speed data collected during a previous field demonstration *(25)*. To accurately replicate the observed traffic conditions, the human driving car-following and lane-changing parameters are calibrated from field data using Genetic Algorithm (GA). The calibrated car-following and lane-changing parameters in VISSIM are shown in Table 1(a). The calibrated values obtained from the target freeway with 100% human-driven vehicles are used as the baseline driving settings for both AVs and human-driven vehicles.

TABLE 1: Car-following and lane-changing parameter values

(a) Calibrated VISSIM car-following and lane-changing parameters

Class	Parameter	Value
Car-Following	CC0 (Standstill Distance) (ft.)	5
	CC1 (Headway Time) (s)	1.20
	CC2 (Following Variation) (ft.)	13.12
	CC7 (Oscillation Acceleration) (ft./s^2)	2.98
	CC8 (Standstill Acceleration) (ft./s^2)	13.62
Lane change	Own: Maximum deceleration (ft./s^2)	-14.43
	Own: -1 m/s2 per distance (ft)	220
	Trailing: Maximum deceleration (ft./s^2)	-10.82
	Trailing: -1 m/s2 per distance (ft)	220

(b) AV Car-following and lane-changing parameter bounds

		Aggressive 2	Aggressive 1	Calibrated	Moderate 1	Moderate 2
Car-Following Parameters	(CC0) Standstill Distance (ft.)	4	4.5	5	5.5	6
	(CC1) Headway Time (s)	0.6	0.9	1.2	1.5	1.8
	(CC2) Following Variation (ft.)	-	6.6	13.1	19.7	-

		Aggressive		Calibrated		Moderate	
Lane-Changing Parameters	Safety Distance Reduction Factor	0.3		0.6		0.9	
	Necessary Lane Change Deceleration	*Own*	*Trailing Vehicle*	*Own*	*Trailing Vehicle*	*Own*	*Trailing Vehicle*
	Maximum deceleration (ft./s^2)	-11.55	-8.66	-14.43	-10.82	-17.32	-12.99
	-1 feet/sec^2 per distance (ft.)	176	176	220	220	264	264
	Accepted deceleration (ft./s^2)	-2.89	-1.44	-3.61	-1.80	-4.33	-2.16

The AV flows' car-following parameters and their sensitivity thresholds are defined using three Wiedemann 99 car-following calibration parameters *(26)*, i.e., CC0 (standstill distance), CC1 (headway time) and CC2 (car-following variation). CC0 and CC1 together describe the specified safety distance maintained between two AVs while CC2 defines the car-following variation distance. Two VISSIM lane-changing parameters, safety distance reduction factor and deceleration rate during a lane change, are selected to describe both mandatory and non-mandatory lane changes undertaken by AVs.

Table 1(b) provides the range of aggressive and moderate car-following and lane-changing parameters for AV flows used in this study. The aggressive and moderate behaviors of autonomous vehicles have been referenced to the parameters calibrated using field and detector data. During the simulation process, CC0 and CC1 are combined to reflect the safety distance to the preceding vehicle. Given the possible range of variation, CC0 and CC1 are divided into five different levels (i.e., Aggressive 2, Aggressive 1, Calibrated, Moderate 1, Moderate 2), while the remaining parameters are analyzed at three levels (i.e., Aggressive, Calibrated and Moderate). Therefore, at each penetration level, there are 135 different driving settings for AV operations.

To replicate the autonomous behavior with VISSIM, a new vehicle class is created and connected to the autonomous vehicle driver behavior set, i.e., car-following and lane-changing parameters. To evaluate the 135 possible driving settings, the VISSIM COM application programming interface (API) is employed. A MATLAB application program is also developed to load the network and start the simulation through the VISSIM API.

Design of Simulation Experiments

The freeway segment is modified and extended upstream of MD-170 to include a 10-mile segment to capture the traffic evolution from moderate to congested conditions. With this addition, the simulated MD-100 network is separated into a 10-mile mainline segment and a 3.72-mile merging segment as shown in Figure 3(c).

