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# Impacts of Connected and Autonomous Vehicles on Transportation Capacity

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# Impacts of Connected and Autonomous Vehicles on Transportation Capacity

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# Chapter 1
# Impacts of Connected and Autonomous Vehicles on Freeway Segments and Facilities

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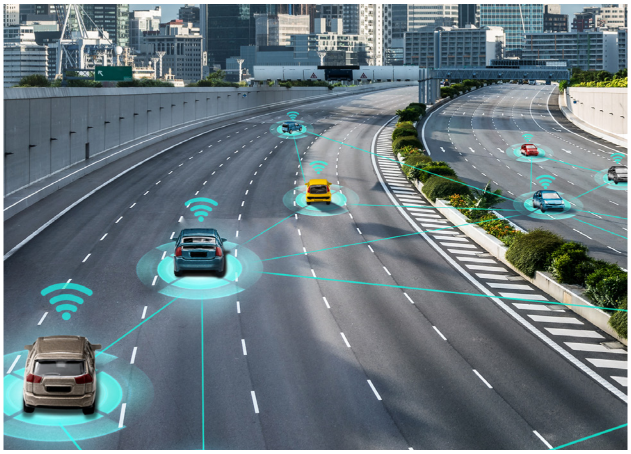
# 1.1 Introduction

This chapter presents the findings of a simulation study focused on the operational treatment of autonomous vehicles (AVs) and connected autonomous vehicles (CAVs) on freeway segments and a real-world freeway facility in mixed and segregated traffic environments, including significant merging and diverging maneuvers. The treatments involve no lane dedication to equipped vehicles (with autonomy or connectivity) and the dedication of a single freeway lane for the exclusive use of CAVs, and the effect of access control to and from that lane along the simulated facility. The latter type of treatment is already widely used, and has been successfully implemented around the nation as HOV, HOT and exclusive Toll lanes. We define CAVs to be those vehicles for which short time and/or space headways can be compressed when operating in a platoon mode with other CAVs, while maintaining longer headways when following other, non-CAV vehicles. Autonomous vehicles (AVs) are also driverless, but do not communicate with other vehicles, and generally maintain longer headways with leading vehicles. Connected vehicles (CVs) are human driven, but can communicate with other such vehicles (V2V) or with the infrastructure (V2I). Finally, traditional vehicles (TVs) represent human driven vehicles, for which ample simulation experience has been gained over the decades.

There is much uncertainty regarding the temporal microscale (1-10 Hz) operational modes of AV's and CAV's given the proprietary nature of the algorithms controlling their longitudinal and lateral spacing with other vehicles, as well as the potential variations in delivered customer options (e.g. settings for aggressive vs. conservative driving modes, or space headway options). Those trends are likely to result in even higher

variability across AV and CAV operating modes. In order to gain an overall perspective of the system performance under various operating scenarios, simplifying assumptions must be made when exercising any simulation environment. For example, the literature generally assumes that AVs will maintain, on average, longer headways with leading vehicles than drivers of TVs do, mostly for safety reasons, at the expense of more efficient mobility (1, 2). On the other hand, CAV headways should be modeled as dynamic and made dependent on whether CAVs are following other CAV's or other vehicle types. In other words, the same vehicle can operate with two different car following modes in simulation, depending on its lead vehicle type. Finally, this research treats CV's as TV's, with the assumption that from a car following and lane changing perspective, those two vehicle types will operate in a similar manner. Much of the advantages of V2V and V2I capabilities apply at the operational or strategic level (route diversion, incident avoidance, etc.) and not at the microscale car following level.

As a result of having different operating modes depending on the nature of the lead vehicles, two important objectives would be (i) an investigation of the impact of AVs and CAVs on different freeway segments' throughput in a mixed flow environment, and (ii) maximization of the throughput of CAVs by having them operate in a dedicated lane exclusively, where they can maintain short headways in platoons. It is assumed that in mixed flow traffic lanes, such headways become infeasible, and the probability of platooning is significantly reduced, depending on market penetration. Therefore, the operational system performance will depend on a slew of parameters including (a) the overall traffic demand per lane, (b) the market penetration rates of TVs,



AVs and CAVs, (c) the level of ramp demands on the facility and (d) the level of access to and from the dedicated lane for CAVs.

While much research work has been published on the effects of items (a) and (b) above, less attention has been given to items (c) and (d). It is clear for example that AVs and CAVs have different operating characteristics and cannot be treated equally in simulation. Similarly, CAVs will operate differently in mixed traffic when compared to an exclusive CAV environment. Research on (b) focuses on homogenous traffic streams that only include certain types of equipped vehicles and usually do not represent scenarios where all vehicle types are present. As such, it is important to study traffic streams that are composed of AVs, CAVs, TVs, and CVs. Furthermore, it is well understood that much of the perturbations which occur in today's freeway facilities tend to take place near interchange areas, particularly—in this case— when CAVs must enter or exit the dedicated lane within restricted lane opening segments. Some of the access problems may be addressed by allowing continuous access to the dedicated lane but the results need to be investigated in the context of how they are affected by variable penetration rates and origin destination demands. These factors have been integrated into a simulation experimental design that generates multiple scenarios and identifies the mobility outcomes for each of them. These outcomes are expressed in terms of overall system throughput, speed-flow diagrams, system level and OD movement travel rates. The simulation model described in this paper considers many of those effects, and has been calibrated to produce appropriate capacity for a fleet of TV's, consistent with macroscopic measures documented in the Highway Capacity Manual. That work is documented elsewhere (3).

This chapter is organized as follows. A review of the technical literature focused on modeling autonomous and connected vehicles in a mixed traffic environment and dedicated lane(s) for AVs and CAVs is presented next. That section is followed by the methodology where the algorithms used to model the behavior of each vehicle type are provided. The analysis and result section is then presented, including the introduction of a planning level calculator for freeway capacity estimation under both mixed traffic and a CAV dedicated lane, followed by the summary and conclusions from this study.

## 1.2 Literature Review

The introduction of CAVs, AVs, and CVs mixed with TVs are expected to bring some mobility benefits for both freeway and arterial facilities. Nonetheless, the different operating characteristics of these vehicles have rendered these impacts to be highly variable. Furthermore, most mobility studies are simulation-based since field observations of CAVs, AVs, or CVs mixed with TVs are very limited. Thus, the modeling assumptions play a significant role in reporting the impacts. The following section discusses the impact of CAVs, AVs, CVs, and TVs on freeway capacity estimation. In addition, mobility implications of the use of dedicated lanes and access control in a mixed traffic environment are presented.

### Mixed Traffic on General Purpose Lanes

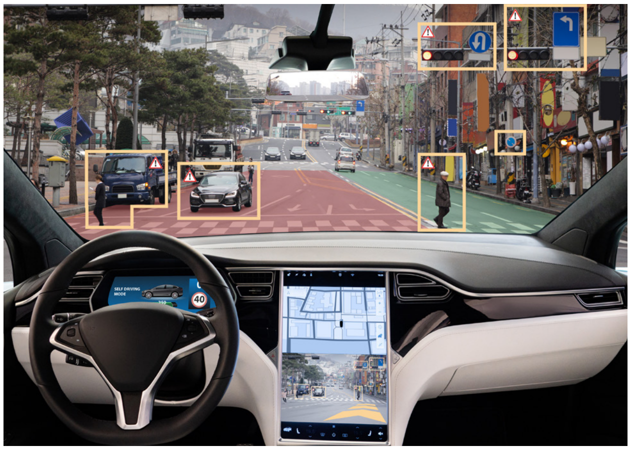
#### *Connected Vehicles (CV)*

There is abundant research regarding the impact of CV on mobility, safety, and the environment. However, the majority of this research is focused on the network-level impacts of these vehicles. Mei et al. (4) studied the impact of V2V communication on network operations using the AIMSUN simulation platform. Two strategies (dynamic route diversion and variable speed limit) were used in response to a severe incident in the network. They concluded that both penetration rate of CV and choice of control strategy impact the overall performance. Furthermore, they found that network performance improves as the market penetration (MPR) of CV increased from 5% to 50% but declined when the MPR was 100% -

compared to the 50% level.

Lee and Park (5) investigated the impact of various route guidance strategies and factors (MPR, congestion level, updating intervals of route guidance information, and drivers' compliance rates) in a CV environment using VISSIM simulation platform. They found a significant reduction in network travel time with the presence of V2V and V2I communication. The amount of improvement in travel times was reported to be directly related to the MPR of connected vehicles. Talebpour and Mahmassani (6) studied the impact of connected vehicles on freeway efficiency. Only V2V communication was simulated with the assumption that the reaction time of drivers would decrease by 50% in the presence of V2V communications. The acceleration behavior of connected vehicles was modeled using the Intelligent Driver Model or IDM (7, 8). Their results showed an increase in freeway efficiency as the MPR of connected vehicles increased. Zhu and Ukkusuri (9) also found that the amount of benefit from CV depends on the MPR and traffic demand. The benefits were found to be especially significant under high demand conditions.

A simulation-based study of the impact of CV on network flow and travel time reliability was conducted by Mittal et al. (10). A microscopic simulation tool was used to establish the speed-density relationships at different MPRs. The resulting speed-density relationships were then used in the mesoscopic simulation tool DYNASMART-P to determine the effect of connectivity on transportation network performance. The acceleration behavior of the connected vehicles was again modeled on the basis of IDM. It was found that an increase in connectivity resulted in a decrease in density or an increase in flow or both at low demand levels. As a result, the authors speculated that there would be an increase in network capacity due to connectivity at all demand levels.



## *Autonomous Vehicles (AV)*

Among various AV technologies, Adaptive Cruise Control (ACC) is one example where onboard sensors automatically adjust vehicle speed and prevent collisions between vehicles (11). Since an AV movement depends entirely on its sensors, its longitudinal behavior resembles the behavior of an ACC.

Chang and Lai (12) investigated the capacity impacts of auto piloted vehicles on a 4 km one-lane freeway section with an on ramp. Different merging and car following rules (separation between vehicles dependent on velocity and velocity squared) for autopiloted vehicles were introduced. While different market penetration rates of the auto-piloted vehicles were investigated, the traffic stream was chiefly kept homogeneous (all passenger cars). Findings of the study indicate a 33% increase in capacity of vehicles that can safely enter the highway in a saturated environment (assuming 100% auto-piloted vehicles).

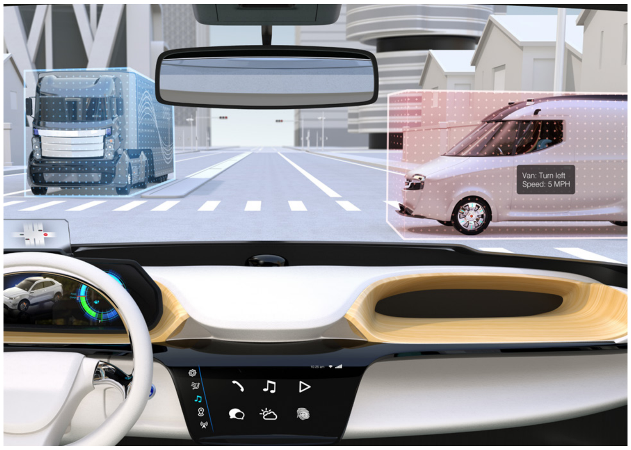
VanderWerf et al. (13) used a 1.4s time gap and found that the introduction of autonomous adaptive cruise control (AACC) had a small, 7% increase in freeway capacity. The AACC acceleration of equipped vehicles was modeled as a function of (a) speed difference between lead and following vehicle and (b) difference of current and desired distance between vehicles (14). Shladover et al. (15) provided a simple model of ACC vehicles where the results showed an insignificant change in capacity for high MPRs of equipped vehicles and a worsening of other traffic flow dynamics.

Minderhoud and Bovy conducted a simulation-based study of the impact of autonomous intelligent cruise control (AICC) on freeway capacity (16). The headway setting was found to have a significant impact on capacity at MPRs in excess of 20 percent. Three distinct headways 1.2 s, 1.0 s, and 0.8 s were examined. Results showed no increase in capacity at a headway of 1.2 s, while an increase of 4% percent occurred at a 1.0 s headway. Finally, the increase in capacity was 12% when the headway was set to 0.8 s.

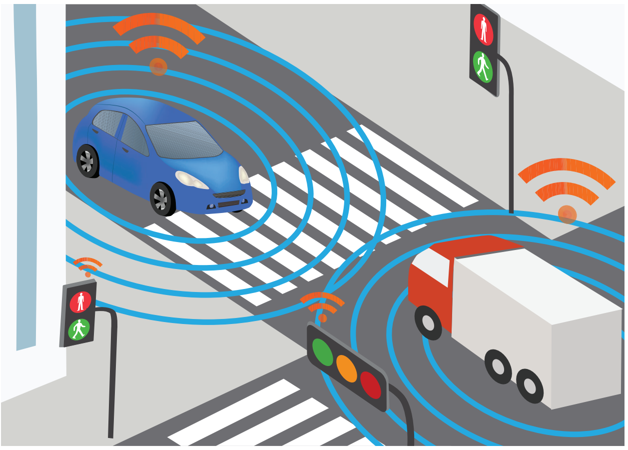
Tientrakool et al. assessed the impact of sensor-equipped vehicles (autonomous) on highway capacity using formal analysis (analytically - using equations of motion to derive speed and acceleration for AV rather than simulations. They assumed the same speed for all vehicles in the traffic stream, a sensing latency of 0.245 s, and mechanical brake delay of 0.1 s. The results showed a 43% increase in freeway capacity for a 100% market penetration rate of autonomous vehicles (17).

Le Vine et al. developed an analytical autonomous vehicle driving (highly-automated by SAE standards) model for freeway capacity estimation that is ACDA (Assured Clear Distance Ahead) compliant (18). They focused on traffic streams of homogenous AVs and did not account for the mix of AV and TV. Compared to human drivers, AV were found to sustain higher flow rates and maximum throughput at free-flow speeds; under congestion, however, the rate of speed degradation was found to be steeper.

Another simulation-based study was conducted on the impact of AV (ACC) on freeway capacity (19). It used the VISSIM simulation platform and considered two types of operating behavior: conservative and aggressive. The conservative scenario had longer headways and lower acceleration/deceleration profiles compared to TVs. The aggressive scenario used an opposite set of assumptions. AV behavior was modeled using VISSIM's native car-following model (Wiedemann 99) with the modification of its parameters. With 50% of MPR, the conservative AV resulted in increase in both travel time and delay, whereas the other scenario resulted in reduction of travel time and delay.




Talebpour et al. (20) investigated the effects of reserved lanes for AVs on congestion and travel time reliability on two freeway sections (a hypothetical 4-lane freeway with one on ramp, and a 4-lane freeway in Chicago with multiple on and off ramps) using a microscopic simulation tool. The longitudinal behavior of AV was modeled based on the work of Van Arem et al. (21) and Reece and Shafer (22) with adjustments for consideration of sensor characteristics (23). Three policies were tested on the use of reserved lanes by AV. The first scenario required the AV to use the reserved lanes. The second scenario required the AV to use the reserved lane but forced the operation to be manual in the general purpose (GP) lanes. The third scenario gave the AV freedom to choose between the reserved lanes and regular lanes with autonomous operation everywhere. Travel time reliability was measured as the mean and standard deviation of the travel time distribution. The standard deviation of the travel time was found to be lower for the third scenario compared to other scenarios. In addition, the travel time reliability was found to increase (decrease in standard deviation) as the MPR of AV increased. However, the first scenario performed better than the other scenarios from the mean travel time perspective.



Findings from previous studies on the impact of AV on capacity and travel time reliability are not consistent. While a majority report that improvements can be achieved due to the introduction of AV in the traffic stream at all MPR's, others indicate that an increase in MPR beyond a threshold results in a lower capacity. It must be noted that studies showing promising improvements report inconsistent levels of improvements for the same MPR. These inconsistencies could be attributed to model selection and assumed AV parameter values.

### *Connected-Autonomous Vehicles (CAV)*

Among different types of CAV technologies, cooperative adaptive cruise control (CACC) is specifically advantageous because of its capability to significantly change roadway traffic characteristics, by enhancing capacity and improving flow stability (24). The availability of vehicle-vehicle communication in coordination with sensors (as in ACC) enables CACCs to maintain shorter following time-gaps and achieve faster system responses. One of the early models of CACC was developed by VanderWerf et al. (14). The model used the acceleration of the lead vehicle, the difference between the speed of lead and following vehicles and the difference between the current and desired distance between vehicles to calculate the acceleration for the following vehicle. Using Monte Carlo and 100% CACC equipped vehicles, a single lane freeway with on and off ramps was simulated. With the assumption of 0.5 s time gap between CACC equipped vehicles, capacity was found to increase in excess of 100% (from 2,050 to 4,550 veh/h). VanderWerf et al. (13) also studied the impact of ACC and CACC in a mixed traffic stream environment (regular vehicles along with CACC and ACC vehicles present). The findings, where 100% of traffic was CACC equipped, were almost similar to those reported in (12).

In a later study, Shladover et al. (25) studied the impact of varying MPR of CACC on highway capacity using the distribution of time gap settings obtained from other publications through a field experiment. The ACC car-following models used were Nissan's proprietary, where CACC behavior was modeled based on the car-following behavior developed by Bu et al. (26). The control algorithms for ACC and CACC were similar in all aspects, except for the desired time gaps. AIMSUN platform was used to conduct this analysis on a 6.5 km long one-lane freeway with a speed limit of 65 mph. Results showed that above certain levels (moderate) of CACC the potential to substantially increase highway capacity is very high. An increase of up to 4,000 vphpl was achieved in a saturated (100%) CACC environment.

Apart from theoretical and simulation studies, a number of recent field experiments have shown promising improvements in roadway capacity and flow stability of this technology (24, 26, 27). Specifically, the field experiments conducted by Milanes et al. (24) and Shladover et al. (13) showed that vehicles equipped with the technology can maintain a time gap as low as 0.6 s, which compared to the conventional 1.5 s time gap of un-automated/un-connected vehicles, yield significant potential for freeway capacity enhancement. Theoretical analysis by Ploeg et al. (27) suggest that even shorter time gaps between equipped vehicles, sub-0.5 s, are feasible – provided an optimized communication latency is available.

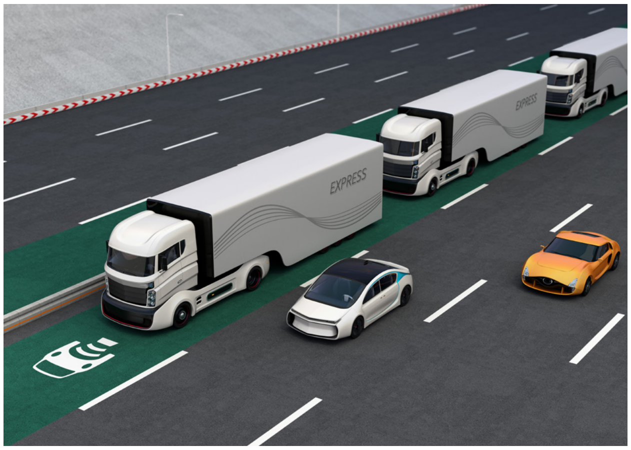
Vanderwerf el al. (13) studied the impact of varying MPR of cooperative autonomous vehicles on traffic flow of a single lane freeway with one on-ramp and one off-ramp using Monte Carlo simulations. The transmitted data consisted of (a) velocity of lead vehicle (b) acceleration of the lead vehicle and (c) braking capability of the lead vehicle. The details of the control logic for the cooperative autonomous vehicles can be found in (14). Results of the study suggest that cooperative autonomous vehicles (CACC) have the potential to enhance highway capacity substantially. The amount of the increase, however, was found to be a quadratically related to the MPR of CACC. Ni et al. (28) showed that assuming a 100% market penetration of IntelliDrive-automated vehicles, those capable of inter-vehicle communication and autonomous driving, highway capacity can be improved by up to 50 percent.


Tientrakool et al. (17) assessed the impact of vehicles equipped with sensing and communication capabilities (CAV) on highway capacity using theoretical analysis. The communication medium was based on a Reliable Neighborcast Protocol (RNP). They assumed the following: homogenous traffic stream, fixed speed for all vehicles in the traffic stream, minimum acceleration of -5 m/s2, and a maximum value of -8.5 m/s2, vehicle length of 4.3 m, communication latency of 0.081 s, and mechanical brake delay of 0.1 s. The findings indicated that a 270% increase in freeway capacity could be achieved for a 100% market penetration rate of CAV.

Van Arem et al. (21) developed one of the most widely used CACC behavior models and employed it to study the impact of CACC on traffic-flow characteristics at a freeway merging location (from four to three lanes) using the simulation platform MIXIC. Results showed that CACC can improve traffic-flow performance. The amount of improvement, however, was found to be directly related to the MPR of CACC. They also investigated the impact of reserving a lane for CACC and found that at low CACC MPR (under 40%) it resulted in worsening the operational performance of the freeway.

It is clear that the majority of the research on AV and CAV has focused on the dynamics of longitudinal control of these technologies and research towards their lateral dynamics is extremely scarce. The only relevant work on lateral control is that of Liu et al. (29), which explores the impact of lateral control algorithms on freeway capacity and other traffic flow dynamics. Their results show that capacity increases from 2,000 vph to 3,070 vph as CAV MPR varied from 0% to 100%. It was found that the impact of lane changing on flow was much less than expected. They reported that almost all of the improvements in traffic flow characteristics (mostly capacity) can be associated with alterations to the car following maneuvers of CAV than their lane-changing operations.