The simulation analysis is carried out at different penetration levels of AVs, ranging from 0% to 100% at increments of 10%. The simulation process at each penetration follows the following steps:

- Distribute the 2015 evening peak-hour volume between autonomous and human-driven vehicles, based on the specified AV penetration rate.
- Simulate the 135 sets of car-following and lane-changing behaviors for the AVs with a 30-minute warm-up, followed by one hour of traffic input based on 2015 volume data. The car-following and lane-changing parameters of the human-driven vehicles are held constant at the calibrated values.
- Replicate each AV car-following and lane-changing combination five times with different random seeds value to account for randomness.
- Analyze the resulting impacts with different MOEs, including travel time, throughput, and ramp and freeway queue lengths.

Additionally, as shown in Figure 3(c), this study has also modeled an incident in the mainline segment between the A2 on and off ramps. This incidence involves a single lane closure for 30 minutes. The lane drop scenario involves the same simulation process as the non-lane drop scenario.

Analysis of Simulation Output

The outputs of the extensive experiments are used to analyzed the following three issues: (1) Whether the prevalence of AV flow has a negative impact on the performance of non-AVs or on the freeway at the system level; (2) What are the impacts of AV flows on the traffic conditions under different car-following and lane-changing behavior of parameters; and (3) What set of behavioral parameters for the AV flows can best benefit the traffic conditions of the entire freeway segment.

AV vs. Non-AV performance

Table 2 summarizes the performance, in terms of the time taken to travel across the mainline and the merging segment, for both AV and non-AV flows. Comparisons are made at low (10%-30%), medium (40%-60%), and high (70%-90%) AV flow rates by comparing the average travel times obtained by simulating the 135 sets of car-following and lane-changing behaviors for the AVs. The t-test results indicate that no significant differences exist between average travel times for AV and non-AV flows under different penetration rates at both mainline and merging segments. This reflects that the change in AV driving settings does not have a disproportionately negative or positive influence on the traffic performance of the non-AV flows. Therefore, it can be concluded that both AV and non-AV flows are equally influenced by the introduction of AVs to the network, and no performance discrepancy exists. Hence, AV operational guidelines can be developed by focusing on the collective performance, instead of analyzing the output by vehicle type.

TABLE 2: Performance discrepancy (MOE: Travel time) between AV and non-AV flows

			Travel Time (seconds)			
			Mainline Segment		*Merging Segment*	
AV Penetration			*AV*	*Non-AV*	*AV*	*Non-AV*
Low Market Penetration	10% AV	Mean (sec)	951	*949*	756	753
		P value	*0.264*		0.358	
	20% AV	Mean (sec)	960.55	958.09	757.44	754.78
		P value	0.333		0.416	
	30% AV	Mean (sec)	972.96	971.13	757.50	755.28
		P value	0.419		0.451	
Medium Market Penetration	40% AV	Mean (sec)	981.21	979.45	743.55	741.17
		P value	0.439		0.459	
	50% AV	Mean (sec)	986.78	985.65	745.62	743.23
		P value	0.469		0.466	
	60% AV	Mean (sec)	1004.54	1003.77	747.59	745.32
		P value	0.482		0.472	
High Market Penetration	70% AV	Mean (sec)	1020.28	1019.47	768.28	766.28
		P value	0.484		0.478	
	80% AV	Mean (sec)	1043.56	1043.22	781.68	779.43
		P value	0.494		0.478	
	90% AV	Mean (sec)	1058.64	1058.19	793.55	786.39
		P value	0.493		0.435	

MOE Performance

Travel time and Throughput: Figure 4(a) and 4(b) shows the travel time and throughput as a function of the AV penetration rate, at both the merging and the mainline segment. Each box plot describes the distribution of the 135 different AV driving settings at each penetration level.