## Lane Dedication for Autonomous Connected Vehicles

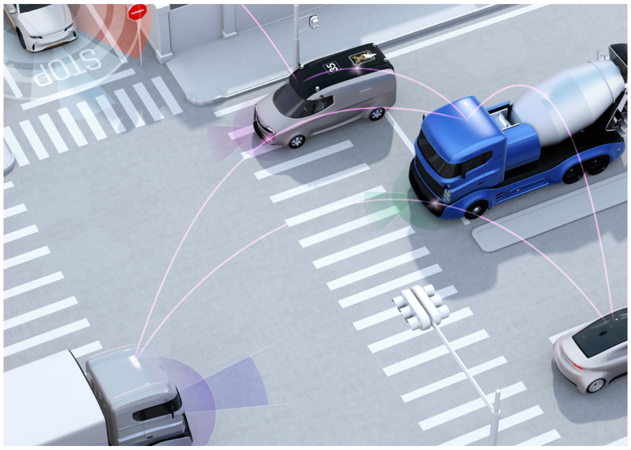



Finally, in an effort to develop a simulation roadmap, existing guidance on simulation needs to be reviewed. The Transportation System Simulation Manual by List et. al. (30) is one such document. Software agnostic, it is designed as a reference for practitioners, students, and teachers on all topics of vehicle simulation. It discusses the concepts pertaining to simulation paradigms that are presently in use (microscopic, mesoscopic, and macroscopic), and simulation verification, calibration, and validation. The simulation with the addition of new vehicle technologies needs a closer look at the aforementioned aspects.

This section provides a review of past work related to the impact of dedicated freeway lanes (DLs) on CAV and AV mobility in mixed traffic conditions. A project funded by the National Academies of Sciences (31) assessed the impact of CAV DLs under mixed flow conditions comprising CAVs and TVs (SOVs and HOVs), on mobility and safety in a simulation environment. The research tracked the speed differential between DL and the adjacent general-purpose lane (GPL), to decide whether to install a physical barrier between the DL and GPLs. The results indicate that it is advisable to (a) operate a mixed-use DL (DL can be used by HOVs as well as CAVs) at lower levels of CAV market penetration rate (MPR) (10%),(b) use exclusive CAV DLs at medium levels of CAV MPR (20% to 45%), and (c) not use any CAV DLs for high CAV MPR (greater than 50%). The research further found that the lane friction is minimal at high or low MPR of CAV with mixed use of the DL but is significant at medium CAV MPR with an exclusive DL. This level of lane friction warrants physical separation for both enforcement and safety purposes. It is evident from the research that a physical barrier is only advisable when the CAV MPR ranges from 20% to 45%.

Making the use of dedicated lanes mandatory for CAVs or AVs can significantly impact traffic dynamics. For example, microscopic simulation-based research by Talebpour et al. (32) assessed the effect of DL on flow breakdown and travel time reliability. The analysis showed that the mandatory lane changing for AVs' to merge or diverge from the DL was the primary source of disturbance and congestion on the GPLs. When AVs had the option to operate in both DL and GPLs, congestion and flow breakdowns on the GPLs decreased significantly. Results indicated that at AV MPR of 30%, the flow breakdown at GPL was minimal. This reduction in flow breakdown is due to the efficient merging and diverging of AVs. Besides, optional use of DLs reduced the standard deviation of travel time. Furthermore, if all AVs are obliged to use the DLs congestion and flow breakdowns on GPLs become more frequent than with the optional lane. A similar study by Xiao et al. (33) found that for a CAV MPR between 30% and 50%, a CAV DL improved throughput and travel time reliability. Additionally, the research found that for a low CAV MPR, the speed difference between the CAV DL and GPLs makes it difficult for CAVs' entry to and exit from the DL. This difficulty often leads to increased travel time for the CAVs.

Zhong et al. (34) also used microsimulation to investigate the effect of CAV DLs on traffic flow at a four-lane directional freeway facility with two on-ramps and two off-ramps. Similar to Talebpour et al. work (32), the research assumed that CAVs could operate in both GPLs and DL. The analysis showed that the allocation of one and two CAV DLs increased the overall throughput above a CAV MPR of 50% and 70%, respectively. Interestingly, the researchers found that the average headway of the overall traffic is optimal when only one CAV DL is allocated, irrespective of CAV MPR.




Research by Guo and Ma (35) showed the effect of a dedicated CAV ramp on freeway mobility in three different DL scenarios. The first scenario includes one DL for HOVs, CAVs, and CVs with dedicated ramps for those vehicles. In the second scenario, the DL was accessible to HOVs, CAVs, and CVs but did not include a dedicated ramp. The third scenario had no dedicated ramps with the DL available only for HOVs. In the first and second scenarios, CAVs and CVs were able to use the DLs at specific access and egress segments. The simulation results show that the first scenario yielded the best performance, mostly for low and medium

CAV MPR. Furthermore, the research suggests that the reduction of weaving maneuvers and the higher probability of CAV platooning are the two most important benefits of dedicated ramps.

Several studies analyzed the impact of CAV DL on freeway basic segment traffic dynamics, see Ye and Yamamoto, Hussain et al., Liu and Song, Ghiasi et al., Zhou and Zhu, Hua et al. (36–41). For example, Ye and Yamamoto (36) investigated the impact of CAV DLs on overall throughput. The results show that setting a CAV DL had minimal effects on the overall throughput under free flow and congested conditions. The research suggests that an increase in CAV MPR increases the span of the free-flow regime. By analyzing the scatter in the fundamental diagram, Zhou and Zhu (40) found that an increase in the platooning probability of CAVs increased the overall throughput; however, the higher platooning probability also increased the scatter in the fundamental diagram for GPLs.

In addition to micro-simulation, analytical optimization models have been widely used to assess the impact of DL provision. For example, Hussain et al. (37) determined the optimal number of CAV DLs on a basic freeway segment that maximizes the overall throughput under mixed traffic conditions. The research found that at a traffic demand of 5,000 vphpl and aggressive car following (0.3 s while following a CAV and 1.2 s while following a TV), the allocation of two DLs of a three-lane directional basic segment is justified at CAV MPR at CAV MPR exceeding 76%. Ghiasi et al. (39) also proposed an analytical model to optimize the number of CAV DLs to maximize throughput under mixed flow conditions and found that at 100 % CAV MPR, with a 0.3 s time gap between CAVs and 5 DLs each 2.45 m (8 ft.) wide, the highest throughput achieved was 30,000 vph. Similarly, for other CAV MPR, narrowing the DLs' widths increased the number of DLs or GPLs, resulting in higher throughput. Benefits of narrowing CAV DL depends on the CAV time-gap setting, MPR, and overall demand levels.

Both the number and the placement of DL have a significant impact on traffic dynamics. For example, Hua et al. (41) investigated the effect of different CAV DL placement policies on freeway basic segment operations under mixed traffic comprising CAVs and TVs. This research considered discretionary lane changing and assumed that the lane change probability for TVs is 0.2, and for CAVs, it ranges from 0.2 to 1.0. Similar to previous findings, the research suggests that it is not advisable to implement a DL at low CAV MPRs. For a three-lane segment, the number of CAV DLs can only be increased if the CAV MPR exceeds 50%. The research also found that providing a DL will increase the average speed of the overall traffic when CAV MPR exceeds 40%. Interestingly, in the case of two CAV DL, the increase in lane changing probability of CAVs increased the average speed.

The studies reviewed herein provide valuable insight into the impact of CAV dedicated lanes under mixed traffic conditions on overall traffic performance. However, some limitations are evident regarding their impact on traffic flow and operations. First, few researchers compared the effect of continuous versus restricted access to DLs. Also, the influence of the various weaving lengths on mobility due to restricted access and egress needs to be investigated. Last, the magnitude of merging and diverging maneuvers on facilities may play a significant role in determining the best treatment for CAV's.


## 1.3 Methodology

The presence of AVs and CAVs in the traffic stream will result in new set of interactions between road users. Vehicles in which the driving task is still relegated to humans (CVs and TVs) will require drivers to adjust their response to the new driving patterns. Accordingly, drastic changes in traffic flow dynamics is expected to occur in the presence of CVs, AVs, and CAVs. It is paramount to realistically model the motion of such vehicles in a mixed driving environment and make sure they account for changes in CV and TV behavior, and the characteristic of each type of vehicle. This research selected SUMO (42), an open source microscopic simulation software. Our focus was to investigate the impact of AVs and CAVs on freeway throughput and CAVs dedicated lanes on traffic flow dynamics, using state-of-the-art motion models to replicate the behavior of each vehicle type. The advantage of using SUMO is its facility allowing users to pick and execute algorithms available in the open literature, without the need to be constrained by those provided by a private model vendor. Based on the comprehensive review of the literature in the previous sections, the necessary details of modeling both longitudinal and lateral controls for various vehicle types and the simulation setup are now explained.

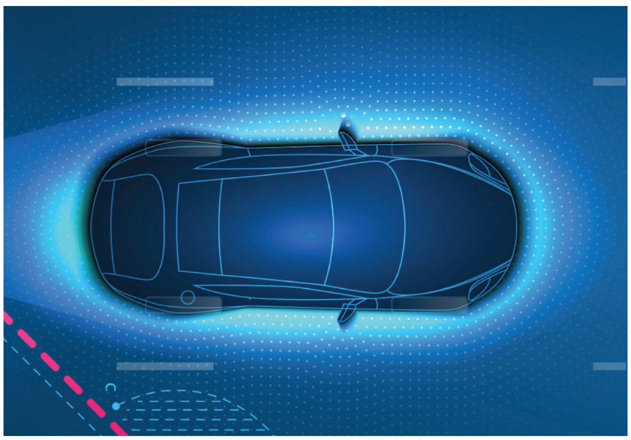
### Lateral Behavior Modeling

This study uses the current lane-changing model in SUMO (43) for all vehicle types. The model uses a 4-layered hierarchy and motivation to determine a vehicle's lane-changing behavior. These lane-changing levels are 1) Strategic change, 2) Cooperative change, 3) Tactical change, and 4) Regulatory change. Due to lack of experimental data on the lateral behavior of different vehicles, most parameters were kept at their default values. Only four parameters were modified in an attempt to reflect the anticipated response of these vehicles in the real-world. The modified parameters are lcStrategic (100 for CAVs and 10 for AVs and TVs), lcLookaheadLeft (1000 meters for all vehicles), lcAssertive (2 for all vehicles), and lcKeepRight (0 for AVs and CAVs, and 1 forTVs).

## Longitudinal Behavior Modeling

### *Traditional Vehicles (TVs)*

In this study, we apply the widely used Wiedemann (44, 45) psycho-physical model to formulate the behavior of regular vehicles in the traffic stream. The model asserts that the driver of a faster moving vehicle approaching a slower vehicle will initiate deceleration upon reaching their personal perception threshold. At any given moment a driver is assumed to be in one of the four modes: free driving, approaching, following or braking. Acceleration by mode is determined by the current speed, speed difference, space headway and the individual characteristics of driver and vehicle. The parameter values for TVs and CVs in this study are given below:



CC0 (Stand still distance) = 2 m,
CC1 (Headway time) = 1 s,
CC2 (Following variation) = 2 m,
CC3 (Threshold for entering following) = -8,
CC4 (Negative following threshold) = -0.35,
CC5 (Positive following threshold) = 0.35,
CC6 (Speed dependency of Oscillation) = 11.44,
CC7 (Oscillation Acceleration) = 0.25 m/s2,
CC8 (Standstill Acceleration) = 3.50 m/s2,
CC9 (Acceleration with 80 km/h) = 1.5 m/s2

The TVs desired speed distribution was estimated from field data, and follows a normal distribution with a minimum of 65 mph, maximum 85 mph, mean of 70 mph and a standard deviation of 2.9 mph.

### *Autonomous Vehicles (AVs)*

Autonomous vehicles use onboard sensors to monitor vehicles and other objects in their immediate environment. This constant monitoring of the environment enables AV's to swiftly cope with changes in driving and environmental conditions in the traffic stream. The reaction time attributed to autonomous vehicles, therefore, is basically sensing and system mechanical delays. The longitudinal behavior of such vehicles can therefore be represented by the acceleration framework developed by Xiao et al. (46). This integrated longitudinal behavioral model is explicitly divided into three modes. The first mode

is cruising (or speed control) mode and is designed to maintain a desired speed. This mode is active when there are no preceding vehicles within the detection range of the AV, which in this study is assumed to be 120 meters. The equation of motion for this mode is shown below.

$$a = k * (v_{des} - v) \tag{1}$$

Where: k is a parameter for determining the rate of speed error for acceleration, $v_{des}$ and v are the desired (a fixed value equal to the speed limit – assumes that AVs never violate the posted speed limit) and current speeds, respectively. This study uses the same k (0.4 $s^{-1}$) value proposed by Xiao et al. The second mode is car-following. The AV acceleration in this mode is a function of gap error and speed difference with the preceding vehicle. This mode is active when a preceding vehicle is within the AV detection range, the speed difference between the AV and its preceding vehicle is less than 0.1 m/s, and the distance error is below 0.2 m between the two vehicles. The calculated AV acceleration is:

$$a_n = k_1 * (x_{n-1} - x_n - d_0 - \tau * v_n) + k_2(v_{n-1} - v_n) \tag{2}$$

where

| | |
|---|---|
| $a_n$ | = acceleration of the subject AV ($n$), |
| $k_1, k_2$ | = feedback gain with values of 0.23 $s^{-2}$ and 0.07 $s^{-1}$, respectively – adopted from *(47)* |
| $x_{n-1}$ | = position of the preceding vehicle, |
| $x_n$ | = position of subject vehicle, |
| $d_0$ | = distance variable (includes the vehicle length), |
| $\tau$ | = desired time-gap in seconds, a value of 1.5 sec adopted from *(48)*, |
| $v_n$ | = speed of subject vehicle, |
| $v_{n-1}$ | = speed of the preceding vehicle |

If the parameter $d_0$ in the above equation equals the length of the vehicle, the desired gap becomes zero at standstill. To prevent rear-end collisions, $d_0$ was formulated as a function of vehicle speed to provide additional space buffer between vehicles at low speeds. Depending on the speed, the value of $d_0$ can be obtained as shown on the right:

$$d_0 = \begin{cases} 5 & \text{if } v \geq 15m/s \\ \frac{75}{v} & \text{if } 10.8 \leq v < 15m/s \\ 7 & \text{otherwise } v < 10.8m/s \end{cases} \tag{3}$$

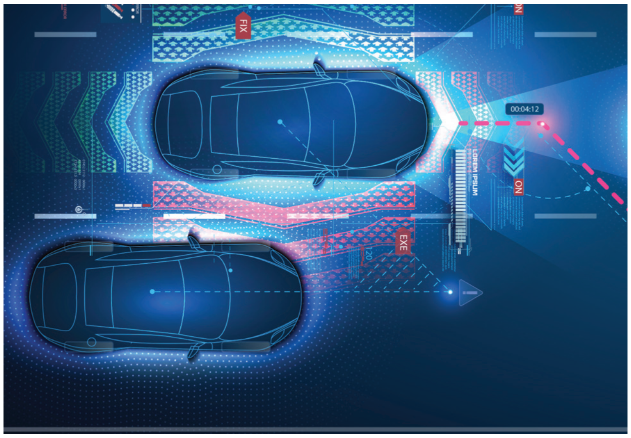
The third mode is the gap-closing mode. This mode is applied when the gap between vehicles is greater than twice the desired gap and the preceding vehicle is within the detection range of the AV. The purpose of this "approaching" mode is to reduce the speed difference and decrease the gap between the vehicles. The function for this model is the same as that of the car-following with different parameters. The values for $k_1$ and $k_2$ are 0.04 $s^{-2}$ and 0.8 $s^{-1}$ in the approaching mode, respectively.

## *Connected-Autonomous Vehicles (CAVs)*

CAVs obtain information about their surroundings using onboard communication and sensing equipment. Critical driving decisions are constantly made based on the line-of-sight and intercepted signals from other connected vehicles/infrastructure. The addition of communication capability enables CAVs to swiftly receive this information, be certain of the motion of other vehicles, respond to driving changes of vehicles in their vicinity and the traffic stream almost instantaneously (mechanical delay and communication latency make up the essential parts of the delay for CAVs). This research assumes that any CAV is able to communicate with other CAVs in its vicinity and CAVs are capable of forming platoons at shorter following time gaps. Considering all these capabilities, a deterministic acceleration modeling approach best represents this environment. This study adopts the works of Xiao et al. (47), Nowakowski et al. (48), Milanes and Shladover (49) and Xiao et al. (50) for modeling CAV movements. This framework confines the operations of a CAV to three different modes:

- A cruising mode is tasked to maintain either a user-defined desired speed or posted speed limit in absence of a preceding vehicle;
- A car-following mode to maintain a fixed time gap with its predecessor in a car-following scenario;
- A gap-closing mode tasked with controlling the transition from the cruising mode to car-following mode when a CAV approaches its leader from a long distance.

The cruising mode for CAVs is treated similarly to AVs. It is activated when there are no preceding vehicles in the range covered by the sensors or when the time-gap with the leading vehicle is larger than 2 seconds. However, the car-following mode for CAVs is quite different from that for AVs and is triggered when the gap and speed deviations are simultaneously smaller than 0.2 m and 0.1 m/s, respectively. Vehicle speed under this mode is calculated from the vehicle speed calculated in the previous time step, as well as the gap error in the previous time step and its derivative. Detailed calculation for the CAV car following mode are provided on the next page.



The third, gap-closing mode, regulates the transition from the cruising mode to the car following mode when a CAV approaches its leader from a long distance. This mode is triggered when the time-gap is less than 1.5 seconds. Under this mode the mathematical formulation of speed is identical to that of the car-following mode. However, the values for kp and kd parameters are 0.005 s-1 and 0.05, respectively.

$$v_{n,j} = v_{n,j-1} + k_p * e_{n,j-1} + k_d \frac{(e_{n,j-1} - e_{n,j-2})}{\Delta t} \tag{4}$$

The gap error $(e_{n,j-1})$ in equation 4 is determined as:

$$e_{n,j} = x_{n-1,j-1} - x_{n,j-1} - L - d_0 - \tau * v_{n,j-1} \tag{5}$$

where

| | |
|---|---|
| $e_{n,j}$ | = time gap error in the current time step $(j)$, |
| $e_{n,j-1}$ | = time gap error in the previous time step, |
| $k_b, k_d$ | = feedback gain with 0.45 $s^{-1}$ and 0.0125 from *(46)* and *(50)* , respectively, |
| $x_{n-1,j-1}$ | = position of the preceding vehicle in the previous time step, |
| $x_{n,j-1}$ | = position of subject vehicle in the previous time step, |
| $d_0$ | = spacing margin, |
| $\tau$ | = desired time-gap in seconds, a value of 0.6 sec adopted from *(51)* , |
| $v_{n,j}$ | = speed of subject vehicle, |
| $v_{n,j-1}$ | = speed of subject vehicle in the previous time step, |
| $L$ | = vehicle length (5 meters), |

The dynamic spacing margins for CAVs $d_0$ is a function of vehicle speed as follows:

$$d_0 = \begin{cases} 0 & v \geq 10m/s \\ -0.125v & v < 10m/s \end{cases} \tag{6}$$

## Simulation Experiments Setup

The simulation runs conducted as part of this project can be classified into two groups covering mixed and segregated flow conditions. Under the mixed flow condition, three freeway segments, 3 miles in length as shown in Figure 1.1 were simulated to investigate the impact of AVs and CAVs on freeway segment throughput. Different market shares of CAVs and AVs were simulated covering the 0%-100% range in increments of 20%. The simulation setup for dedicated lane is more involved and is detailed in the following two paragraphs.

The dedicated lane (DL) simulation design proceeded in two steps. The first was to identify the appropriate CAV MPR range over which having a dedicated CAV lane would be feasible. This part was carried by simulating individual basic, merge and diverge freeway segments. Within that feasible range, a simulated facility, six miles in length, modeled after the EB I-540 facility in Raleigh, North Carolina focused on the combined mobility effects of the DL access and egress strategies, and the effects of merging and diverging demands. A schematic of the segments and facility is also shown in Figure 1.1.