When AVs are programmed to reflect the baseline settings (i.e., all parameters are set to calibrated values), the average time for both AV and non-AV flows to travel across the merging segment and mainline segment is 747 seconds and 940 seconds. The segment's average throughputs are 3,520 vehicles/hour and 3,242 vehicles/hour, respectively, for merging and mainline segments.

The impacts of different AV driving settings on throughput and travel time are observed even at the 10% AV market penetration rate. Depending on the selected AV driving setting, the travel time on the merging segment can either increase to 879 seconds or reduce to 619 seconds. Similarly, the throughput either increases to 3,690 vehicles/hour or drops to 3,392 vehicles/hour.

Note that the impacts of different driving settings are significant both within a specific AV penetration level (e.g., at 10% penetration level) and between different AV penetration levels (e.g., between 10% and 100% market penetration levels). This can be viewed by comparing the travel time and throughput results between 10% and 50% AV penetration rates in the merging segment. With appropriate AV driving settings, the lowest merging segment travel time decreases from 619 seconds to 338 seconds and the throughput increases from 3,690 vehicles/hour to 4,127 vehicles/hour. In contrast, if appropriate AV settings are not assigned, then the system's performance can deteriorate significantly. For instance, at 50% AV flow rates, the travel time increases to 1,217 seconds while the throughput drops to 3,101 vehicles/hour, compared with 747 seconds and 3,520 vehicles/hour in the base case scenario.

At the current demand levels, as vehicles move from the mainline segment to the merging segment, the traffic flow moves from a region of moderate to congested conditions. As the mainline segment is uncongested, significant improvements in travel time and throughput are not observed beyond 10% AV flow rates. However, the performance of traffic flow is impeded significantly when AVs are prescribed incorrect driving settings. The travel time and throughput in the mainline segment, as shown in Figure 4(a) and 4(b), highlight the negative impact of incorrect AV driving settings as AVs gain 100% market share, resulting in increasing the travel time to 1,584 seconds and decreasing the throughput to 1,783 vehicles/hour.