Two DL scenarios were modeled: a) restricted access where CAVs are mandated to use the CAV DL and b) unrestricted access, where CAVs can use any lane; non-CAV's , however, are confined to the general purpose lanes in both

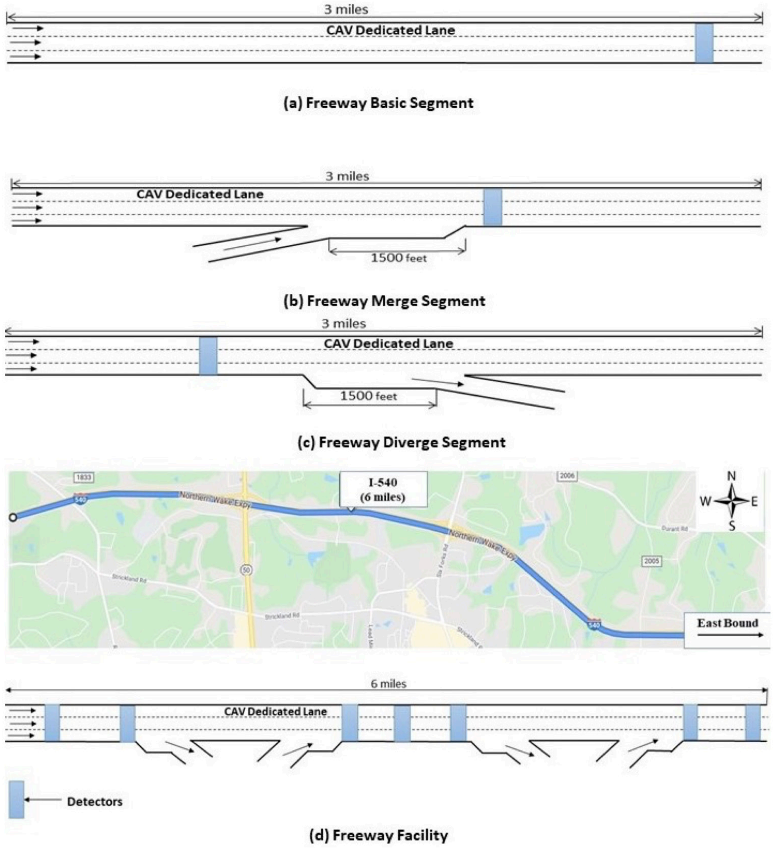



**Fig. 1.1** Geometric characteristics of modeled a) basic b) merge c) diverge segments d) I-540 facility

scenarios. In the restricted access or egress case, CAVs may enter or exit from the DL within 3,000 ft or 4,500 ft from the ramp gore, respectively. Furthermore, the setup considered three mainline demand values of 1,000 veh/hr/ln, 1,800 veh/hr/ln and 3,000 veh/hr/ln. Finally, in order to evaluate the effect of merging and diverging traffic, ramp volumes were set at 5%, 15% and 25% of the mainline demand. Six replications per scenario were made, yielding 3,402 facility runs (3 demand levels × 3 access strategies × 3 ramp demands × 21 MPR × 6 replications).

As shown in Figure 1.1, simulated flow detectors were placed at key segment and facility locations in order to identify the critical throughput associated with each set of experiments. Runs of one hour duration using the above stated flow rates were conducted.


# 1.4 Analysis and Results

In this section, we first report the impact of introducing AVs and CAVs on freeway segments' throughput in a mixed traffic environment. This investigation sheds light on the potential impact that equipped vehicles will have on the overall throughput of freeway segments as a function of their MPR. Subsequently, we report the impact of CAV dedicated lane on freeway segment throughput. This analysis aims at identifying the range of CAV market share that would justify lane reservations for such vehicles. Next, we explore the impact of CAV dedicated lane on the section of I-540 facility with the aim of unraveling the combined effects of demand, MPR, ramp volume, and DL access policies for merging and diverging traffic. The last section uses travel rate and the fundamental diagram scatter of speed vs flow simulation data to quantify the impact of said factors on the mobility when applied to a real-world facility.

## Segment Analysis

This analysis is conducted at the segment level, and uses three hypothetical freeway segment types namely basic, merge, and diverge segments.

## Longitudinal Behavior Modeling

### *Basic Segment Throughput*

Figure 1.2 shows a heat map of the maximum throughput per lane for the basic segment shown in Figure 1(a) without a dedicated lane. The vertical axis shows the CAV MPR and the horizontal axis shows the MPR for AVs. Visual observations of the heatmap reveal three emerging patterns. First, moving along the horizontal axis with increasing AV MPR, we observe a decrease in throughput up to a certain AV MPR and increase in throughput beyond certain MPR. This is believed to be a result of the nature of interaction between AVs and TVs – as the interaction increases--- the throughput of the segment decreases. Second, moving down along the y-axis, we observe systematic increases in throughput as the MPR for CAVs increase. Thirdly, the diagonal movement from top right corner to bottom left corner shows that the throughput increases as the market share of AVs are reduced and added to the market share of CAVs. All in all, this shows that AV effects are generally similar to TVs, but that the combination of automation and connectivity (CAVs) can close to double the TV capacity at very high MPRs.

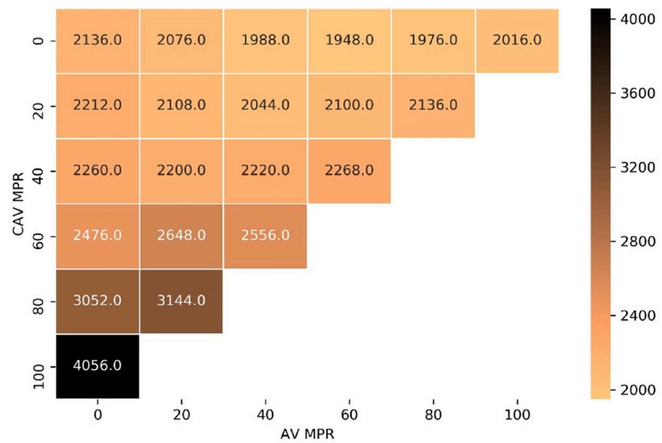



**Fig. 1.2** Maximum lane throughput for basic segment while varying CAV, AV and TV MPRs in a mixed traffic environment

## *Merge Segment Throughput*

Figure 1.3 shows the heat map of maximum lane throughput for the merge segment shown in Figure 1(b) without the dedicated lane. Similar to the basic segment findings, three distinct patterns emerge for the merge segment as well. First, an increase in throughput is indirectly related to AV MPR – the higher the MPR the lower the overall throughput of the merge segment. Second, the increase in throughput is directly related to the MPR of CAVs. The higher the MPR of CAVs the higher the throughput. Lastly, as shown by the outer diagonal cells of the heatmap, the more AVs are replaced in the traffic stream by CAVs the higher the throughput.

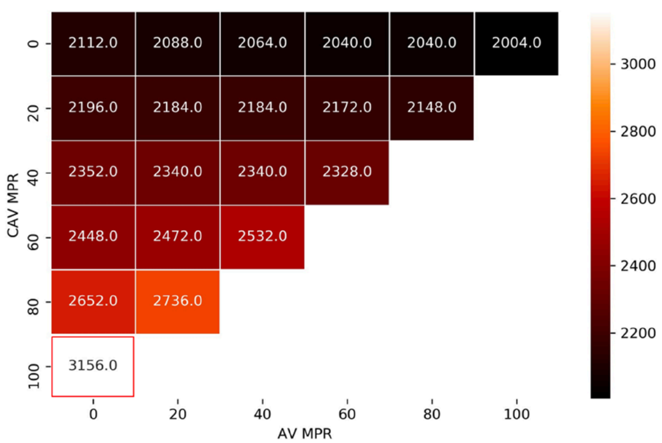



**Fig. 1.3** Maximum throughput per lane for merge segment varying CAV, AV and TV MPRs in a mixed traffic environment

### *Diverge Segment Throughput*

Figure 1.4 shows the heat map for the diverge segment portrayed in Figure 1(c). Similar patterns that were evident for the basic segment can be observed for a diverge segment as well. The rate of throughput increase, however, appears to be lower than that for the basic segment.

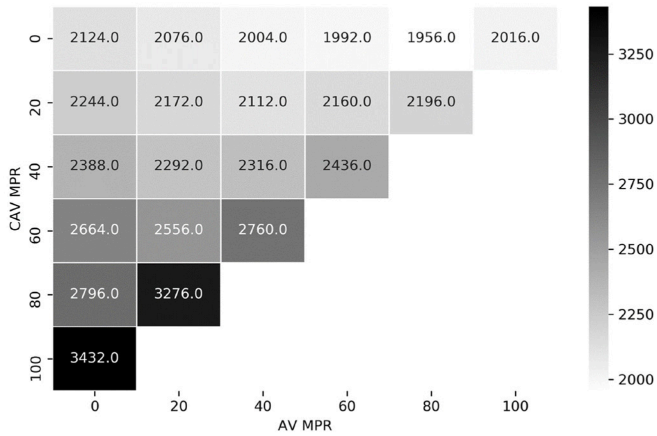



**Fig. 1.4** Maximum throughput per lane for diverge segment varying CAV, AV and TV MPRs in a mixed traffic environment

## Segregated Traffic Stream

This section provides the results and analysis for scenarios that assume a reserved lane for CAVs is in place.

### *Basic Segment Throughput*

Figure 1.5 shows a heat map of the difference in maximum throughput per lane between a basic segment with a DL and one without, i.e. with mixed traffic flow on all three lanes. It summarizes the results from 21 scenarios, varying MPR of CAVs, AVs, and TVs. For comparison purposes, maximum throughput (in vphpl) of basic segment for homogeneous traffic (100% MPR) was found to be 2,150, 2,020,

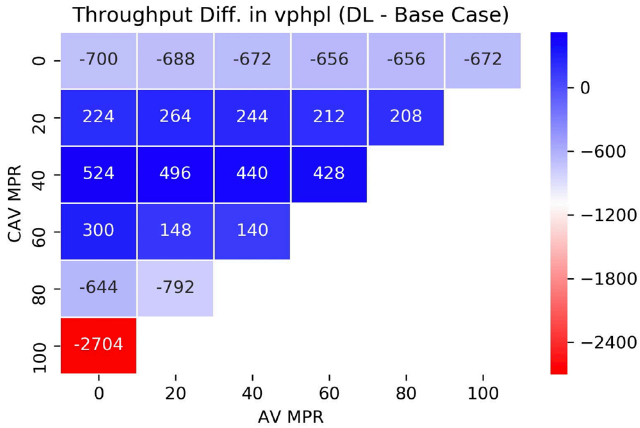



**Fig. 1.5** Maximum throughput differential (v/hr/lane) for basic segment while varying

and 4,050 for TVs, AVs, and CAVs, respectively. Visual observations of the heatmap cells indicate improvements due to a CAV DL when their market penetration is in the range of 20% to 60%. Outside this range, dedicating a CAV-only lane will significantly reduce the segment throughput. These MPRs represent conditions with either very low levels of CAVs on the DL (generating congestion on GP lanes and free flow on the DL) or very high ones (generating congestion on DL lane and free flow on GP lanes), respectively.

The amount of throughput gain within the feasible regime is not constant. The highest improvements are observed at the 40% CAV level, followed by 20% and lastly at 60%. The introduction of AVs within the improvement interval results in lowering the throughput level. This is mainly due to the fact that the presence of multiple types of vehicles in the traffic stream will ultimately result in lower overall segment throughput. The resulting degradation in performance is associated with the percent of the AVs in the traffic stream, which is in line with the previous findings indicated in a previous study (3).

### *Merge Segment Throughput*

Two policies, one optional and one requiring mandatory use of the DL by CAVs are investigated in the context of merge segments. In the mandatory case, CAVs entering the facility from the on-ramp have 4,500 feet to enter the DL. This case, as shown in Figure 1.6(a), indicates that the MPR at which the DL becomes feasible is identical to that for the basic segment (20% - 60% CAVs). The amount of improvement, however, is significantly lower than that observed for the basic segment. The maximum throughput gain was also detected at 40% CAV MPR. To reiterate, in neither scenario, non-CAVs are only allowed to operate in the two general purpose lanes.

Results of the case where CAVs are not mandated to use the DL (Figure 1.6b) show that the range at which improvement is observed remains between 20% and 60% MPR of CAVs, with maximum improvement occurring at 40% CAVs. The amount of improvement, however, is quite different compared to the limited access case. At low MPR range (20% CAVs) throughput is dramatically lower, while at the 40% and 60% CAVs MPR it is significantly higher than the limited access case. Under this policy, some CAVs will opt not to use the DL, which when compounded with the low CAV demand results in negligible throughput improvement as observed in the 20% CAVs MPR range. Optional use of the DL by CAVs is beneficial when the DL demand is close to its operating capacity with 40% and 60% CAVs MPRs in Figure 6b.

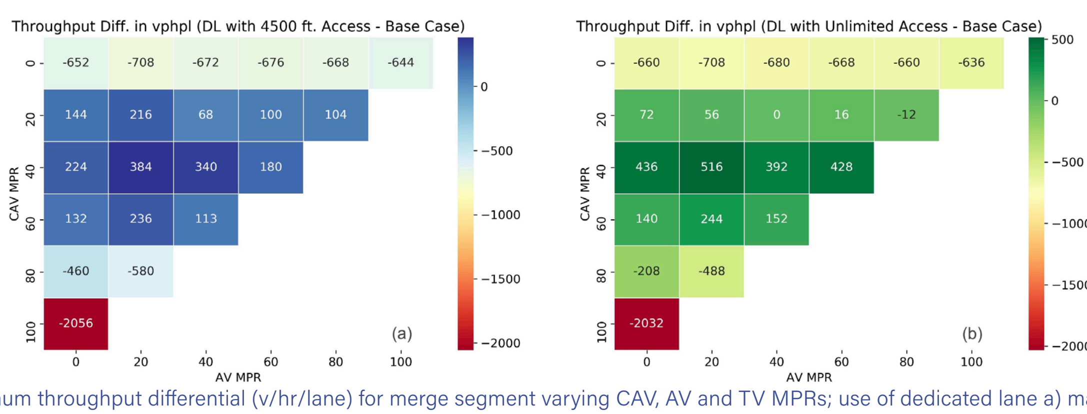



**Fig. 1.6** Maximum throughput differential (v/hr/lane) for merge segment varying CAV, AV and TV MPRs; use of dedicated lane a) mandatory and b) optional

## *Diverge Segment Throughput*

Figure 1.7 shows the results for the freeway diverge segment. Visual observations of the figure reveal improvement regions similar to those found for the merge and basic segments (20%-60% MPRs). Heat maps for both policies (restricted and unrestricted egress lengths) show similar patterns to the other segment types. First, the maximum throughput gains occur at CAVs MPR of 40%. Second, the introduction of AVs into the traffic stream seems to improve throughput under both policies, and the magnitude of the improvement is directly related to the share of these vehicles in the traffic stream. Third, loosening the mandatory use of DL when CAV MPRs are in the 20% range results in a lower improvement of the throughput compared to the scenario with the restriction in place.

In summary, the segment analysis has confirmed that for a three-lane segment, the feasibility of dedicating a single CAV lane is likely to start at an MPR of 20% and up to 60%. Outside that range, a CAV-only lane will yield severe congestion on either the dedicated (at high CAV MPR) or the general purpose (at low CAV MPR) lanes.

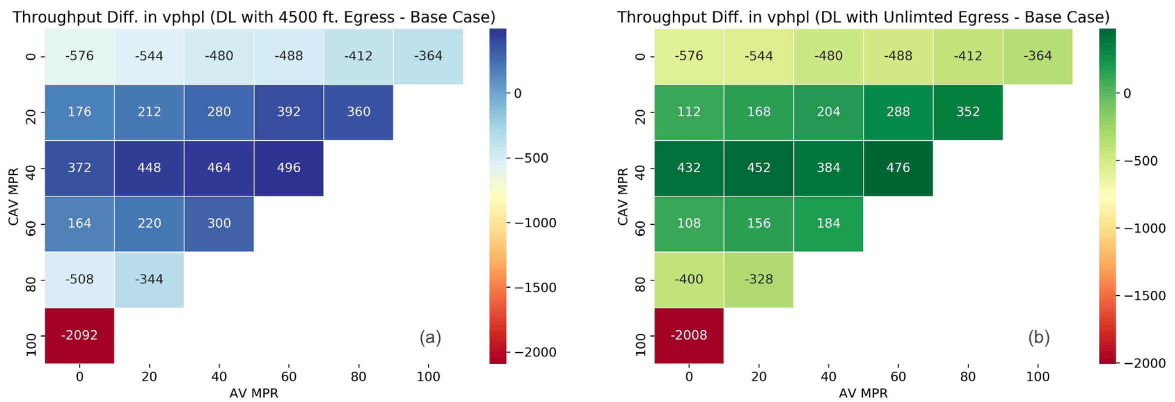



**Fig. 1.7** Maximum throughput differential (v/hr/lane) for diverge segment varying CAV, AV and TV MPRs; use of dedicated lane a) mandatory and b) optional

## *Facility Analysis*

This section provides the results for a segment of EB I-540 facility with the primary goal of exploring the impact of demand, MPR, ramp volume, and three policies regarding the use of DL by CAVs. Two measures of performance are reported: a system level travel rate (in minutes/mile) distribution approach and an OD movement travel rate segregated by vehicle class. The rationale for using travel rate is to also distinguish between through, entering and exiting vehicle performance on the facility, who travel over different distances. Relying on the segments' findings, this analysis focused on a subset CAV MPRs from 20% to 60%. All runs are based on a mainline volume of 1,800 vph/lane.

### *Travel Rate Distribution*

Figure 1.8 depicts the travel rate distribution (TRD) for the entire population of vehicles in the traffic stream across all scenarios. Each subplot represents a unique MPR composed of CAVs, AVs, and TVs. There are nine such distributions within each subplot for specific combinations of ramp volumes (there are 3) and access policy for the dedicated lane (there are 3).

At the 20% CAV MPR, three distinct clusters of TRD associated with different ramp volumes (5%, 15%, and 25%) emerge. Visual observations of each distribution within the cluster reveal significant overlap among them, show substantial impact from the ramp volumes, and much lower impact due to the CAV DL access policies. Under this lower CAV MPR the 5% ramp volume distributions have two dominant modes: a lower mode at around 1 minute/mile and an upper mode at approximately 3-4 minutes/mile. Those are mostly reflective of CAV travel rates on the DL and the non CAVs on the two general-purpose lanes, respectively. The TRDs for the 15% ramp volumes also have two prominent modes: one at around 1 minute/mile and the other at about 6 minutes/mile. The first mode also exists with the 25% ramp volume but the second mode is nonexistent. Segregation of distributions based on the ramp volumes persisted at the 40% CAV MPR. The multimodality is evident in a couple of the scenarios but is not very clear in others. At the 5% ramp volume, access policies for DL do not significantly impact the TRD. However, at higher ramp volumes (15% and 25%) mandating the CAVs to use the DL and providing a 3,000 access zone will have negative travel rate consequences. Those two distributions peel-off from other distributions in their class and are shifted to the right, portraying the worsening of travel conditions on the facility.

Visual inspections at the 40% CAVs MPR exhibit a lower spread of the TRD compared to the 20% case. Furthermore, increasing AV MPRs results in lowering the spread of the TRD as more human drivers are swapped by AVs that are traveling at a fixed desired speed. At this CAV level, it becomes obvious that the ramp volume and policies regarding the use of the DL have a significant impact on the facility congestion.

The third row of subplots in Figure 1.8 show the 60% CAV MPRs. Within each ramp volume group, the best travel rate-producing scenario occurs when DL use is optional (RV5AELx, RV15AELx, and RV25AELx). This clearly shows that at high CAV demands removing the mandate on CAVs to use the DL results in significant improvements. Similarly, the distributions with the highest spread are those where CAVs are constrained to the DL and are given 3,000 ft to merge/diverge to/from the facility. In the middle lies distributions where CAVs are mandated to use the dedicated lane and are given 4,500 ft to conduct access/egress maneuvers to/from the DL.