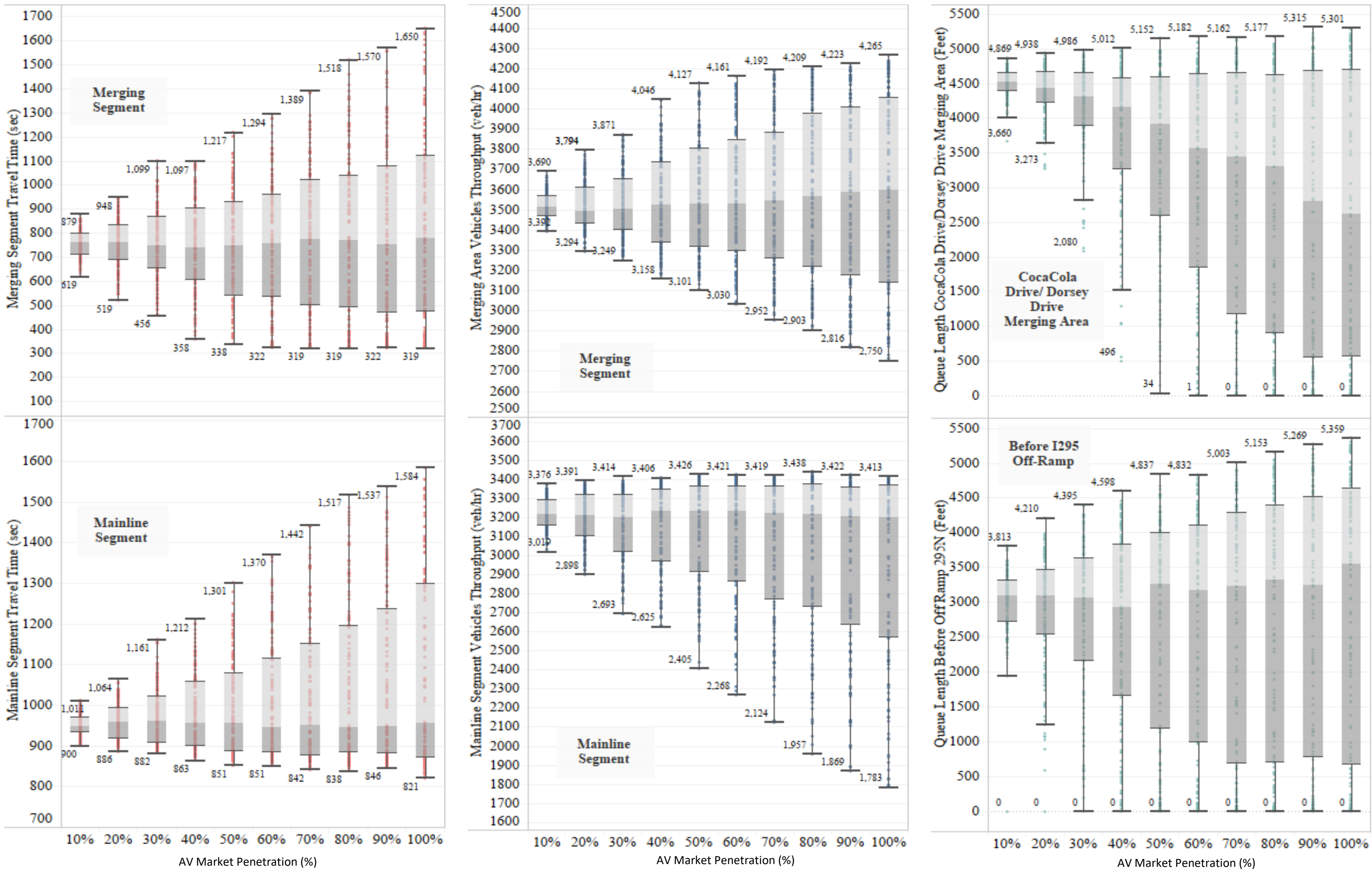
Table 3 shows the percent change, in comparison with the average travel time, for the longest and the shortest travel time taken to cover the MD-100 segments and the adopted AV behavior mechanisms (Note: These are not the recommended settings) at low (10%), medium (40%) and high penetration rates (70%). As highlighted in Table 3, at the medium level of AV penetration (i.e., 40%), depending on the AV driving settings the travel time either increases by 47% or decreases by 52%. Such results not only demonstrate the potential negative and positive impacts of AV flows on the overall traffic conditions, but also justify the need to guide AV flows to adopt the proper behavior mechanisms to benefit both AV and non-AV flows in the entire system.

TABLE 3: Positive and negative impact on travel time due to AV behavioral mechanisms

		Lane-Changing		Car-Following		Travel Time[1,2] (seconds)
AV Penetration Rate		Deceleration	SD Reduction Factor	Safety Distance	Following Variation	Change
(a) Merging Segment						
Low (10%)	**Shortest**	Calibrated	Aggressive	Aggressive-2	Aggressive	**-17.27%**
	Longest	Moderate	Aggressive	Moderate -2	Moderate	**25.84%**
Medium (40%)	**Shortest**	**Moderate**	**Aggressive**	**Aggressive-2**	**Aggressive**	**-52.07%**
	Longest	**Moderate**	**Moderate**	**Moderate-2**	**Moderate**	**46.85%**
High (70%)	**Shortest**	Aggressive	Aggressive	Aggressive-2	Aggressive	**-57.30%**
	Longest	Aggressive	Moderate	Moderate-2	Moderate	**85.94%**
(b) Mainline Segment						
Low (10%)	**Shortest**	Calibrated	Aggressive	Aggressive-2	Aggressive	**-4.26%**
	Longest	Calibrated	Moderate	Moderate -2	Moderate	**7.02%**
Medium (40%)	**Shortest**	**Moderate**	**Calibrated**	**Aggressive-2**	**Aggressive**	**-8.19%**
	Longest	**Aggressive**	**Moderate**	**Moderate-2**	**Moderate**	**28.94%**
High (70%)	**Shortest**	Aggressive	Aggressive	Aggressive-2	Aggressive	**-10.42%**
	Longest	Moderate	Moderate	Moderate-2	Moderate	**53.40%**

[1]Average travel time Merging area: 747 seconds, [2]Average travel time Mainline segment: 940 seconds

Queue Length: At the baseline settings, queue lengths do not propagate on the mainline segment or its on/off-ramps. However, queue lengths in the range of 4,500 feet are observed in the bottleneck area between the Coca-Cola Drive on-ramp and Dorsey Drive off-ramp, and extend upstream. Also, the changes in vehicle speed and merging behavior due to high on-and-off-ramp volumes cause significant queues in the vicinity of the I-295 off-ramp. Figure 4(c) shows how the queue length evolves with the change in the AV driving settings. The figure shows that at 50% penetration rate the queue length at both locations reduces significantly, concurrently reaching below 50 feet in comparison to 4,606 feet at the Coca-Cola Drive/Dorsey Drive merging area and 2,967 feet before I-295 off-ramp if the vehicles had been programmed to operate at the calibrated settings.



(a) Travel time at Merging and Mainline segment under the 135 different AV driving settings

(b) Throughput at Merging and Mainline segment under the 135 different AV driving settings

(c) Queue length variation in the merging segment under the 135 different AV driving settings

NOTE: Each plot defines the upper and lower limit of the MOE. The shaded region defines the lower quartile, median value and the upper quartile.

FIGURE 4: The upper and lower bounds of travel time, throughput, and queue lengths under different AV driving settings and penetration rates

Note that the three MOEs shown in Figure 4 clearly indicate that incorrectly programmed AVs could result in a situation where traffic breakdowns become more prevalent and severe. Therefore, proper control with adequate knowledge of the resulting impact of a particular driving setting is essential for the operational agency to effectively manage traffic conditions.

Optimal AV Driving Settings

Table 4 shows the most appropriate AV driving settings for the merging and mainline segments (with/without lane-drop) with respect to the improvement in travel time, throughput, and queue lengths as a result of administering the suggested driving settings. The choice set was filtered down by using the K-mean clustering method while considering all three MOEs.

On the mainline segment, the lane-changing setting at all AV market penetration levels is recommended to be set at the moderate levels. The car-following settings should both be set to aggressive levels. With such behavioral settings for AV flows, all vehicles traversing through the mainline segment observe about a 3% drop in travel time and 2% increase in throughput at 10% AV market penetration. As shown in Figure 4(a) and 4(b), at 50% penetration levels and above, the travel time and throughput do not improve, and at these levels a 10% decrease in travel time and an almost 5% increase in throughput is achieved.

The improvements in the merging area, which sees a daily bottleneck due to high on/off-ramp volume, are more considerable. The recommended car-following setting is aggressive for both safety distance and the car-following variation at all AV market penetration levels. However, between 10% and 60% AV market penetration, the lane-changing behavior should be set at the calibrated settings (i.e., same as non-AV driving population) for the deceleration parameter and aggressive settings for the safety distance reduction parameter. At the penetration levels of 70% and above the lane-changing behavior should be set to calibrated settings.

The magnitude of improvement is considerable even at lower AV market penetration levels. As shown in Table 4(b), at 10% levels throughput is increased by over 4% and travel time decreases by upwards of 17%. The traffic performance continues to improve until 50% penetration levels, beyond which the improvements level off. At the 60% and above AV market penetration levels, the queue lengths in the merging area are eliminated, the travel time is improved by over 50%, along with the throughput increase of 19%, compared to when no control is administered. Table 4(c) shows the recommended car-following and lane-changing behaviors for AVs traversing through the mainline segment under a single-lane closure. It is observed that the change in the lane-changing behavior of AVs does not have a significant impact on traffic improvement at all penetration levels. Also, at 10% AV penetration levels, change in the car-following behavior does not result in significant traffic improvements; therefore AVs are recommended to operate under calibrated car-following settings. At penetration levels greater than 10%, AVs are recommended to operate under aggressive car-following settings in order to yield maximum benefit from AV flows. As highlighted in Table 4(c) when 40% AV flows operate with aggressive car-following settings, traffic flows experience up to 10% reduction in travel time and up to 32% reduction in queue lengths.