Thus, for a given DL access policy, one can observe that ramp volume significantly impacts travel rates. Compare, for example, the distributions at RV5AELx with RV15AELx, and RV25AELx. The effect of increasing AV MPR in the traffic stream is mixed at this level of CAVs. At a ramp volume of 5%, increasing the AV MPR decreases the spread for both the unrestricted and restricted (4,500 ft access/egress lengths) use of the dedicated lane. However, it yielded the opposite effect on the scenario with restricted use of dedicated lane with the 3,000ft access/egress length. At both the 15% and 25% ramp volumes, however, the increase of AVs market share

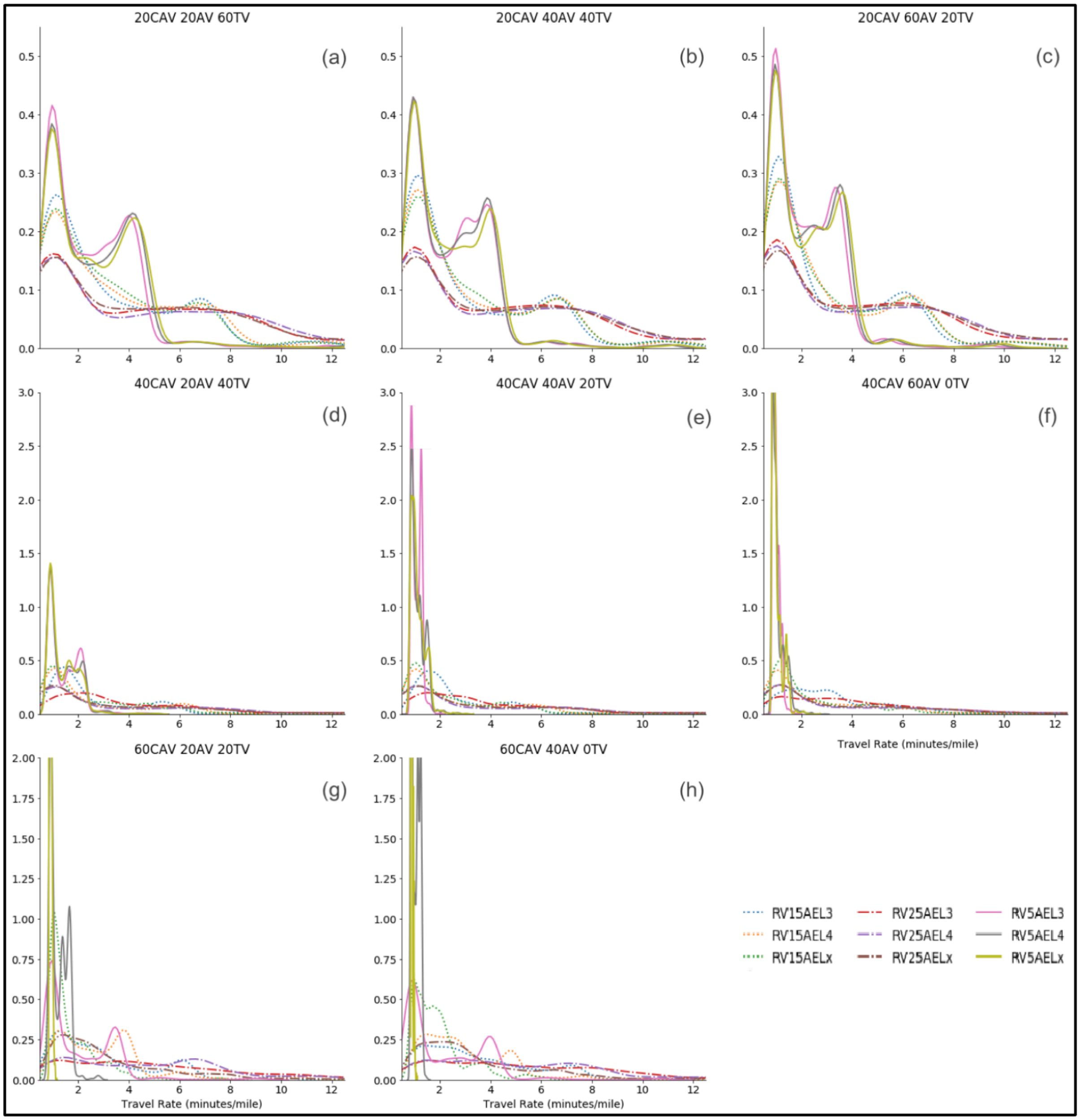



**Fig. 1.8** Travel rate distribution for I-540subsection showing the impact of ramp volume, and DL access policy for different CAVs, AVs, and TV MPRs.

Legend: RV: Ramp Volume 5%, 15%, and 25% of mainline flow); AEL3: mandatory use of DL with Access/Egress Length of 3,000 ft, AEL4: mandatory use of DL with Access/Egress Length of 4,500 ft; AELx: continuous DL access

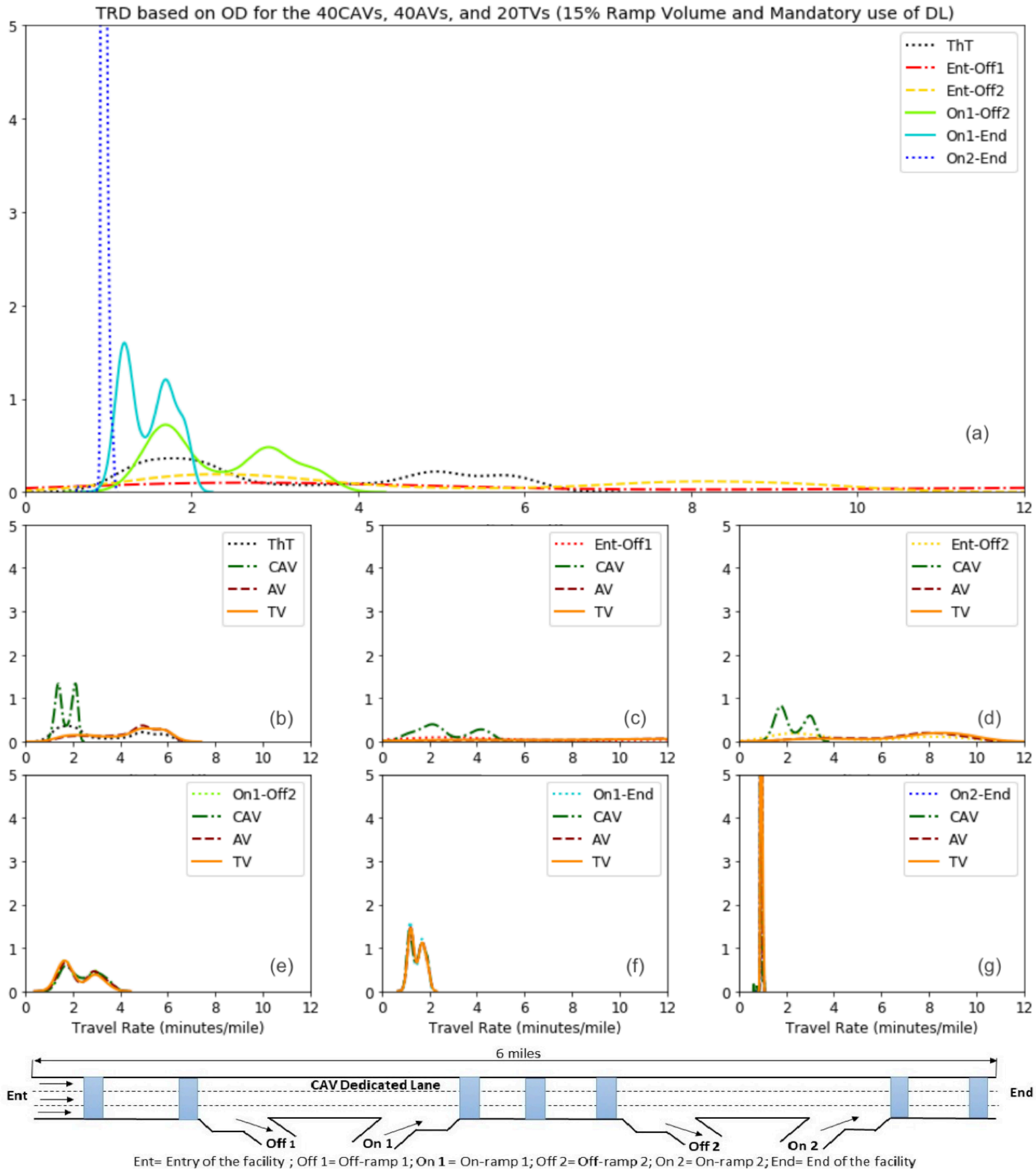



**Fig. 1.9** OD based travel rate distribution with 15% ramp volume and mandatory use of DL at 40% CAVs, 40%AVs, and 20% TVs, segregated by vehicle type

degrades the travel rate conditions significantly for all the dedicated lane access policies.

While the TRD plots shown in Figure 1.8 provide an aggregate picture of how different factors impact travel rates, segregating trips based on OD and vehicle type is likely to shed more insight into the trends observed. In this analysis, we fixed the CAV MPR to 40% and ramp volumes to 15% of mainline demand.

Two scenarios, one representing the mandatory DL use policy and the other representing the optional use of the DL are then contrasted. Figure 1.9a and Figure 1.10a display the segregated TRD by OD and dedicated lane access policy, respectively. For the modeled facility, a total of 6 origin-destination pairs are shown in the schematics above the figure. Figures 1.9b to Figure 1.9g and Figure 1.10b - Figure 1.10g break down each OD distribution shown in Figure 1.9a and Figure 1.10a into TRD by each vehicle type.

Comparison of Figure 1.9a and Figure 1.10a show that restricting CAVs to the DL has negative consequences on the TRDs for all ODs as evident by a distribution shift to the right and an increase in their range. This observation holds for all vehicle classes when comparing the associated subplots of Figure 1.9b- Figure 1.9g on the one hand, with Figure 1.10b - Figure 1.10g on the other. Another important observation is that the TRDs having a merge origin are very similar across vehicle types (Figure 1.9e-Figure 1.9g and Figure 1.10e-Figure 1.10g). However, the through and diverging OD distributions (per Figures 1.9b-Figure 1.9c and Figures 1.10b-Figure 1.10c) show significant variation in their TRD dependent on the vehicle type. The TRD of CAVs exhibit lower spread and shifts leftwards, indicating lower travel rates than TVs and AVs. The poor TRDs for AVs and TVs are mainly due to perturbations experienced during merging and diverging vehicles to and from the traffic stream. As such, their TRDs are on average, higher than those for CAVs.

### *Speed Flow Scatters*

The fundamental diagram analysis focuses on the observed speed-flow relationship for various vehicle classes and their OD paths. It explores the impact of factors such as MPR, dedicated lane use policy, and ramp volume on lane-based congestion patterns. This analysis is limited to a subset of scenarios where the dedication of a lane for CAVs is justified based on the throughput results shown earlier.

At the 20% CAVs scenario, top row in Figure 1.11, two patterns emerge on the DL. In the first pattern, the data points form a straight line at around 70 mph speed with almost no scatter. The second pattern shows significant spread and is bounded by the 60-70 mph region. The first pattern is related to the optional use of CAV DL scenarios. Under this policy, CAVs may choose to use the general-purpose lanes throughout the facility or use the DL as they see fit. This flexibility, in turn, results in balanced and smooth merge and diverge maneuvers of vehicles to and from the DL and thus minimizes the perturbations on the DL as portrayed in Figure 1.11a.

The second pattern is related to the mandatory use of DL scenarios where CAVs are limited to use the DL and carry out the merge and diverge maneuvers within a specified distance from the ramps' gore. These maneuvers result in significant degradation of traffic conditions on the DL as witnessed by the scatter in the fundamental diagram for the lane. Observations in Figure 1.11b and Figure 1.11c reveal that the conditions on the two general-purpose lanes remain fairly

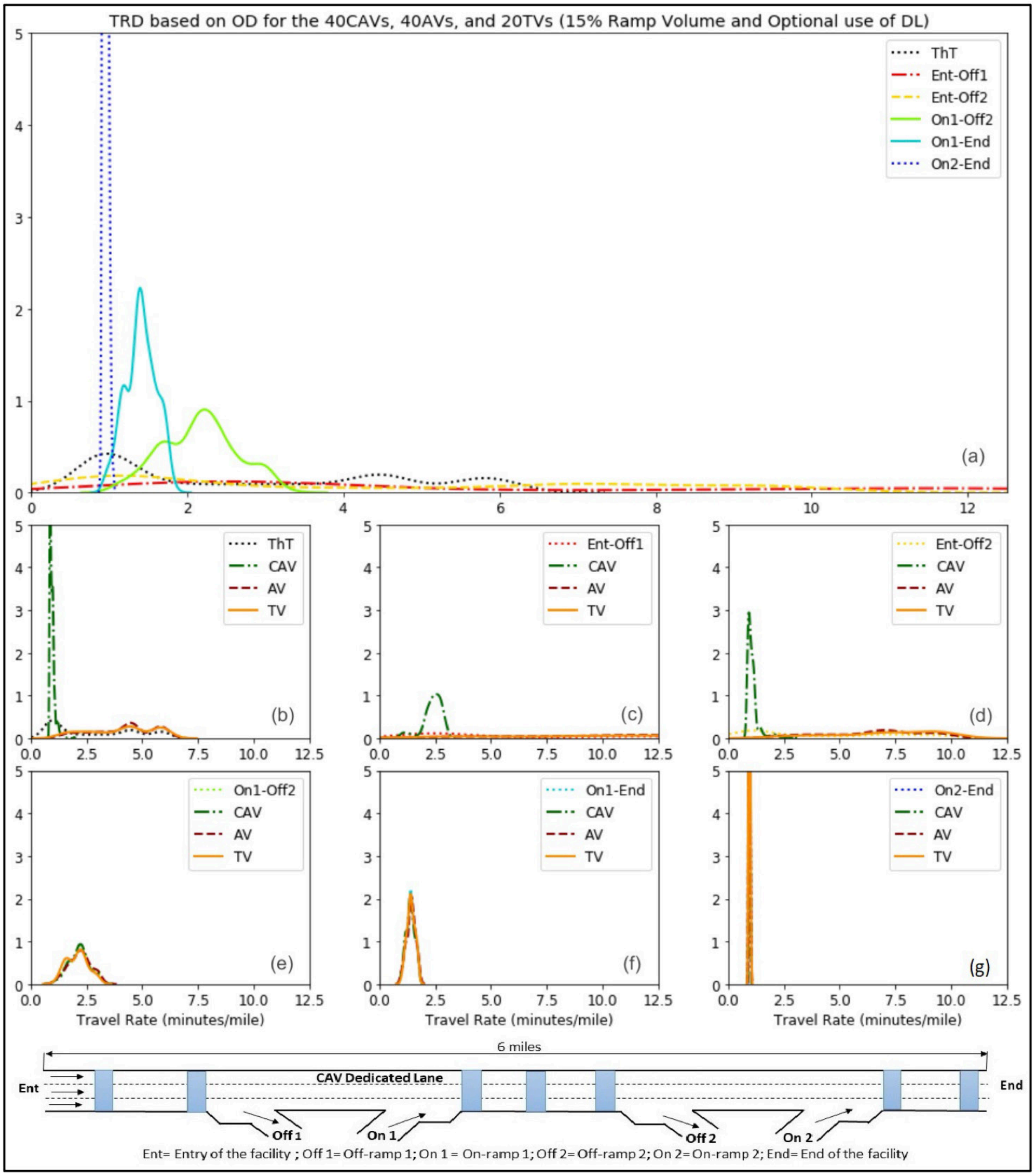



**Fig. 1.10** OD based travel rate distribution for 15% ramp volume and optional use of DL at the 40% CAVs, 40%AVs, and 20% TVs segregated by vehicle type

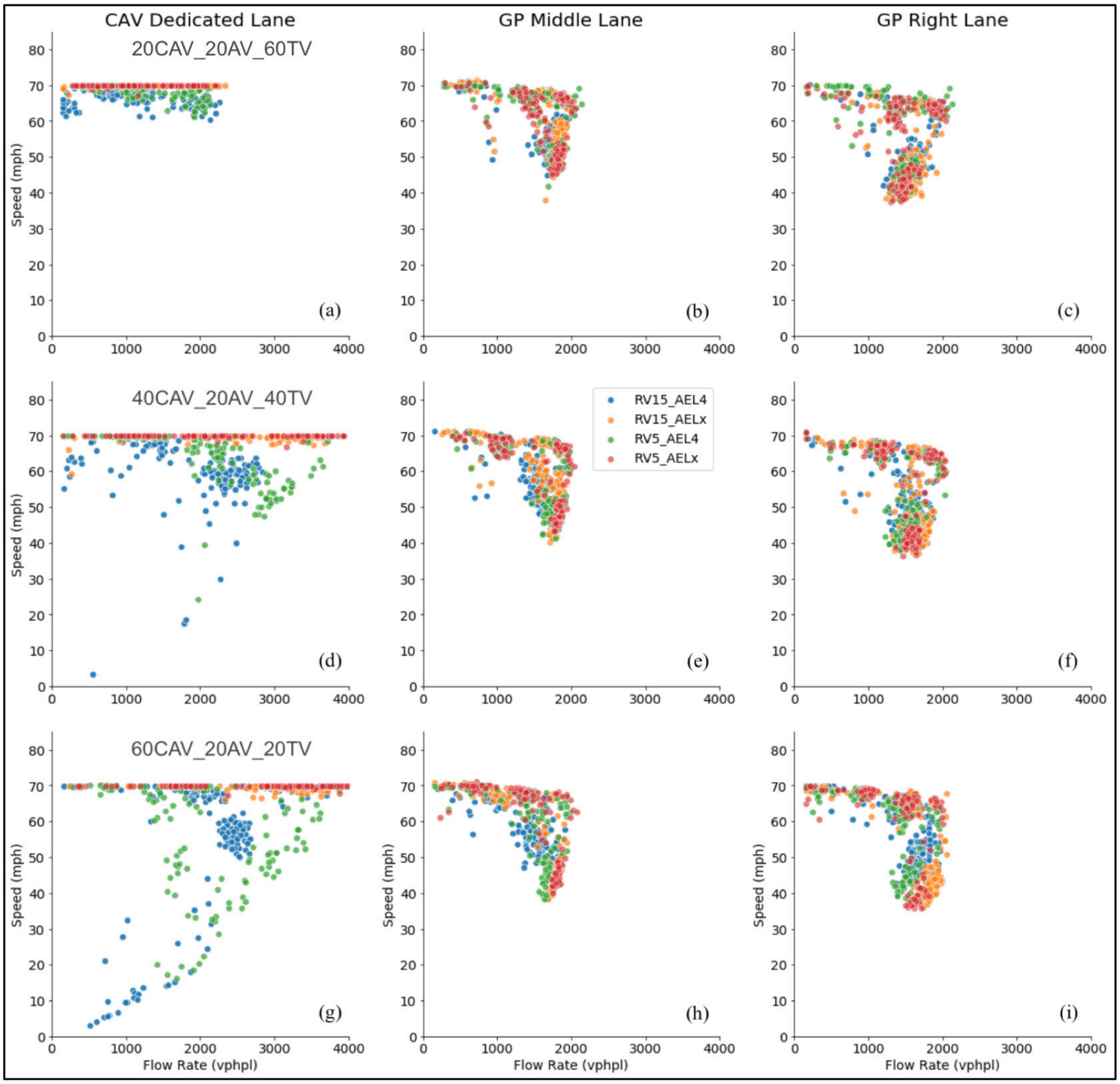



**Fig. 1.11** Speed flow relationships for different DL use policy and MPRs
Legend: AEL4: mandatory use of DL with Access/Egress Length of 4500 ft,; AELx: Optional use of DL);
Ramp volume (RV: Ramp Volume 5, 15, and 25%), and MPR (20% CAV, 40% CAV, and 60%CAV)

constant with changes in the ramp volumes and DL policies. These observations provide insights into each lane separately and indicate that at the 20% CAVs MPR traffic conditions on the DL are significantly impacted by the DL policy, and not necessarily by the ramp volume.

At the 40% CAVs, the two previously identified patterns still exist in the DL. In this scenario, however, the scatter of the data points are significantly higher than that of the 20% MPR. At this CAV level, it appears that both the DL policy and ramp volume impact the traffic conditions on the DL. First, under optional use of DL, a slight scatter can be observed in the DL fundamental diagram at 15% ramp volume, where it is non-existent at the 5% level. This phenomenon occurs at flows higher than 2,000 vphpl.

Second, significant scatter in the fundamental diagram is observed for the scenarios where CAVs are forced to use the DL. The degradation is directly proportional to the ramp volume – the higher the more the scatter in the fundamental diagram. Furthermore, it can be observed that under the limited use of DL, the CAV lane becomes congested at lower flows, the higher the ramp volumes. The mixed-flow lanes exhibit similar characteristics detailed for the 20% CAVs.

Finally, at the 60% MPR of CAVs, the DL shows similar patterns as was commented on for the 40% CAVs. The general purpose lanes, however, show that under the mandatory use of CAV DL, the scatter in the fundamental diagram is higher. Similar observations can be made for higher ramp volumes compared to the lower ones.

# 1.5 A Planning-Level Capacity Calculator

The previous analysis has focused on the role of microsimulation in assisting decision makers regarding expected throughput and speed flow relationships at the lane level. These methods may not be suitable at an early stage for planning level decisions regarding expected link capacities under both mixed and dedicated lane conditions. This section addresses concerns at the high level. It presents a simplified, Excel-based, capacity calculation method for freeway segments servicing CAVs, AVs and TVs. It is intended to highlight two items that many studies do not consider: that capacity is dependent on the market penetration of vehicle types in the case of mix traffic and that capacity is very sensitive to the user or OEM gap settings in the AV or CAV. This is important since most research studies usually pick a gap and produces results that are only applicable for that gap setting. Following the analysis previously presented in this chapter, two versions of the calculator are presented, one assuming mixed flow of AVs, CAVs and TVs operating in general purpose lanes, and a second version where one or more lane is dedicated to CAVs to take advantage of their communication capabilities to operate in platoons. Connected vehicles (CVs) are assumed to operate similar to traditional vehicles (TVs) and that their benefits derive primarily at the macro level, for example in avoiding incident locations, or congested lanes when receiving alerts within range. Finally, the presented capacity values are targeted for basic segments. In the event there is considerable merge or diverge maneuvers, the prevailing capacity is expected to be slightly lower than the calculator reports.

## Inputs to Calculator

Two types of inputs are required. One is related to vehicle characteristics and attributes, and the second is the tested market penetration rate (MPR) for CAV, AV and TV in the traffic stream. Figure 1.12 shows the first set of inputs by vehicle type. We describe the key inputs next.

***Market Penetration Rates:*** These simply are the percentages of CAVs, AVs and TVs to be analyzed in the capacity calculator.

***Time gap:*** represents the clear time gap between two consecutive vehicles of the same class. A range of values between an upper and lower bound can be specified for AV and CAVs. As one would expect, CAVs having both autonomy and connectivity features are expected to be able to safely operate with lower time gaps when following other CAVs in a platoon. Time headway between two vehicles, on the other end, is the sum of both the time gap and the time it takes the vehicle length to travel at the designated speed.

***Max platoon size:*** this represents the maximum length of a platoon, which operates at a given time gap between the two bounds. Platoons are separated from each other by an inter-platoon headway which is equivalent to the selected platoon time gap multiplied by a multiplier (1.5 times value in Figure 1.12). One would expect that longer platoons will generate higher mainline capacity, but lower merge capacity due to the paucity of large gaps.

***Other Inputs:*** The capacity for TVs is taken from the US HCM, Version 6 and is dependent on the designated input free flow speed, which is also an input for all vehicle classes. Finally, the number of total and CAV dedicated lanes are also entered in the calculator.

Figure 1.13 is the input MPR for different vehicles types. These values are used to weigh the various vehicle type capacities when operating in the same lane(s). For example, in the case of mixed traffic on general purpose lanes, the following sample weights are given for pairs of vehicles following each other: CAV (following)→CAV= .3×.3 = .09 and in this case CAV capacity applies;
CAV→TV = .3 ×.4= 0.12.

| DATA INPUTS IN RED TEXT (ONLY) | | | |
|---|---|---|---|
| **User DATA Entries** | | | |
| | **CAV** | **AV** | **TV** |
| **Average Free Flow Speed (mph)** | **70** | **70** | **70** |
| **Average Vehicle Length (ft)** | **15** | **15** | **15** |
| **Time Gap Upper Bound (seconds)** | **0.9** | **2.1** | |
| **Time Gap Lower Bound (seconds)** | **0.5** | **1.4** | |
| **Max Platoon Size (vehicles)** | **10** | | |
| **Inter Platoon Headway Multiplier** | **1.5** | | |
| **Average Headway for TV (Seconds)** | | | **1.50** |
| **Total Number of Lanes** | | **3** | |
| **Number of CAV Exclusive Lanes** | | **1** | |

**Fig. 1.12** Calculator Inputs

In this case, CAV cannot communicate with the lead TV vehicle and simply is limited to the use of its autonomous features for car-following thus the AV capacity is used; TV→ Any Vehicle always uses TV capacity, regardless of lead vehicle type. The sum of all weights accounting for all vehicle pairs will add up to one. So for the input shown in Figure 1.13, CAV capacity applies 9% of the time, AV capacity applies 41% of the time, and TV capacity applies 40% of the time.

| Enter Market Penetration Rate (%) | CAV | AV | TV |
|---|---|---|---|
| | 30 | 30 | 40 |

Fig. 1.13 MPR Inputs for Calculator

## Calculator Outputs

In this section we present the capacity estimates under both mixed flow and CAV dedicated lane conditions. The internal model computations are not shown for ease of reading and following.

### *Output for Mixed Traffic on GP Lanes*

Figure 1.14 shows a screenshot of the predicted per lane capacities for the range of gap settings applicable to both CAVs and TVs and for the MPRs shown in Figure 1.13. The top left corner cell gives the highest possible capacity per lane under the estimated MPRs and (most aggressive) gap settings, while the bottom right cell gives the opposite capacity value under the most conservative gap settings. It is clear under this MPR selection, the effect on capacity, compared to current HCM values for TVs is not significant, varying from a decrease of 15% to an increase of about 7%. This 22% range in possible capacity variation highlights the effect of uncertainty that is dependent on the gap settings that OEMs will make available to the consumers. That level of uncertainty must be considered when planning for future freeway facilities as planners cannot always assume the most optimistic scenarios on those gap settings. Interestingly, by increasing the CAV MPR to 50%, while keeping the relative MPRs for both AVs and TVs vehicles the same, the capacity changes varied from a lower decrease of 10.5% to a tripling of the original increase to 22%.

PER LANE CAPACITY FOR INDICATED MPR

| OEM OR USER SETTINGS CAV Time Gap (Sec.) | OEM or USER SETTINGS FOR AV Time Gap (Sec.) | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1.40 | 1.46 | 1.52 | 1.58 | 1.63 | 1.69 | 1.75 | 1.81 | 1.87 | 1.93 | 1.98 | 2.04 | 2.10 |
| 0.500 | 2,565 | 2,522 | 2,482 | 2,445 | 2,410 | 2,377 | 2,346 | 2,317 | 2,290 | 2,264 | 2,240 | 2,217 | 2,195 |
| 0.600 | 2,509 | 2,466 | 2,426 | 2,389 | 2,354 | 2,321 | 2,290 | 2,261 | 2,234 | 2,208 | 2,184 | 2,161 | 2,139 |
| 0.700 | 2,466 | 2,424 | 2,383 | 2,346 | 2,311 | 2,278 | 2,248 | 2,219 | 2,192 | 2,166 | 2,142 | 2,119 | 2,097 |
| 0.800 | 2,433 | 2,390 | 2,350 | 2,312 | 2,277 | 2,244 | 2,214 | 2,185 | 2,158 | 2,132 | 2,108 | 2,085 | 2,063 |
| 0.900 | 2,405 | 2,363 | 2,322 | 2,285 | 2,250 | 2,217 | 2,187 | 2,158 | 2,131 | 2,105 | 2,081 | 2,058 | 2,036 |

| Percent Increase/Decrease in Capacity from 100 % TV Base | | | | |
|---|---|---|---|---|
| Highest Value= | 2,565 | pcphpl | 6.88 | % |
| Lowest Value= | 2,036 | pcphpl | -15.18 | % |

Fig. 1.14 Calculator Output: Capacity / Lane under Mixed Traffic Conditions and Indicated Gap Settings

## *Output for CAVs Operating in a Dedicated Lane*

In this section, we present the capacity predictions for the case where one of three directional freeway lanes is reserved for CAVs, while the other two are GP lanes servicing a mix of AVs and TVs. For comparison purposes, the same set of MPRs shown in Figure 1.13 are used in this example as well.

The first observation here is that once a lane is dedicated to a single, specific vehicle class, that lane capacity is independent of that vehicle MPR in the traffic stream. Capacity can be thought of in this case as the saturation flow rate, which is independent of demand. This makes the dedicated lane capacity strictly dependent on the gap settings and the maximum platoon size, since inter-platoon headways are 50% longer than intra-platoon headways. The second observation is that the GP lane capacity will depend on the relative MPR of the constituent vehicles. In our case, and based on Figure 1.13, the relative MPR for AVs is 30/ (30+40) = 42.9% and the corresponding TV values is 57.1%. These are the weights that are used for estimating the mixed flow capacities in the GP lanes.

Figure 1.15 shows the capacity for the single, exclusive CAV lane. Since there are no AVs on this lane, the AV time gap settings—or columns-- have no effect on capacity, only the CAV time gap setting. As can be seen those capacities are substantially higher than those observed on the mixed flow lanes.

| | | TOTAL CAPACITY FOR EXCLUSIVE LANES | | | | | | | | | | | N= | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | OEM or USER SETTINGS FOR AV Time Gap (Sec.) | | | | | | | | | | | | |
| OEM OR USER SETTINGS CAV Time Gap (Sec.) | | 1.40 | 1.46 | 1.52 | 1.58 | 1.63 | 1.69 | 1.75 | 1.81 | 1.87 | 1.93 | 1.98 | 2.04 | 2.10 |
| | 0.500 | 4,643 | 4,643 | 4,643 | 4,643 | 4,643 | 4,643 | 4,643 | 4,643 | 4,643 | 4,643 | 4,643 | 4,643 | 4,643 |
| | 0.600 | 4,021 | 4,021 | 4,021 | 4,021 | 4,021 | 4,021 | 4,021 | 4,021 | 4,021 | 4,021 | 4,021 | 4,021 | 4,021 |
| | 0.700 | 3,546 | 3,546 | 3,546 | 3,546 | 3,546 | 3,546 | 3,546 | 3,546 | 3,546 | 3,546 | 3,546 | 3,546 | 3,546 |
| | 0.800 | 3,171 | 3,171 | 3,171 | 3,171 | 3,171 | 3,171 | 3,171 | 3,171 | 3,171 | 3,171 | 3,171 | 3,171 | 3,171 |
| | 0.900 | 2,868 | 2,868 | 2,868 | 2,868 | 2,868 | 2,868 | 2,868 | 2,868 | 2,868 | 2,868 | 2,868 | 2,868 | 2,868 |

**Fig. 1.15** Calculator Output: Capacity / Lane under Mixed Traffic Conditions and Indicated Gap Settings

Figure 1.16 shows the combined capacity of the two GP lanes servicing AVs and TVs. Again, since there are no CAVs on those lanes, the CAV time gap setting – or rows---have no impact on capacity, only the AV settings do. And finally, Figure 1.17 shows the average per lane capacity for the entire freeway cross section combining the single CAV dedicated lane and the two GP lanes servicing AVs and TVs and taking the lane average.

| | | TOTAL CAPACITY FOR GENERAL PURPOSE LANES | | | | | | | | | | | N= | 2 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | OEM or USER SETTINGS FOR AV Time Gap (Sec.) | | | | | | | | | | | | |
| OEM OR USER SETTINGS CAV Time Gap (Sec.) | | 1.40 | 1.46 | 1.52 | 1.58 | 1.63 | 1.69 | 1.75 | 1.81 | 1.87 | 1.93 | 1.98 | 2.04 | 2.10 |
| | 0.500 | 4,738 | 4,666 | 4,599 | 4,536 | 4,477 | 4,422 | 4,371 | 4,322 | 4,276 | 4,233 | 4,192 | 4,154 | 4,117 |
| | 0.600 | 4,738 | 4,666 | 4,599 | 4,536 | 4,477 | 4,422 | 4,371 | 4,322 | 4,276 | 4,233 | 4,192 | 4,154 | 4,117 |
| | 0.700 | 4,738 | 4,666 | 4,599 | 4,536 | 4,477 | 4,422 | 4,371 | 4,322 | 4,276 | 4,233 | 4,192 | 4,154 | 4,117 |
| | 0.800 | 4,738 | 4,666 | 4,599 | 4,536 | 4,477 | 4,422 | 4,371 | 4,322 | 4,276 | 4,233 | 4,192 | 4,154 | 4,117 |
| | 0.900 | 4,738 | 4,666 | 4,599 | 4,536 | 4,477 | 4,422 | 4,371 | 4,322 | 4,276 | 4,233 | 4,192 | 4,154 | 4,117 |

**Fig. 1.16** Calculator Output: Capacity / Lane under Mixed Traffic Conditions and Indicated Gap Settings

| | | AVERAGE PER LANE CAPACITY- FOR SECTION WITH EXCLUSIVE LANE(S) | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | OEM or USER SETTINGS FOR AV Time Gap (Sec.) | | | | | | | | | | | | |
| | | 1.40 | 1.46 | 1.52 | 1.58 | 1.63 | 1.69 | 1.75 | 1.81 | 1.87 | 1.93 | 1.98 | 2.04 | 2.10 |
| OEM OR USER SETTINGS CAV Time Gap (Sec.) | 0.500 | 3,127 | 3,103 | 3,081 | 3,060 | 3,040 | 3,022 | 3,005 | 2,988 | 2,973 | 2,959 | 2,945 | 2,932 | 2,920 |
| | 0.600 | 2,920 | 2,896 | 2,873 | 2,852 | 2,833 | 2,814 | 2,797 | 2,781 | 2,766 | 2,751 | 2,738 | 2,725 | 2,713 |
| | 0.700 | 2,761 | 2,737 | 2,715 | 2,694 | 2,674 | 2,656 | 2,639 | 2,623 | 2,607 | 2,593 | 2,579 | 2,567 | 2,554 |
| | 0.800 | 2,636 | 2,612 | 2,590 | 2,569 | 2,549 | 2,531 | 2,514 | 2,498 | 2,482 | 2,468 | 2,454 | 2,442 | 2,429 |
| | 0.900 | 2,535 | 2,511 | 2,489 | 2,468 | 2,448 | 2,430 | 2,413 | 2,397 | 2,381 | 2,367 | 2,353 | 2,341 | 2,328 |

**Fig. 1.17** Calculator Output: Capacity / Lane under Mixed Traffic Conditions and Indicated Gap Settings

It is instructive to compare the relative capacity improvements of dedicating a single lane to CAVs, as opposed to the use of mixed traffic on all lanes. Figure 1.18 reports the ratio of lane capacities that are generated from Figure 1.17 to those generated in Figure 1.14, in order to highlight the effect of CAV lane dedication under various gap settings for a specific MPR distribution. Again, under this market penetration rate, the overall effect of lane dedication is not substantial, topping perhaps a 22% increase under the most favorable conditions.

| | | CAPACITY RATIO- PER LANE- WITH VS. WITHOUT AN EXCLUSIVE LANE | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | OEM or USER SETTINGS FOR AV Time Gap (Sec.) | | | | | | | | | | | | |
| | | 1.40 | 1.46 | 1.52 | 1.58 | 1.63 | 1.69 | 1.75 | 1.81 | 1.87 | 1.93 | 1.98 | 2.04 | 2.10 |
| OEM OR USER SETTINGS CAV Time Gap (Sec.) | 0.500 | 1.219 | 1.230 | 1.241 | 1.252 | 1.262 | 1.271 | 1.281 | 1.290 | 1.298 | 1.307 | 1.315 | 1.322 | 1.330 |
| | 0.600 | 1.164 | 1.174 | 1.184 | 1.194 | 1.204 | 1.213 | 1.221 | 1.230 | 1.238 | 1.246 | 1.253 | 1.261 | 1.268 |
| | 0.700 | 1.120 | 1.129 | 1.139 | 1.148 | 1.157 | 1.166 | 1.174 | 1.182 | 1.190 | 1.197 | 1.204 | 1.211 | 1.218 |
| | 0.800 | 1.084 | 1.093 | 1.102 | 1.111 | 1.120 | 1.128 | 1.135 | 1.143 | 1.150 | 1.158 | 1.164 | 1.171 | 1.178 |
| | 0.900 | 1.054 | 1.063 | 1.072 | 1.080 | 1.088 | 1.096 | 1.103 | 1.111 | 1.118 | 1.125 | 1.131 | 1.138 | 1.144 |

**Fig. 1.18** Capacity Ration Per Lane with and without exclusive lane

## Additional Thoughts

It is important for the reader not to mix the concepts of capacity – or maximum throughput, presented here, with the actual vehicle throughput. Capacity assumes there is sufficient demand to use up all the available space, which is a freeway lane in our example. It should be clear that the value of having a CAV dedicated lane will depend on the demand for that lane, compared to the demand for AVs and TVs in the GP lanes. At low CAV MPRs, dedicating one of three lanes may result in underutilization of that lane, and perhaps creating additional congestion on the GP lanes. The earlier analysis in this chapter has indicated that for a 3 lane section, the optimal CAV MPR for which a dedicated lane becomes feasible is in the neighborhood of 40%. In essence, we are proposing to use 1/3 of the existing right of way to move 40% of the traffic, a fairly efficient process. The same process has been used in dedicating HOV or HOT lanes on urban freeways.

One last important comment on CAV lane dedication. Some studies have suggested that because of the combined autonomy and connectivity, lateral control of vehicles can be much improved, thus requiring narrower lanes for their operations, compared to TVs. One can envision cases where an existing freeway cross section can be retrofitted to narrow all lanes by say one foot and shoulders by two feet each to create a 7-9 ft. CAV lane without the need to take out a full GP lane. This analysis is left for future work. An Excel spreadsheet of the presented material in this section will be delivered to NCDOT as part of the final report.

## 1.6 Summary and Conclusions

This report explored the mobility effects of connected-autonomous vehicles (CAVs) operating on freeways in a mixed traffic environment, and in platoons on a dedicated freeway lane. In the first instance, CAVs operate along with autonomous (AV) and traditional (TV) vehicles in general purpose lanes. Microscopic simulation that is capable of distinguishing between vehicle technologies and employs state-of-the-art, vehicle type dependent car following and lane changing models to capture the interaction of those vehicles in the traffic stream was used for this analysis. In addition, the report provides a planning level Excel tool for capacity estimation under both mixed and dedicated lane scenarios.

In general, both the literature review and microsimulation work have indicated that CAVs in most cases will yield significant improvements in freeway capacity, whether they operate in mixed flow, but more dramatically when using a dedicated lane. Under mixed flow, the level of improvements is highly dependent on the CAV MPR, since platooning is only feasible when multiple CAVs are in proximity of each other. The effect of AVs in mixed traffic is less clear, as their effect depends on the OEM gap setting which was found to cover a very wide range in the literature, with often conflicting impacts on capacity. Our simulation, which used a conservative gap setting generally shows a reduction in capacity with AV presence. Part of the potential negative impacts on capacity may be due the OEM policies to put a premium on crash avoidance in the early AV pilot studies, to the detriment of enhanced mobility considerations.

Freeway segment throughput simulations indicated that reserving a lane for CAVs is beneficial when their market penetration is within 20%-60% and optimally at 40%. Outside of this range, throughput degrades significantly due to congestion on either the dedicated or general purpose lanes. Furthermore, mandating CAVs to operate exclusively in the dedicated lane negatively impacted the throughput at the medium and high feasible ranges (40%-60%), but proved beneficial at the low CAV MPR of 20%. The analysis of travel rate distribution demonstrated the effect of CAV dedicated lane access control restrictions. For CAVs, the distribution was clearly bimodal independent of origin and destination points. The second mode is thought to be due to perturbations at the access and egress segments. Under the same conditions, but with continuous access allowed, the travel rate distribution became unimodal and the travel rate dropped significantly. In fact this shift from two modes to one applied to most vehicle classes and to most OD paths under the continuous access strategy.

The planning level calculator analysis has shown that CAV's capacity contribution is not proportional to their market share in the fleet when operating in mixed traffic. Platooning – a key contributor to capacity increases requires multiple CAV vehicles to be in proximity of each other, which is not guaranteed in the case of mixed traffic. When CAV demand makes it feasible, a dedicated lane will yield significant capacity improvements to the freeway facility.

Further research is needed to generate additional speed flow relationships from microsimulation, covering a range of market penetrations of vehicle technologies, with the possible objective of generating passenger car (or TV) equivalencies for mixed traffic flow. Another important direction is to model the heterogeneity in car following and lane changing behavior which will be available to OEM clients in the future and which will impact the capacity estimates. Thirdly, an analysis of lane width requirements for CAVs to operate is recommended. The literature provided some evidence that, because of automation and connectivity, seven or eight or feet lanes may be sufficient, raising the prospect of being able to retrofit existing freeway cross sections to serve CAVs without taking out any of the GP lanes. Finally, the team recommends the use of real world pilot test data of CAVs and AVs, in order to assist the development and testing of surrogate safety measures in a microscopic simulation environment.

## REFERENCES


1. Adebisi, A., Y. Liu, B. Schroeder, J. Ma, B. Cesme, A. Jia, and A. Morgan, Developing Highway Capacity Manual (HCM) Capacity Adjustment Factors (CAF) for Connected and Automated Traffic on Freeway Segments. In Transportation Research Board, Washington D.C., 2020.

2. Bierstedt, J., A. Gooze, C. Gray, J. Peterman, L. Raykin, and J. Walters, Effects of Next- Generation Vehicles on Travel Demand and Highway Capacity. In FP Think Working Group, 2014, 8, pp. 1–10.

3. Samandar, M. S., S. Sharma, N. M. Rouphail, E. Bardaka, B. M. Williams, and G. F. List, Roadmap for Incorporating Autonomy and Connectivity: Modeling Mobility Impacts in Simulation. In 99th Annual Meeting of Transportation Research Board, Washington D.C., 2020.

4. Mei, B., H. Hu, N. M. Rouphail, and J.J. Lee. Simulation Model for Studying Impact of Vehicle-to-Vehicle Wireless Communications on Traffic Network Operations. Transportation Research Record: Journal of the Transportation Research Board, 2010. 2189(1): 107–115. https://doi.org/10.3141/2189-12.

5. Lee, J., and B. Park. Evaluation of Route Guidance Strategies Based on Vehicle-Infrastructure Integration under Incident Conditions. Transportation Research Record: Journal of the Transportation Research Board, 2008. 2086(1): 107–114. https://doi.org/10.3141/2086-13.

6. Talebpour, A., and Hani S. Mahmassani and F. E. Bustamante. Modeling driver behavior in a connected environment: Integrated microscopic simulation of traffic and mobile wireless telecommunication systems. Transportation Research Record: Journal of the Transportation Research Board, 2016. 2560(1): 75–86. https://doi.org/10.3141/2560-09

7. Treiber, M., A. Hennecke, and D. Helbing. Congested Traffic States in Empirical Observations and Microscopic Simulations. Physical review E, 2000. 62 (2): 1805-1824. https://doi.org/10.1103/PhysRevE.62.1805.

8. Kesting, A., M. Treiber, and D. Helbing. 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, 2010.368 (1928): 4585–4605. https://doi.org/10.1098/rsta.2010.0084.

9. Zhu, F., and S. V. Ukkusuri. An Optimal Estimation Approach for the Calibration of the Car-Following Behavior of Connected Vehicles in a Mixed Traffic Environment. IEEE Transactions on Intelligent Transportation Systems, 2017.18 (2): 282–291. https://doi.org/10.1109/TITS.2016.2568759.

10. Mittal, A., H. S. Mahmassani, and A. Talebpour. Network Flow Relations and Travel Time Reliability in a Connected Environment. Transportation Research Record: Journal of the Transportation Research Board, 2017. 2622: 24–37. https://doi.org/10.3141/2622-03.