The selection of the AV driving settings for both the mainline and merging segments of MD-100 are discussed below:

- For both the merging and mainline segments the suggested car-following behavior is aggressive, i.e., AVs follow a shorter headway and respond to the following vehicle at shorter distances. The resulting positive impact on travel time and throughput are consistent with what has been reported in the literature *(9,10,11,12).*
- The lane-changing behavior in the mainline segment is recommended to be moderate (i.e., AVs will decelerate at a lower rate and will accept non-mandatory lane changes at a smaller reduction to their safety distance than their human counterparts). The specified lane-changing behavior will result in fewer non-mandatory lane changes, thereby requiring the vehicles to minimize their lane changes and limiting them only to mandatory lane changes.
- The prescribed lane-changing behavior in the merging segment is different for market penetration levels between 10%-60% and 70%-100%. At 10%-60% penetration levels AVs are recommended to set the calibrated setting (i.e., the same as the non-AV driving populations) for their deceleration behavior during the mandatory lane change and aggressive settings for a reduction in their safety distance. The behavior is changed to calibrated for both parameters at 70%-100% penetration levels. The change in the settings for the lane-changing parameters is the result of a higher proportion of AVs in comparison to human-driven vehicles. Therefore, the added benefits of having aggressive lane-changing behavior along with aggressive car-following behavior becomes insignificant once AVs constitute 70% or higher of the traffic flows.

TABLE 4: AV parameter settings and resulting improvements (with reference to the baseline settings, i.e., MD-100 calibrated settings) at each penetration level

(a) Mainline Segment

AV Penetration Rate	Lane-Changing		Car-Following		Improvement		
	Deceleration	SD Reduction Factor	Safety Distance	Following Variation	Travel Time	Throughput	Queue Length
10%	**Moderate**	**Moderate**	**Aggressive-2**	**Aggressive**	**2.93%**	**1.98%**	**no queue**
20%	Moderate	Moderate	Aggressive-2	Aggressive	4.56%	3.27%	no queue
30%	Moderate	Moderate	Aggressive-2	Aggressive	4.86%	2.17%	no queue
40%	Moderate	Moderate	Aggressive-2	Aggressive	6.27%	4.27%	no queue
50%	Moderate	Moderate	Aggressive-2	Aggressive	9.40%	4.75%	no queue
60%	Moderate	Moderate	Aggressive-2	Aggressive	8.82%	3.85%	no queue
70%	Moderate	Moderate	Aggressive-2	Aggressive	9.25%	4.46%	no queue
80%	Moderate	Moderate	Aggressive-2	Aggressive	8.85%	4.79%	no queue
90%	Moderate	Moderate	Aggressive-2	Aggressive	9.74%	4.30%	no queue
100%	Moderate	Moderate	Aggressive-2	Aggressive	10.24%	4.93%	no queue

(b) Merging Segment

AV Penetration Rate	Lane-Changing		Car-Following		Improvement		
	Deceleration	SD Reduction Factor	Safety Distance	Following Variation	Travel Time	Throughput	Queue Length
10%	**Calibrated**	**Aggressive**	**Aggressive-2**	**Aggressive**	**17.72%**	**4.28%**	**11.45%**
20%	**Calibrated**	**Aggressive**	**Aggressive-2**	**Aggressive**	**32.30%**	**7.79%**	**27.80%**
30%	**Calibrated**	**Aggressive**	**Aggressive-2**	**Aggressive**	**39.70%**	**9.73%**	**54.21%**
40%	**Calibrated**	**Aggressive**	**Aggressive-2**	**Aggressive**	**48.59%**	**14.84%**	**87.93%**
50%	**Calibrated**	**Aggressive**	**Aggressive-2**	**Aggressive**	**52.53%**	**16.15%**	**89.05%**
60%	**Calibrated**	**Aggressive**	**Aggressive-2**	**Aggressive**	**54.74%**	**16.83%**	**99.67%**
70%	Calibrated	Calibrated	Aggressive-2	Aggressive	52.49%	19.09%	98.27%
80%	Calibrated	Calibrated	Aggressive-2	Aggressive	49.80%	19.12%	98.66%
90%	Calibrated	Calibrated	Aggressive-2	Aggressive	54.05%	19.51%	99.27%
100%	Calibrated	Calibrated	Aggressive-2	Aggressive	51.55%	20.04%	100%

(c) Mainline Segment – Single Lane Drop

AV Penetration Rate	Lane-Changing		Car-Following		Improvement		
	Deceleration	SD Reduction Factor	Safety Distance	Following Variation	Travel Time	Throughput	Queue Length
10%	**Calibrated**	**Calibrated**	**Calibrated**	**Calibrated**	**-**	**-**	**-**
20%	Calibrated	Calibrated	Aggressive-1	Aggressive	3.08%	4.79%	5.34%
30%	Calibrated	Calibrated	Aggressive-1	Aggressive	3.76%	4.96%	14.26%
40%	**Calibrated**	**Calibrated**	**Aggressive-2**	**Aggressive**	**10.43%**	**15.44%**	**31.73%**
50%	Calibrated	Calibrated	Aggressive-2	Aggressive	13.55%	19.52%	26.53%
60%	Calibrated	Calibrated	Aggressive-2	Aggressive	10.56%	13.54%	23.05%
70%	Calibrated	Calibrated	Aggressive-2	Aggressive	15.66%	25.40%	47.25%
80%	Calibrated	Calibrated	Aggressive-2	Aggressive	16.46%	23.27%	43.73%
90%	Calibrated	Calibrated	Aggressive-2	Aggressive	17.08%	20.98%	37.59%
100%	Calibrated	Calibrated	Aggressive-2	Aggressive	16.57%	21.09%	44.74%

CONCLUSIONS AND REMARKS

This study has addressed an issue often overlooked when the topic of AVs is discussed in the literature. Instead of focusing on different AV-specific car-following and lane-changing models alone, this study has focused on the role of an operational agency in coordinating with the AV traffic flows. In this effort, a methodology has been presented to analyze the impacts of different AV flows on a highway network using microsimulation.

The methodology was applied to a two-lane congested highway in Maryland, and the results of different AVs settings show that improper AV behavioral mechanisms can severely impede the traffic operations at all AV penetration levels. Under appropriate settings administered by the external traffic controller, the experimental analysis shows that the introduction of AVs even at the 10% penetration rate can result in a reduction of average travel time, increase in throughput and decrease in queue lengths on the merging and mainline segments. These improvements due to the exercise of optimal behavioral mechanisms for AV flows have yielded the same benefits to both AV and non-AV flows. The experimental results, tested in the study, highlight the existence of an optimal set of behavioral mechanisms for AV flows that are required to be executed over different segments of the commuting freeway under the given traffic volume to maintain and improve traffic flow. A responsible highway agency can follow our proposed method to develop operational guidelines that will enable the traffic operators to properly coordinate with AV flows to make the best use of the roadway capacity and avoid any potential negative impacts of AVs.

Other ongoing research tasks associated with AV traffic flow include: developing models that take into account lower reaction time of the automated system, evaluating the impact of different AV behavior compliance rates and the need for enforcement, the V2V communication component, and the use of AVs to implement VSL (variable speed limit) strategies on recurrently congested freeway segments.

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