11. Bishop, R. Intelligent Vehicle Applications Worldwide. IEEE Intelligent Systems and Their Applications, 2000. 15(1): 78–81. https://doi.org/10.1109/5254.820333.

12. Chang, T. H., and I. S. Lai. Analysis of Characteristics of Mixed Traffic Flow of Autopilot Vehicles and Manual Vehicles. Transportation Research Part C: Emerging Technologies, 1997. 5 (6): 333–348. https://doi.org/10.1016/S0968-090X(97)00020-X.

13. Vander Werf, J., S. E. Shladover, M. A. Miller, and N. Kourjanskaia. Effects of Adaptive Cruise Control Systems on Highway Traffic Flow Capacity. Transportation Research Record: Journal of the Transportation Research Board, 2002. 1800 (1): 78–84. https://doi.org/10.3141/1800-10.

14. VanderWerf, J., S. Shladover, N. Kourjanskaia, M. Miller, and H. Krishnan. Modeling Effects of Driver Control Assistance Systems on Traffic. Transportation Research Record: Journal of the Transportation Research Board, 2001. 1748 (1): 167–174. https://doi.org/10.3141/1748-21.

15. Shladover, S. E., D. Su, and X. Y. Lu. Impacts of Cooperative Adaptive Cruise Control on Freeway Traffic Flow. Transportation Research Record: Journal of the Transportation Research Board, 2012. 2324: 63–70.

16. Minderhoud, M. M., and P. H. L. Bovy. Impact of Intelligent Cruise Control on Motorway Capacity. Transportation Research Record: Journal of the Transportation Research Board, 1999. 1679 (1): 1–9.

17. Tientrakool, P., Y. C. Ho, and N. F. Maxemchuk. Highway capacity benefits from using vehicle-to-vehicle communication and sensors for collision avoidance. 2011 IEEE Vehicular Technology Conference (VTC Fall), San Francisco, CA. doi: 10.1109/VETECF.2011.6093130.

18. Le Vine, S., Y. Kong, X. Liu, and J. Polak. Vehicle Automation and Freeway ‘Pipeline’ Capacity in the Context of Legal Standards of Care. Transportation, 2017. 1–30.

19. Bierstedt, J., A. Gooze, C. Gray, J. Peterman, L. Raykin, and J. Walters. Effects of Next-Generation Vehicles on Travel Demand and Highway Capacity. 10-14. Fehr & Peers, 2014.

20. Talebpour, A., H. S. Mahmassani, and A. Elfar. Investigating the Effects of Reserved Lanes for Autonomous Vehicles on Congestion and Travel Time Reliability. Transportation Research Record: Journal of the Transportation Research Board, 2017. 2622: 1–12.

21. Van Arem, B., C. J. G. Van Driel, and R. Visser. The Impact of Cooperative Adaptive Cruise Control on Traffic-Flow Characteristics. IEEE Transactions on Intelligent Transportation Systems, 2006. 7 (4): 429–436.

22. Reece, D. A., and S. A. Shafer. A Computational Model of Driving for Autonomous Vehicles. Transportation Research Part A: Policy and Practice, 1993. 27 (1): 23–50.

23. Talebpour, A., and H. S. Mahmassani. Influence of Connected and Autonomous Vehicles on Traffic Flow Stability and Throughput. Transportation Research Part C: Emerging Technologies, 2016. 71: 143–163.

24. Milanes, V., S. E. Shladover, J. Spring, C. Nowakowski, H. Kawazoe, and M. Nakamura. Cooperative Adaptive Cruise Control in Real Traffic Situations. IEEE Transactions on Intelligent Transportation Systems, 2014. 15 (1): 296–305.

25. Nowakowski, C., J. O'Connell, S. E. Shladover, and D. Cody. Cooperative Adaptive Cruise Control: Driver Acceptance of Following Gap Settings Less than One Second. Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 2010. 54 (24): 2033–2037.

26. Bu, F., H. Tan, and J. Huang. Design and Field Testing of a Cooperative Adaptive Cruise Control System. Proceedings of the 2010 American Control Conference, Baltimore, MD, 2010. 4616–4621.

27. Ploeg, J., B. T. M. Scheepers, E. van Nunen, N. van de Wouw, and H. Nijmeijer. Design and Experimental Evaluation of Cooperative Adaptive Cruise Control. 14th International IEEE Conference on Intelligent Transportation Systems (ITSC), Washington, D.C., 2011. 14–19.

28. Ni, D., J. Li, S. Andrews, and H. Wang. Preliminary Estimate of Highway Capacity Benefit Attainable with IntelliDrive Technologies. 13th International IEEE Conference on Intelligent Transportation Systems, Funchal, 2010. 819-824.

29. Liu, Y., J. Guo, J. Taplin, and Y. Wang. Characteristic Analysis of Mixed Traffic Flow of Regular and Autonomous Vehicles Using Cellular Automata. Journal of Advanced Transportation, 2017. 2017: 10.1155/2017/8142074.

30. List, G., M. Mashayekhi, R. L. Bertini, and B. Nevers. Development of a Transportation System Simulation Manual Framework: From Theory to Practice. Transportation Research Record: Journal of the Transportation Research Board, 2016. 2561 (1): 45–52.

31. National Academies of Sciences, E., Medicine, et al.,Dedicating Lanes for Priority or Exclusive Use by Connected and Automated Vehicles, 2018.

32. Talebpour, A., H. S. Mahmassani, and A. Elfar, Investigating the effects of reserved lanes for autonomous vehicles on congestion and travel time reliability. Transportation Research Record, Vol. 2622, No. 1, 2017, pp. 1–12.

33.Xiao, L., M. Wang, and B. van Arem, Traffic flow impacts of converting an HOV lane into a dedicated CACC lane on a freeway corridor. IEEE Intelligent Transportation Systems Magazine, Vol. 12, No. 1, 2019, pp. 60–73

34. Zhong, Z., J. Lee, and L. Zhao, Dedicated Lane for Connected and Automated Vehicle: How Much Does A Homogeneous Traffic Flow Contribute? arXiv preprint22arXiv:1907.00422, 2019.

35. Guo, Y. and J. Ma, Leveraging existing high-occupancy vehicle lanes for mixed-autonomy traffic management with emerging connected automated vehicle applications. Transportmetrica A: Transport Science, Vol. 16, No. 3, 2020, pp. 1375–1399.

36. Ye, L. and T. Yamamoto, Impact of dedicated lanes for connected and autonomous vehicle on traffic flow throughput. Physica A: Statistical Mechanics and its Applications, Vol. 512, 2018, pp. 588–597.

37. Hussain, O., A. Ghiasi, and X. Li, Freeway lane management approach in mixed traffic environment with connected autonomous vehicles. arXiv preprint arXiv:1609.02946,312016.

38. Liu, Z. and Z. Song, Strategic planning of dedicated autonomous vehicle lanes and autonomous vehicle/toll lanes in transportation networks. Transportation Research Part C:Emerging Technologies, Vol. 106, 2019, pp. 381–403.

39. Ghiasi, A., O. Hussain, Z. ian, and X. i, Lane Management with Variable Lane Width and Model Calibration for Connected Automated Vehicles. Journal of Transportation Engineering, Part A: Systems, Vol. 146, No. 3, 2020, p. 04019075.

40. Zhou, J. and F. Zhu, Modeling the fundamental diagram of mixed human-driven and connected automated vehicles. Transportation Research Part C: Emerging Technologies, Vol.115, 2020, p. 102614.

41. Hua, X., W. Yu, W. Wang, and W. Xie, Influence of Lane Policies on Freeway Traffic Mixed with Manual and Connected and Autonomous Vehicles. Journal of Advanced Transportation, Vol. 2020, 2020.

42. Lopez, P. A., M. Behrisch, L. Bieker-Walz, J. Erdmann, Y.-P. Flötteröd, R. Hilbrich, L. Lücken, J. Rummel, P. Wagner, and E. Wießner, Microscopic Traffic Simulation using SUMO. In The 21st IEEE International Conference on Intelligent Transportation Systems, IEEE, 2018.

43. Data, J. E. M. M. w. O. and u. 2015, SUMO's lane-changing model. Springer.

44. Wiedemann, R., Simulation Des straßenverkehrsflusses. Institut für Verkehrswesen der Universität Karlsruhe, 1974.

45. Wiedemann, R., Modelling of RTI-Elements on multi-lane roads. Drive Conference, 1991.

46. Xiao, L., M. Wang, and B. Van Arem, Realistic car-following models for microscopic simulation of adaptive and cooperative adaptive cruise control vehicles. Transportation Research Record, Vol. 2623, No. 1, 2017, pp. 1–9.

47. Milanés, V. and S. E. Shladover, Modeling cooperative and autonomous adaptive cruise control dynamic responses using experimental data. Transportation Research Part C: Emerging Technologies, Vol. 48, 2014, pp. 285–300.

48. Nowakowski, C., J. O'Connell, S. E. Shladover, and D. Cody, Cooperative Adaptive Cruise Control: Driver Acceptance of Following Gap Settings Less than One Second. Proceedings of the Human Factors and Ergonomics Society Annual Meeting, Vol. 54, No. 24, 2010, pp. 2033–2037.

49. Xiao, L., M. Wang, W. Schakel, and B. van Arem, Unravelling effects of cooperative adaptive cruise control deactivation on traffic flow characteristics at merging bottlenecks. Transportation Research Part C: Emerging Technologies, Vol. 96, 2018, pp. 380–397.

50. Liu, H., X. Kan, S. Shladover, X. Lu, and R. Ferlis, Impact of cooperative adaptive cruise control (cacc) on multilane freeway merge capacity, 2018.

51. Milanes, V., S. E. Shladover, J. Spring, C. Nowakowski, H. Kawazoe, and M. Nakamura, Cooperative Adaptive Cruise Control in Real Traffic Situations. IEEE Transactions on Intelligent Transportation Systems, Vol. 15, No. 1, 2014, pp. 296–305.

# Chapter 2
# The Effects of Connectivity and Automation on Traffic Operations at Signalized Intersections

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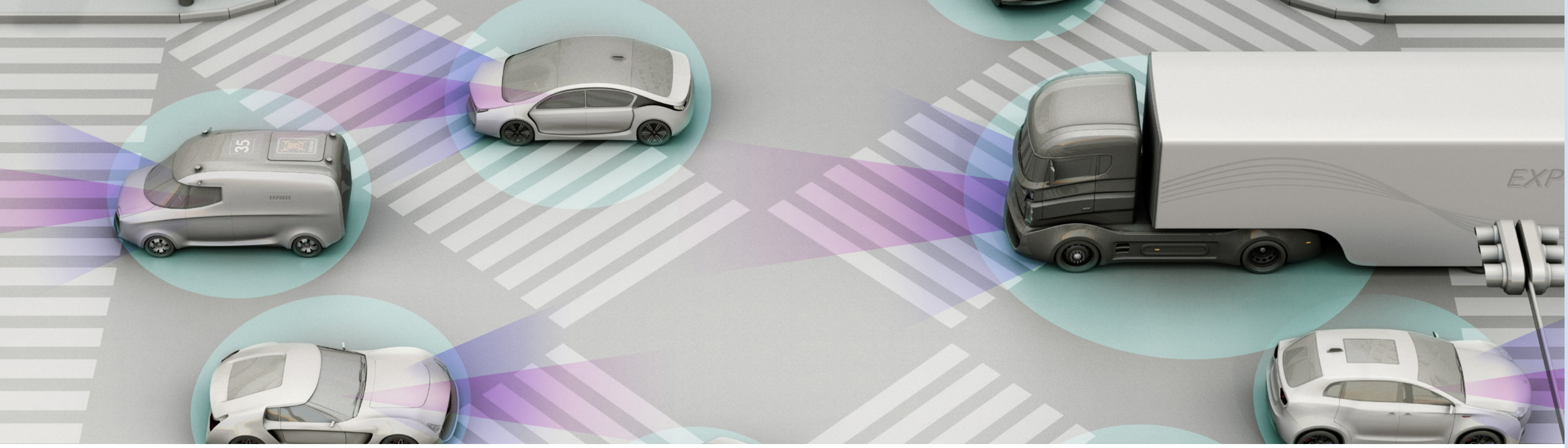


# 2.1 Introduction

Autonomous vehicles (AVs) are emerging with the promise of improving mobility and safety on highway facilities. Many research laboratories, vehicle manufacturers, and technology companies are currently researching the potential impacts of AVs on highway facilities. For instance, Waymo's AVs have traveled about 10 million miles on public roads in 25 cities across the US (1). Several car manufacturers such as Tesla, Cadillac, and Audi are building semi-autonomous commercial vehicles, while fully autonomous vehicles are expected to emerge by 2050 gradually (2, 3).

Vehicle connectivity is also expected to play an essential role in improving mobility and safety (4–7). Current studies show that AVs are programmed to behave conservatively, perhaps to reduce the likelihood of severe crashes in the absence of information from other vehicles and obstacles that are not visible to the sensors of AVs. Establishing a dynamic communication among vehicles, infrastructure, and other wireless devices enables AVs to collect real-time data and predict the future states of other users on the road more accurately and consequently reduces the likelihood of crashes. As a result, connected AVs can drive more aggressively without increasing the risk of collision with other users. The advisory information also helps human drivers to oversight the upcoming traffic condition and adjust their speed and maneuvers appropriately (8–12).

This study aims to understand the potential effects of connectivity and automation on traffic operations at signalized intersections. Existing studies paid attention to the operations of AVs on freeway facilities. Still, the interaction of AVs with other vehicles and the signal controller has not received the same amount of attention. We have considered four levels of connectivity/automation to account for different driving

behaviors and their interactions in traffic stream: I) human-driven vehicles (HVs), II) connected vehicles (CVs), III) automated vehicles (AVs), and IV) connected and automated vehicles (CAVs). Various scenarios are defined based on different market penetration rates of these vehicles.

The potential effects of CVs, AVs, and CAVs on traffic operations will be studies using a simulated testbed created in Vissim. A signalized intersection and the mentioned four vehicle types are created in Vissim. These different vehicle types are made by changing car following model parameters in Vissim: Automated vehicles are assumed to have shorter reaction time and start-up lost time than human drivers. Besides, automated vehicles have a shorter stand-still distance. Connected vehicles are assumed to receive information about the future state of traffic lights and adjust their speeds to avoid stopping at the intersection. As a result, the movements of connected vehicles are expected to be smoother with a lower number of stops. Connected automated vehicles are assumed to have all these mentioned capabilities. A default Python script code developed by Vissim is used to provide the communication between the signal controller and connected vehicles and CAVs to adjust their speed accordingly.

## 2.2 Literature Review

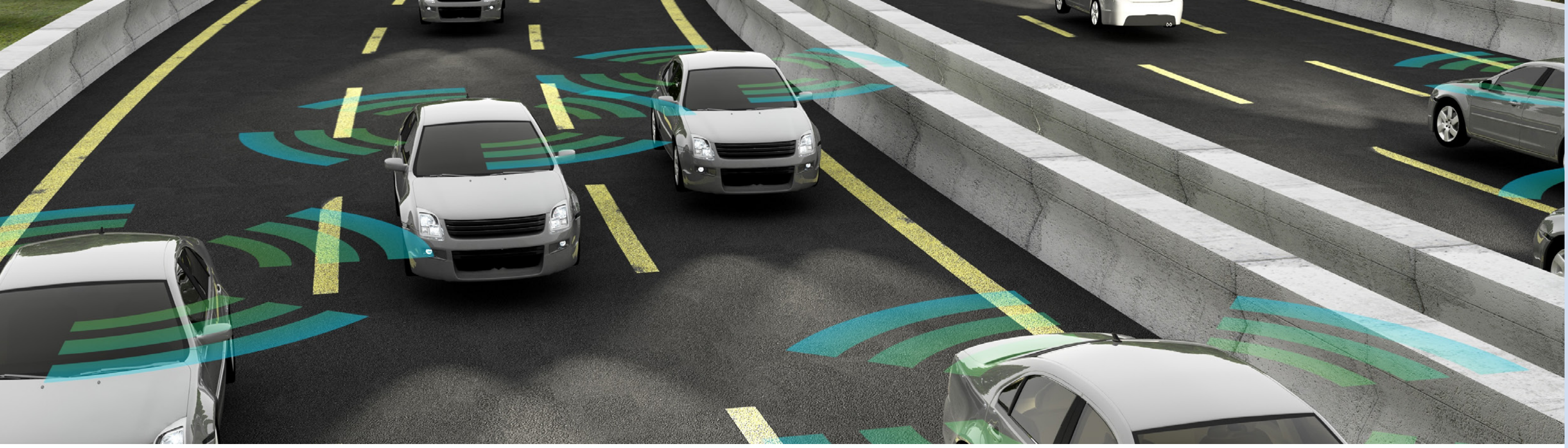
Different levels of automation and connectivity are associated with different driving behaviors for HVs, CVs, AVs, and CAVs. Lower automation levels aim to assist human drivers by technologies such as adaptive cruise control (13), collision warning (14, 15), collision avoidance (16), or assistant braking (17) utilizing onboard computers and sensors. On the other hand, higher automation levels let AVs and CAVs take complete control of vehicle's movements without any assistance from the human driver by predicting the future trajectory of surrounding vehicles and avoiding any potential collisions.

The interaction between vehicles with different levels of connectivity and automation will be a challenge in the near future since these vehicles have different driving behaviors (18). AVs, as of now, are programmed to behave cautiously while interacting with human drivers (19, 20). Human drivers require a higher reaction time to respond to any changes in the driving situation. Therefore, AVs need to consider various decision scenarios to overcome the uncertainty associated with human driver's decisions (21). Since AVs have shorter reaction times and lower uncertainty in their performance, Sadigh et al. (16) showed that a proper AV behavior could modify the human driver's behavior by leveraging their actions toward a more efficient driving behavior. Sezer et al. (22) also clarified that making AVs more aggressive could yield to operating higher traffic volumes in a mixed autonomy environment without compromising the safety when there is communication between vehicles.

Connectivity can further improve the efficiency and reliability of autonomous systems (as well as human-controlled systems). The information sharing between vehicles and infrastructure affects the driving behavior of

vehicles by increasing the chance of making reliable decisions, especially with respect to car-following and lane-changing (23). CAVs can improve traffic mobility without sacrificing safety. For instance, controlling the trajectory of CAVs upstream of signalized intersections based on advanced knowledge of signal phase and timing (SPaT) increases intersection throughput and reduces the experienced delay and risk of collisions among vehicles (15, 24–29). Moreover, the trajectory of CAVs can be managed to avoid stops at the intersection and minimizing fuel consumption (9, 25, 30). In a traffic stream of 100% CAVs, traffic lights could be theoretically removed to achieve significant improvements in traffic operations (31, 32)

While many studies have examined the possible effects of connected and autonomous vehicles on traffic operations on uninterrupted flow facilities, the impact of connectivity and automation on interrupted flow facilities, especially signalized intersections, are not thoroughly studied. This study aims to fill this gap and provide insights into how different market penetration rates of CVs, AVs, and CAVs will influence driving behavior and mobility on signalized intersections.



## 2.3 Experimental Design

### *Vissim Simulation*

A microscopic simulation testbed was developed in Vissim to study the connectivity and automation technologies' effects on traffic operations at signalized intersections. The simulation testbed provides the ability to consider various driving behaviors associated with different connectivity and automation levels. Vissim microscopic simulation is used in this study because it can simulate connected and automated vehicles and their interaction with conventional human-driven vehicles. In addition, information exchange is possible between cars and the infrastructure through Vissim's Component Object Model (COM) interface. Finally, Vissim provides a host of outputs ranging from vehicle-level output to network-level performance measures.

### *Driving Behavior*

The driving behavior of vehicles with different levels of automation is adopted from existing practical studies on the behavior of automated vehicles. In particular, the findings of the CoEXist project (33) are used as the default AV model in Vissim. The recommendations of this project are based on the empirical analysis of data collected in the Netherlands. The experimental results were confirmed through Vedecom Tech and several simulation tests done by PTV Group.

### *Car-following Behavior*

The CoEXist project recommended three variants of driving models associated with different AV driving behavior: 1) CoEXist cautious model, 2) CoEXist normal model, and 3) CoEXist all-knowing model. The cautious driving behavior respects the road-code and always ensures moving safely on the road. There is always a brick wall distance between the cautious-driving

| Parameters | Definition | HV | CV | AV | CAV |
|---|---|---|---|---|---|
| CC0 | Stand still distance ($m$) | 1.5 | 1.5 | 1.5 | 1 |
| CC1 | Headway time ($s$) | 1.6 | 1.6 | 2.2 | 1 |
| CC2 | Following variation ($m$) | 4 | 2 | 0 | 0 |
| CC3 | Threshold for entering following ($s$) | -8 | -8 | -10 | -6 |
| CC4 | Negative following threshold ($m/s$) | -0.35 | -0.35 | -0.1 | -0.1 |
| CC5 | Positive following threshold ($m/s$) | 0.35 | 0.35 | 0.1 | 0.1 |
| CC6 | Speed dependency of oscillation ($1/(m/s)$) | 11.44 | 11.44 | 0 | 0 |
| CC7 | Oscillation acceleration ($m/s^2$) | 0.25 | 0.25 | 0.1 | 0.1 |
| CC8 | Standstill acceleration ($m/s^2$) | 3.5 | 3.5 | 2 | 4 |
| CC9 | Acceleration with 50 mph ($m/s^2$) | 1.5 | 1.5 | 1.2 | 2 |

**Table 2.1:** Wiedemann 99 car-following model Calibration Components (CC)

| Attribute | HV | CV | AV | CAV |
|---|---|---|---|---|
| behavior at the amber signal | continuous check | continuous check | continuous check | one decision |
| behavior at red/amber signal | go | go | stop | stop |
| reduced safety distance factor | 0.6 | 0.6 | 1 | 1 |
| reduced safety start upstream of stop line (m) | 100 | 100 | 100 | 100 |
| reduced safety end upstream of stop line (m) | 100 | 100 | 100 | 100 |

**Table 2.2:** Car-following behavior near signalized intersections

| Driving logic | enforce absolute braking distance (EABK) | use implicit stochastics | number of interaction vehicles* | increased desired acceleration |
|---|---|---|---|---|
| HV | OFF | ON | 1 | 100-110% |
| CV | OFF | ON | 1 | 100% |
| AV | ON | OFF | 1 | 100% |
| CAV | OFF | OFF | >1 | 110% |

**Table 2.3:** Other driving behaviors for various automation levels

vehicles and its immediate leading car. In addition, a large gap will be required to perform a lane change maneuver or pass the un-signalized intersections. The driving behavior of automated vehicles is assumed to be cautious. The normal driving behavior is very similar to the behavior of a human driver with the additional capacity of measuring distances and speeds of surrounding vehicles by collecting information from sensors. All-knowing driving behavior assumes a perfect perception of the surrounding environment and receives vehicle-to-vehicle and vehicle-to-infrastructure communications. This driving behavior is associated with smaller gaps for all maneuvers. Table 2.1 summarizes the calibrated components of Wiedemann 99 car-following parameters through the CoEXist project. It should be noted that the signal timing information is shared with connected human-driven vehicles and connected automated vehicles. As a result, the driving behavior of vehicles under these two types will be different than the cases that the information is not received.

It should be noted that Vissim considers a normal distribution for the headway time and the desired speed to account for the randomness in driving behaviors. However, higher automation levels are associated with less uncertainty in driving behaviors. As a result, the standard deviation of normal distribution decreases from HVs to CVs, AVs, and CAVs.

### *Signal Control Behavior*

When there is no information available about the future signal timing plan at an intersection, vehicles either follow their lead vehicles or travel at their own desired speed. If they hit the green signal, they will go through the intersection; otherwise, they stop for the red light. Sharing signal timing information with upcoming vehicles can change their driving behavior as they approach the intersection. Table 2.2 shows Vissim's car following behavior for different connectivity and automation levels as vehicles arrive at an intersection. HVs and AVs need to continuously check the signal timing status during the yellow time to avoid red-light violations. Although CVs receive the signal timing plans, the human driver still needs to check to constantly ensure safe entrance to the intersection.

On the other hand, CAVs have a perfect sense of future plans. Therefore, one decision will be made, and CAV will stick to that over time. In addition, the safety factor for AVs and CAVs is considered higher to make sure that no collision will occur with other vehicles at the intersection.

### *Other Behaviors*

Other driving behavior parameters suggested by the CoEXist project are shown in Table 2.3. Enforce absolute braking distance (EABK) is active for AVs since they drive cautiously on the road. Based on EABK, a further gap between the following and leading vehicle is kept to let AVs stop safely anytime, even if the lead vehicle stops instantly. Vissim also does not consider the stochasticities associated with human driving for automated vehicles. CAVs are allowed to interact with more than one vehicle around, but other cars interact with the most immediate vehicle.

### *Vissim Calibration*

Wiedemann's 99 car-following model is selected as it can model autonomous and connected autonomous vehicles (33). Model parameters were calibrated to match the saturation headway.

The headway depends on two main factors in Vissim: 1) the desired speed and 2) the car-following characteristics. Since the desired speed is assumed fixed for all vehicle types, only the car-following parameters should be calibrated. As shown in Table 2.1, the Wiedemann 99 car-following model contains ten parameters. However, only two parameters (i.e., CC0 and CC1) influence the intersection headway significantly (34). CC0 is the average desired distance between two vehicles in meters at a stand-still while queuing before the traffic signal. The headway CC1 describes the speed-dependent part of the safety distance a driver desires. Therefore, various combinations of these two factors were tested to calibrate the model. The saturation headway is considered as the average headway between fourth and tenth passenger cars in the queue when the traffic light changes from red to green.

### *Advisory Speeds*

CVs and CAVs can adjust their speeds based on the received information on future signal timing plans to smoothen their movement and arrive at the intersection during the green signal. This research utilized a default Python script code developed by the PTV group to allow communications between the signal controller and CVs and CAVs. The script adjusts the minimum and maximum speed required to arrive at the intersection during a green light. If the minimum speed is less than the desired speed, the vehicle moves with the desired speed; otherwise, a constant smooth speed will be provided. It should be noted that the constant speed needs to be higher than a certain amount to avoid crawling. For instance, a five mph speed will not be provided to vehicles. Similarly, the maximum speed to the intersection is calculated and compared to the desired speed. If the maximum speed is greater than the desired speed, the desired speed will be used. Otherwise, the maximum speed is considered as the optimal speed for arriving at the intersection during the green signal.

## Intersection Testbed

Figure 2.1 shows the layout of the intersection testbed used in this research. The testbed is designed to include various lane groups: The eastbound approach has exclusive left turn, through, and right turn lane groups. Other approaches include a shared right turn and through lane. Fixed-time signal timing is used, and the signal timing parameters are optimized using Vistro (35). The demand for the eastbound entry is 900 veh/hour, and the demand for other approaches is 1200 veh/hour. The turning percentage for left-turn movement is 15% for all approaches. The right-turn percentage for eastbound, northbound, westbound, and southbound are assumed to be 15%, 5%, 15%, and 25%, respectively. Six different market penetration rates for CVs, AVs, and CAVs are used: 0%, 20%, 40%, 60%, 80%, and 100%. In total, 56 scenarios are considered. Each scenario is run ten times with different random seeds to account for randomness.

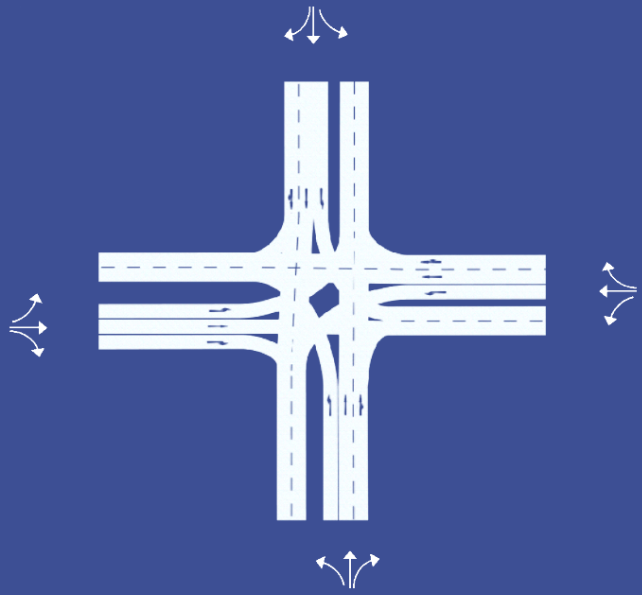
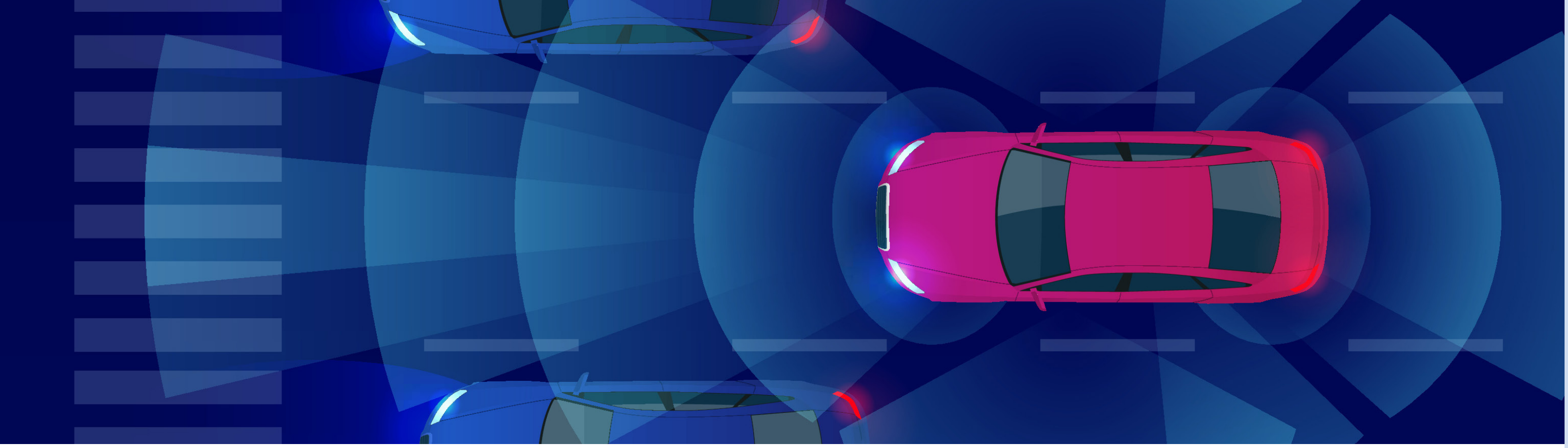


**Figure 2.1:** Case Study Intersection



## 2.4 Results

### *Lane Group-Level Analysis*

#### *Saturation Headway*

Figure 2.2 shows the saturation headway of CVs, AVs, and CAVs compared to the base case, i.e., 100% HVs. The results are shown for exclusive right turn, through, and left turn lanes. Increasing the market penetration rate of CVs and CAVs decreases the saturation headway at all these exclusive lanes. This trend could be attributed to having access to advanced information about the future signal plan of the traffic light. As a result, the drivers of CVs are ready to start to move with shorter start-up lost time and reaction times. CAVs have shorter saturation headway than CVs due to less uncertainty in their behavior when there is no human driver to control them. In contrast to CVs and CAVs, increasing the penetration rate of AVs increases the saturation headway since AVs travel more cautiously near the intersection to avoid collisions. As expected, the saturation headway is lower on exclusive through lanes compared to the exclusive left- and right-turn lanes because vehicles need to slow down to negotiate the curve.

A similar analysis was performed for shared right-turn and through lanes, and the results are shown in Figure 2.3. The observed trends are similar to exclusive right-turn lanes. Different right turn percentages did not significantly impact the saturation headway in the shared right and through lanes.

#### *Total Delay*

In addition to saturation headway, the delay of vehicles at each lane group under different market penetration rates and lane configuration were determined. Figure 2.4 shows that increasing the market penetration rate of CVs and CAVs will decrease the delay. On the other hand, increasing the AV market share will increase the delay due to AVs' cautious driving behavior in the vicinity of the intersection.

Figure 2.5 shows the total delay of vehicles in shared lanes with different turning percentages. Similar trends were observed: increasing the market penetration rates of CVs and CAVs decreased the total delay while increasing the AV market share lead to an increase in the total delay.

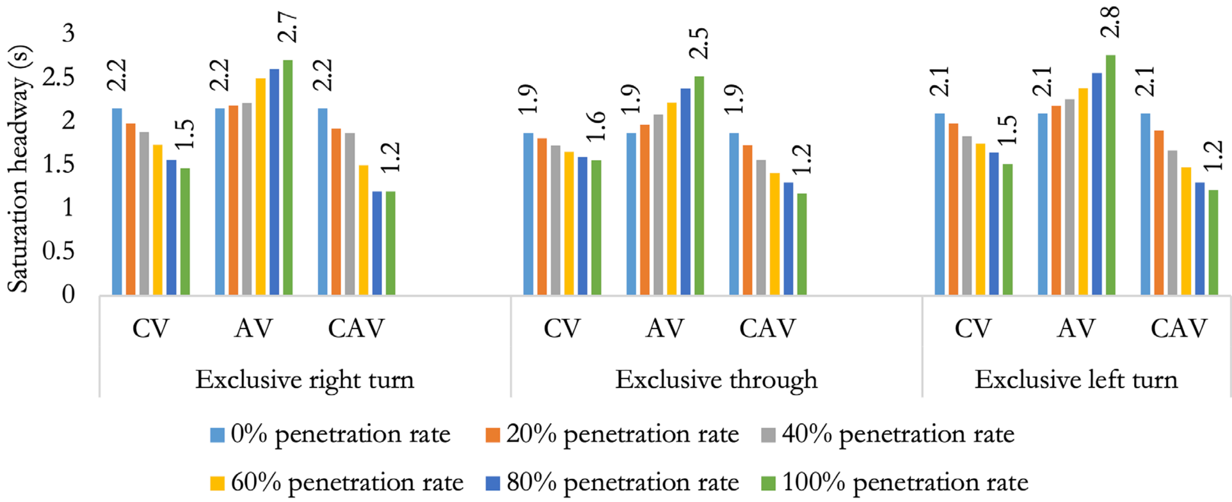



Figure 2.2: Saturation headway for exclusive right, through, and left turning lanes

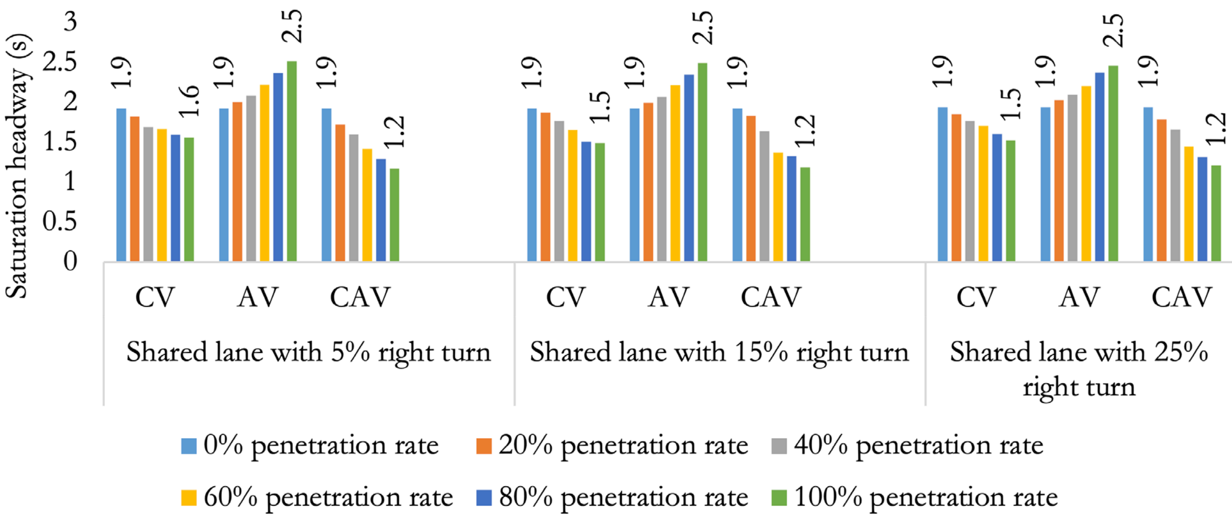



Figure 2.3: Saturation headway for shared right and through lanes with 5%, 15%, and 25% right turn percentages

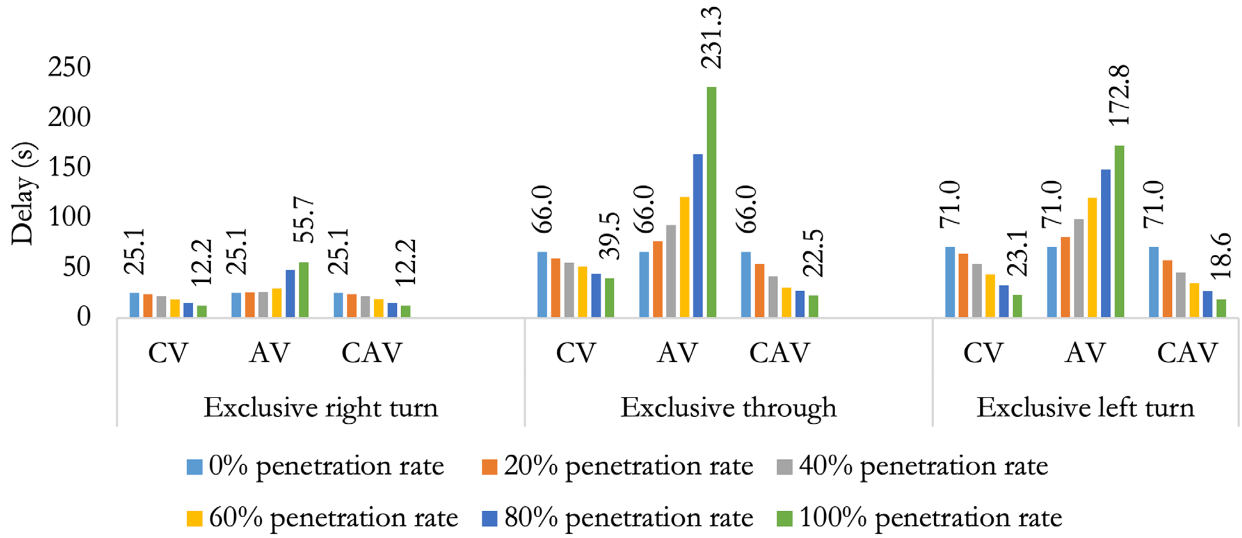



**Figure 2.4:** Average delay for exclusive right, exclusive through, and exclusive left turning lanes

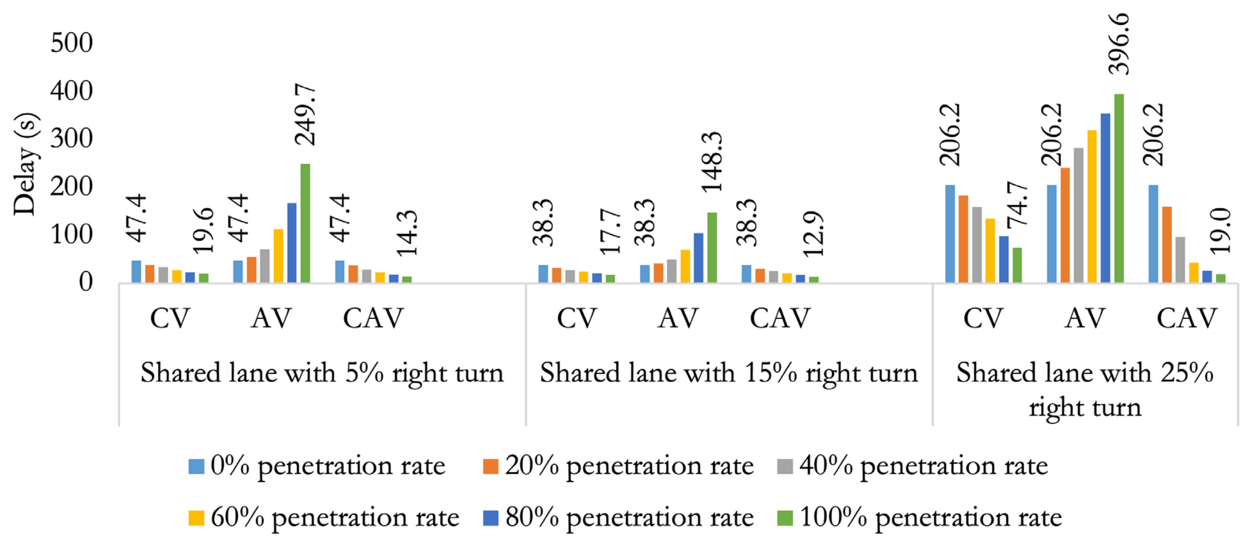



**Figure 2.5:** Average delay for shared right and through lanes with 5%, 15%, and 25% turning percentages

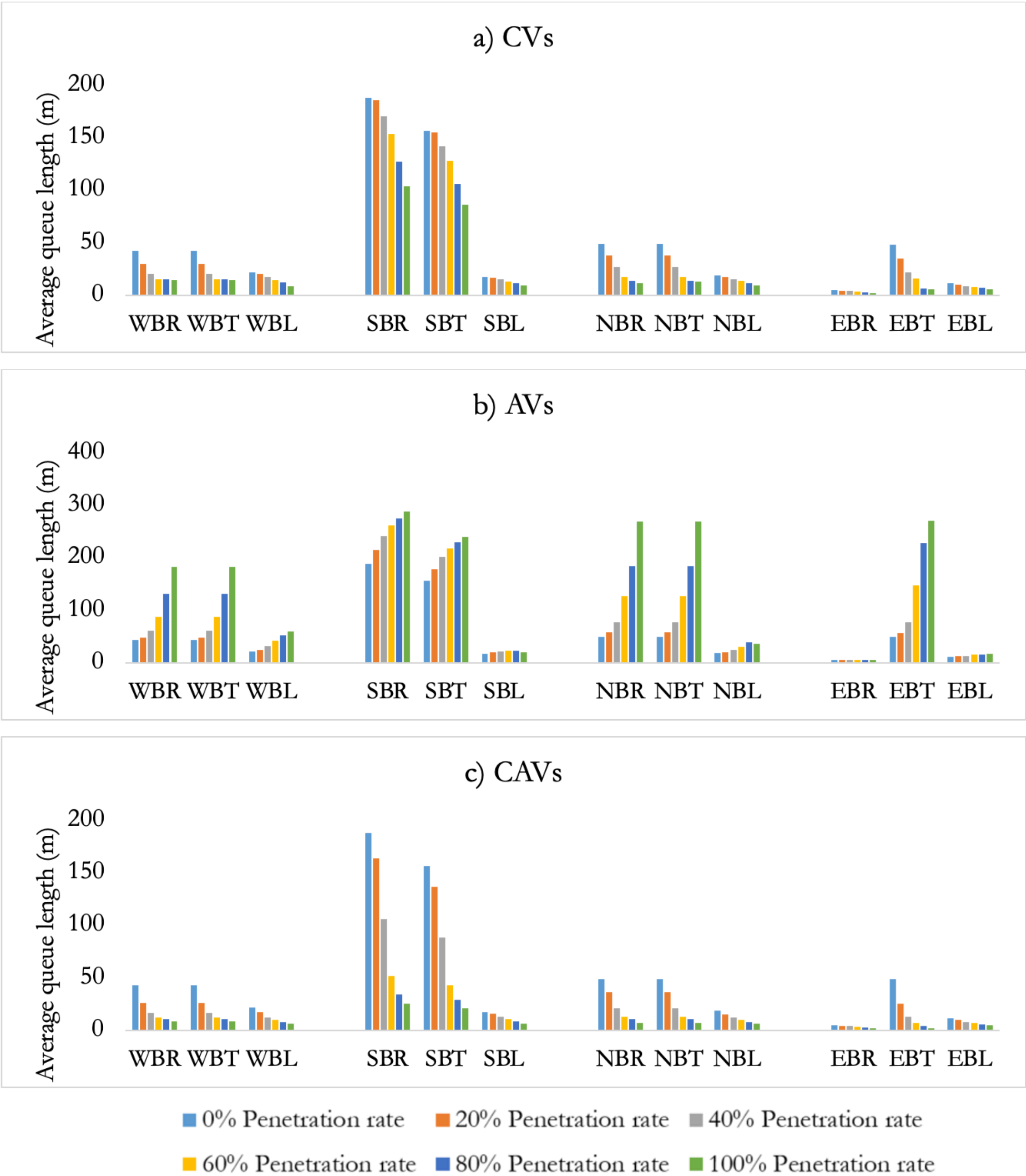



**Figure 2.6:** Average queue length for all movements of the intersection

| Penetration rate | WB R | WB L | WB T | SB L | SB T | SB R | NB R | NB T | NB L | EB T | EB L | EB R |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | a) CVs | | | | | | |
| 0% | D | F | F | D | D | D | D | C | D | E | E | E |
| 20% | C | E | E | C | C | D | D | C | D | D | D | D |
| 40% | C | E | E | C | C | C | D | B | C | C | C | C |
| 60% | C | E | E | C | C | C | C | A | B | C | B | B |
| 80% | B | D | D | C | C | C | C | A | A | B | A | A |
| 100% | B | C | D | C | C | C | C | A | A | A | A | A |
| | | | | | | b) AVs | | | | | | |
| 0% | D | F | F | D | D | D | D | C | D | E | E | E |
| 20% | D | F | F | D | D | D | D | C | D | E | E | E |
| 40% | D | F | F | D | D | D | E | C | E | F | E | F |
| 60% | F | F | F | F | F | F | F | C | E | F | E | F |
| 80% | F | F | F | F | F | F | F | E | F | F | F | F |
| 100% | F | F | F | F | F | F | F | E | F | F | F | F |
| | | | | | | c) CAVs | | | | | | |
| 0% | D | F | F | D | D | D | D | C | D | E | E | E |
| 20% | C | E | E | C | C | D | D | C | D | D | D | D |
| 40% | C | E | D | C | C | C | C | B | C | C | C | C |
| 60% | C | C | D | C | C | C | C | A | B | C | B | A |
| 80% | B | C | C | B | B | B | B | A | A | A | A | A |
| 100% | B | B | C | B | B | B | B | A | A | A | A | A |

**Table 2.7:** Level of service for all movements of the intersection

### *Queue Length*

Figure 2.6 shows the average queue length for each lane group of the intersection, separately. Increasing the market penetration rate of CVs and CAVs decreases the average queue length for all lane groups. The reduction rate is more significant for through movements since they have higher demand volumes. On the other hand, increasing the market penetration rate of AVs increases the queue length because AVs maintain longer headway compared to other vehicle types. We observe that the queue length for southbound through (SBT) and southbound right (SBR) lane groups are longer than others due to high right-turning percentages (i.e., 25% right turn).

### *Level of Service*

Table 2.4 shows the level of service for each lane group of the intersection. The results show that increasing the penetration rate of CVs and CAVs improves the level of service, but increasing the AVs market penetration rate deteriorates the level of service for all movements. When the CAV penetration rate becomes more than 60%, the level of service improves significantly compared to the same market penetration rate of CVs.

## *Intersection-Level Analysis*

In addition to the lane group-level analysis, the research team analyzed the effects of different connectivity and automation levels on mobility performance measures at the intersection level. Figure 2.7 shows the average delay for the entire intersection, where increasing the penetration rate of CVs and CAVs decreases the average delay. However, increasing the AV penetration rate increases the average delay at the intersection. We observe that the lowest delay is associated with the highest number of CAVs in the intersection. Similar trends are also observed for average travel time, which is shown in Figure 2.8.

Figure 2.9 shows that increasing the penetration rate of CVs and CAVs increases the intersection throughput slightly. However, increasing the AVs penetration rate decreases intersection throughput significantly. The maximum throughput for 1 hour of the simulation was 4,375 vehicles with 100% CAVs in traffic stram. On the other hand, the lowest throughput was 2,763 vehicles associated with 100% AV in the traffic stream.

Figure 2.10 shows the average saturation headway of through movements. The saturation headway of human drivers was equal to two seconds, which was achieved by the calibration process. Increasing the CV market penetration rate decreased the average saturation headway to 1.5 seconds representing a 25% reduction while increasing the AV market penetration rate increased it up to 2.6 seconds representing a 30% increase. CAVs moved more efficiently through the intersection with 1.2 seconds of saturation headway, indicating a 40% reduction.

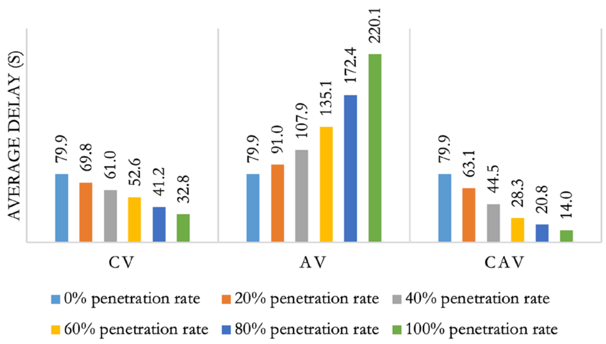



**Figure 2.7:** Intersection average delay

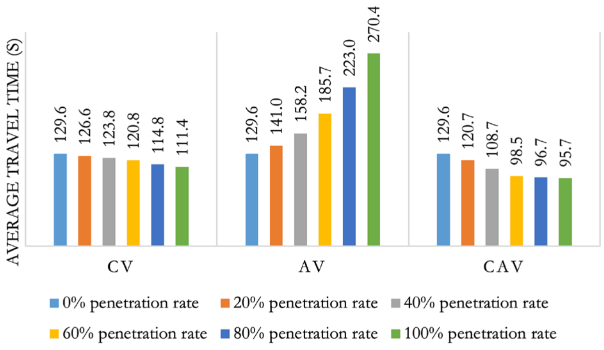



**Figure 2.8:** Intersection average travel time

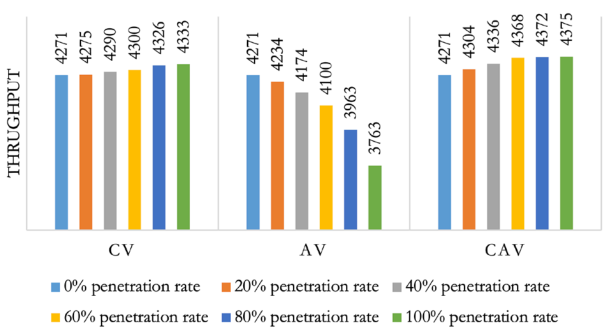



**Figure 2.9:** Intersection throughput

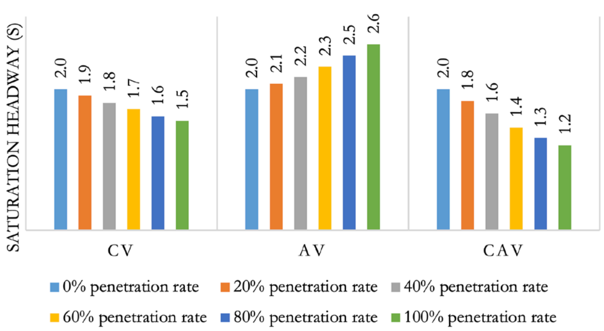
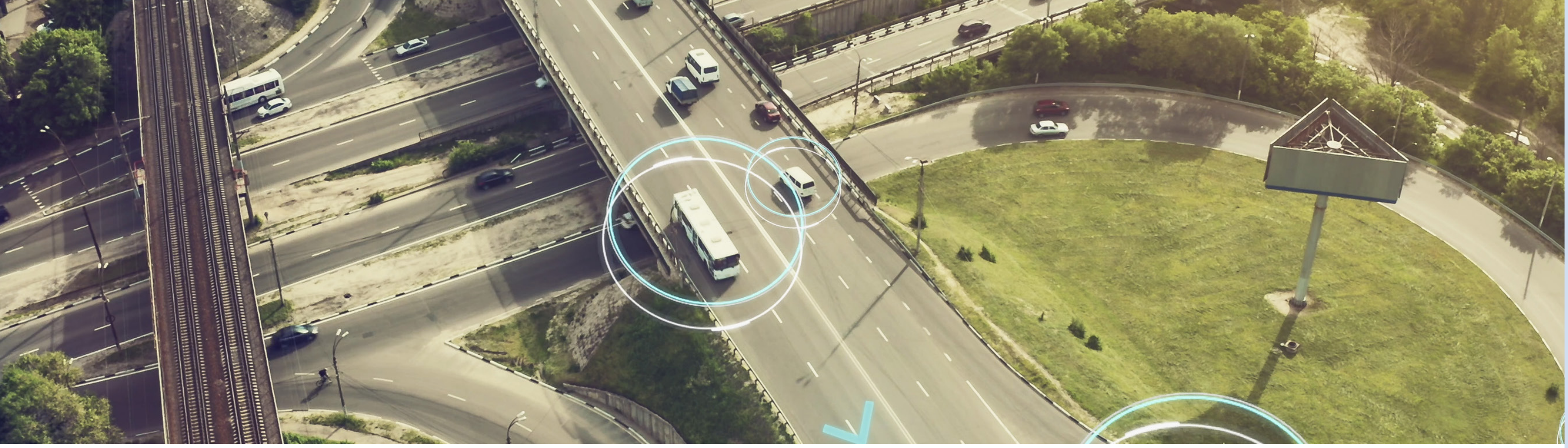



**Figure 2.10:** Intersection saturation headway



## 2.5 Conclusion

This chapter evaluated the potential effect of different connectivity and automation level on saturation headway and several mobility performance measures at signalized intersections. Previous studies mainly focused on the operation of connected and/or automated vehicles on freeway facilities. However, the behavior of automated vehicles in signalized intersections could be significantly affected by the information received on future signal timing plans. The research team considered four vehicle types in this project as (I) human-driven vehicles, (II) connected vehicles, (III) automated vehicles, and (IV) connected and automated vehicles. Vissim was used as a testbed to simulate the movement of vehicles with different driving behaviors and study their potential effects on mobility when they interact with each other and traffic signal controllers under various market penetration rates. The result of this study showed that CAVs provide the most efficient mobility. CVs also improve mobility due to receiving advance information about the future signal timing plans. As a result, CVs will adjust their speed upstream of the intersection and arrive during the green traffic light. In contrast with CVs and CAVs, AVs drive more cautiously and yield longer saturation headways and delays.

This study determined saturation headway for different lane groups under various CV, AV, and CAV market penetration rates. These values could be used to calculate the saturation flow rate and capacity of various lane groups in the presence of CAVs. The results of this study are based on making changes in certain parameters of car-following and lane-changing models of Vissim, which were originally designed to represent human driving behavior. Further studies are required to replace the car following and lane changing logics of existing simulation packages with logics specifically designed for CVs, AVs, and CAVs.

## REFERENCES


1. Krafcik, J. Where the next 10 Million Miles Will Take Us.

2. Milakis, D., M. Snelder, B. Van Arem, B. Van Wee, and G. H. de Almeida Correia. Development and Transport Implications of Automated Vehicles in the Netherlands: Scenarios for 2030 and 2050. European Journal of Transport and Infrastructure Research, Vol. 17, No. 1, 2017.

3. Kyriakidis, M., R. Happee, and J. C. F. de Winter. Public Opinion on Automated Driving: Results of an International Questionnaire among 5000 Respondents. Transportation research part F: traffic psychology and behaviour, Vol. 32, 2015, pp. 127–140.

4. Islam, S., and A. Hajbabaie. Distributed Coordinated Signal Timing Optimization in Connected Transportation Networks. Transportation Research Part C: Emerging Technologies, Vol. 80, 2017, pp. 272–285. https://doi.org/10.1016/j.trc.2017.04.017.

5. Islam, S., A. Hajbabaie, and H. Aziz. A Real-Time Network-Level Traffic Signal Control Methodology with Partial Connected Vehicle Information. Transportation Research Part C: Emerging Technologies, Vol. 121, No. 102830, 2020. https://doi.org/10.1016/j.trc.2020.102830.

6. Islam, S., M. Tajalli, R. Mohebifard, and A. Hajbabaie. The Effects of Connectivity and Traffic Observability on an Adaptive Traffic Signal Control System. Transportation Research Record, Vol. Accepted, 2021.

7. Mohebifard, R., S. Islam, and A. Hajbabaie. Cooperative Traffic Signal and Perimeter Control in Semi Connected Urban-Street Networks. Transportation Research Part C: Emerging Technologies, Vol. 104, 2019, pp. 408–427. https://doi.org/10.1016/j.trc.2019.05.023.

8. Niroumand, R., M. Tajalli, L. Hajibabai, and A. Hajbabaie. Joint Optimization of Vehicle-Group Trajectory and Signal Timing: Introducing the White Phase for Mixed-Autonomy Traffic Stream. Transportation Research Part C: Emerging Technologies, Vol. 116, 2020, p. 102659. https://doi.org/10.1016/j.trc.2020.102659.

9. Niroumand, R., M. Tajalli, L. Hajibabai, and A. Hajbabaie. The Effects of the "White Phase" on Intersection Performance with Mixed-Autonomy Traffic Stream. 2020.

10. Tajalli, M., and A. Hajbabaie. Traffic Signal Timing and Trajectory Optimization in a Mixed Autonomy Traffic Stream. IEEE Transactions on Intelligent Transportation Systems, 2021, pp. 1–14. https://doi org/10.1109/TITS.2021.3058193.

11. Mohebifard, R., and A. Hajbabaie. Trajectory Control in Roundabouts with a Mixed-Fleet of Automated and Human-Driven Vehicles. Computer-Aided Civil and Infrastructure Engineering, Vol. Accepted, 2021.

12. Mohebifard, R., and A. Hajbabaie. Effects of Automated Vehicles on Traffic Operations at Roundabouts. 2020.

13. Rajamani, R., and C. Zhu. Semi-Autonomous Adaptive Cruise Control Systems. IEEE Transactions on Vehicular Technology, Vol. 51, No. 5, 2002, pp. 1186–1192.

14. Tu, L., and C.-M. Huang. Forwards: A Map-Free Intersection Collision-Warning System for All Road Patterns. IEEE Transactions on Vehicular Technology, Vol. 59, No. 7, 2010, pp. 3233–3248.

15. Tajalli, M., and A. Hajbabaie. Collision Mitigation at Signalized Intersection Using Connected Vehicles Data and Technologies. 2018.

16. Kusano, K. D., and H. C. Gabler. Safety Benefits of Forward Collision Warning, Brake Assist, and Autonomous Braking Systems in Rear-End Collisions. IEEE Transactions on Intelligent Transportation Systems, Vol. 13, No. 4, 2012, pp. 1546–1555.

17. Vahidi, A., and A. Eskandarian. Research Advances in Intelligent Collision Avoidance and Adaptive Cruise Control. IEEE transactions on intelligent transportation systems, Vol. 4, No. 3, 2003, pp. 143–153.

18. Seth, D., and M. L. Cummings. Traffic Efficiency and Safety Impacts of Autonomous Vehicle Aggressiveness. simulation, Vol. 19, 2019, p. 20.

19. Sadigh, D., S. Sastry, S. A. Seshia, and A. D. Dragan. Planning for Autonomous Cars That Leverage Effects on Human Actions. No. 2, 2016.

20. Sunberg, Z. N., C. J. Ho, and M. J. Kochenderfer. The Value of Inferring the Internal State of Traffic Participants for Autonomous Freeway Driving. 2017.

21. Treiber, M., A. Kesting, and D. Helbing. Influence of Reaction Times and Anticipation on Stability of Vehicular Traffic Flow. Transportation Research Record, Vol. 1999, No. 1, 2007, pp. 23–29.

22. Sezer, V., T. Bandyopadhyay, D. Rus, E. Frazzoli, and D. Hsu. Towards Autonomous Navigation of Unsignalized Intersections under Uncertainty of Human Driver Intent. 2015.

23. Talebpour, A., and H. S. Mahmassani. Influence of Connected and Autonomous Vehicles on Traffic Flow Stability and Throughput. Transportation Research Part C: Emerging Technologies, Vol. 71, 2016, pp. 143–163.

24. Asadi, B., and A. Vahidi. Predictive Cruise Control: Utilizing Upcoming Traffic Signal Information for Improving Fuel Economy and Reducing Trip Time. IEEE transactions on control systems technology, Vol. 19, No. 3, 2010, pp. 707–714.

25. Tajalli, M., and A. Hajbabaie. Dynamic Speed Harmonization in Connected Urban Street Networks. Computer-Aided Civil and Infrastructure Engineering, Vol. 33, No. 6, 2018, pp. 510–523. https:/doi.org/10.1111/mice.12360.

26. Tajalli, M., and A. Hajbabaie. Distributed Optimization and Coordination Algorithms for Dynamic Speed Optimization of Connected and Autonomous Vehicles in Urban Street Networks. Transportation Research Part C: Emerging Technologies, Vol. 95, 2018, pp. 497–515. https://doi org/10.1016/jtrc.2018.07.012.

27. HomChaudhuri, B., A. Vahidi, and P. Pisu. A Fuel Economic Model Predictive Control Strategy for a Group of Connected Vehicles in Urban Roads. 2015.

28. He, X., H. X. Liu, and X. Liu. Optimal Vehicle Speed Trajectory on a Signalized Arterial with Consideration of Queue. Transportation Research Part C: Emerging Technologies, Vol. 61, 2015, pp. 106–120. https://doi.org/10.1016/j.trc.2015.11.001.

29. Tajalli, M., M. Mehrabipour, and A. Hajbabaie. Network-Level Coordinated Speed Optimization and Traffic Light Control for Connected and Automated Vehicles. IEEE Transactions on Intelligent Transportation Systems, 2020, pp. 1–12. https://doi.org/10.1109/tits.2020.2994468.

30. Guo, Y., J. Ma, C. Xiong, X. Li, F. Zhou, and W. Hao. Joint Optimization of Vehicle Trajectories and Intersection Controllers with Connected Automated Vehicles: Combined Dynamic Programming and Shooting Heuristic Approach. Transportation research part C: emerging technologies, Vol. 98, 2019, pp. 54–72.

31. Mirheli, A., L. Hajibabai, and A. Hajbabaie. Development of a Signal-Head-Free Intersection Control Logic in a Fully Connected and Autonomous Vehicle Environment. Transportation Research Part C: Emerging Technologies, Vol. 92, 2018, pp. 412–425. https://doi.org/10.1016/j.trc.2018.04.026.

32. Mirheli, A., M. Tajalli, L. Hajibabai, and A. Hajbabaie. A Consensus-Based Distributed Trajectory Control in a Signal-Free Intersection. Transportation Research Part C: Emerging Technologies, Vol. 100, 2019, pp. 161–176. https://doi.org/10.1016/j.trc.2019.01.004.

33. Sukennik, P., P. T. V Group, and others. Micro-Simulation Guide for Automated Vehicles. COEXIST (h2020-coexist. eu), 2018.

34. Buck, H. S., N. Mallig, and P. Vortisch. Calibrating VISSIM to Analyze Delay at Signalized Intersections. Transportation Research Record, Vol. 2615, No. 1, 2017, pp. 73–81.

35. America, P. PTV VISTRO User Manual.