Measuring Autonomous Vehicle Impacts on Congested Networks Using Simulation

Corresponding Author:
David Stanek, PE
Fehr & Peers
1001 K Street, 3rd Floor, Sacramento, CA 95814
Tel: (916) 329-7332; Fax: (916) 773-2015; Email: D.Stanek@fehrandpeers.com

Co-authors:
Elliot Huang, PE
City of Costa Mesa
77 Fair Drive, Costa Mesa, CA 92626
Tel: (714) 754-5000; Email: ELLOIT.HUANG@costamesaca.gov

Ronald T. Milam, AICP
Fehr & Peers
1013 Galleria Boulevard, Suite 255, Roseville, CA 95678
Tel: (916) 773-1900; Fax: (916) 773-2015; Email: R.Milam@fehrandpeers.com

Yayun (Allen) Wang, PE
Fehr & Peers
160 West Santa Clara Street, Suite 675, San Jose, CA 95113
Tel: (408) 278-1700; Fax: (408) 278-1717; Email: A.Wang@fehrandpeers.com

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ABSTRACT

Autonomous vehicles offer a wide variety of potential benefits. One commonly discussed benefit is improved traffic operations (that is, decreased congestion, decreased delay, and improved efficiency) due to the way that autonomous vehicles are expected to behave in a traffic stream. In this research, we evaluate the effect of varying the percentage of autonomous vehicles in the overall vehicle fleet mix on transportation network performance.

To perform this analysis, we began with calibrated microsimulation models created in the Vissim microsimulation traffic analysis software. An appropriate set of driver behavior parameters for autonomous vehicles was then determined from a review of previous research including recommendations from the software developer. Efficiencies in traffic flow from connected vehicles was not considered in this analysis. Finally, different levels of autonomous vehicle penetration were tested and compared to the calibrated baseline scenario. The findings are intended to guide decision makers when considering future vehicle fleet mixes that include autonomous vehicles.

INTRODUCTION

Autonomous vehicles (also known as automated vehicles, driverless cars, or self-driving cars) offer a wide variety of potential benefits. One commonly discussed benefit is improved traffic operations (that is, decreased congestion, decreased delay, and improved efficiency) due to the way that autonomous vehicles, or AVs, are expected to behave in a traffic stream. In this research, we evaluate the effect of varying the percentage of AVs in the overall vehicle fleet mix on transportation network performance.

AVs are expected to perform differently from human-driven vehicles in many aspects (*1*). While the automation systems developed by different car manufacturers could differ slightly depending on the specific driving logic applied, AVs are expected to operate with smaller headways, shorter reaction times, and higher speeds than human-driven vehicles. In addition, it is expected that AVs will be programmed to act more cooperatively than human drivers to achieve greater system-wide benefits (*1-3*). However, as most AV operating technologies and regulations are still under development, there is limited publicly available empirical data on how they will behave in traffic flow.

Traffic operations can be analyzed using macroscopic, deterministic methods – as presented in the *Highway Capacity Manual* (*4*) – or microscopic, stochastic methods – as applied using computer software. The first approach considers vehicle flow as a group and compares the demand volume with the roadway capacity to estimate delay, speed, and other performance measures. The relationship is based on empirical observations of traffic conditions in various facility types. The second approach seeks to model individual vehicles and their interaction with other vehicles, the roadway geometry, and traffic control elements. The microscopic simulation of traffic operations uses models for car-following, lane changing, and other driver models of behavior or performance. Since empirical observations of AVs in traffic is not yet possible, the simulation model approach was selected to determine AV effects on traffic operations.

AVs have the potential to increase roadway capacity, or more specifically vehicle throughput per lane. The reaction time for a computer is significantly faster than for a human driver. This could allow, for example, an AV to follow a leading vehicle at a shorter headway than practical or safe for a human-driven vehicle. And, headway is indirectly proportional to capacity. Reaction time would also affect lane changing, reaction to traffic signals, and other driving tasks. Microscopic simulation models use reaction time and other driver behavior and vehicle performance parameters as inputs. As a result, they provide a useful platform for evaluating the effect of AVs on traffic operations.

With automation of vehicle navigation, vehicles also have the potential to become connected. AVs that are connected to and communicating with other AVs in the traffic stream have the potential to form virtual trains, which would further improve capacity. Connection to infrastructure could also improve capacity if the vehicle were given advance information about signal phasing or other traffic control plans. For this analysis, capacity improvements due to connected vehicles was not considered. Establishing a communication network for vehicles and infrastructure will take a greater level of effort compared to simply automating vehicles. As a result, AVs are more likely to be become operational before connected vehicles do. Creating

connected vehicle operations in a simulation model is also more complex than modeling individual AVs.

This paper describes how simulation analysis software was adapted to determine AV impacts on congested study networks. First, the assumptions for how AVs will operate are addressed. Then, the driver behavior model parameters for AVs are developed. Finally, the AV driver behavior is applied to two case studies of large freeway and arterial networks to determine how the percentage of AVs in the vehicle fleet affect network performance.

MODELING AUTONOMOUS VEHICLE OPERATIONS

The integration of AVs into daily traffic operations will depend on the following key factors that influence or govern roadway operations.

- Regulatory conditions governing adherence to traffic laws
- Network design and traffic control operation priorities
- Vehicle performance capabilities
- Driver behavior capabilities

Regulatory Conditions

The presumption for this analysis is that AVs would be allowed to operate on existing roadways in mixed-flow traffic conditions. As such, California was selected as the test state since they have proposed operational rules for AVs consistent with this presumption as noted below from the draft code of regulations (*5*).

> *<u>§ 227.32 Requirements for Autonomous Vehicle Test Drivers</u>*
> *(c) The autonomous vehicle test driver shall obey all provisions of the Vehicle Code and local regulation applicable to the operation of motor vehicles whether the vehicle is in autonomous mode or conventional mode.*

The requirement for the vehicle to obey all provisions of the vehicle code and local regulations sets the operational expectation for modeling traffic operations. However, this expectation is problematic for analyzing AVs in a freeway setting because the California Vehicle Code Section 21703 requires that drivers follow the vehicle in front at a “reasonable and prudent” distance (*6*). No guidance has been provided about what is ‘reasonable and prudent’ for vehicles operated in autonomous mode versus conventional mode. In conventional mode, the California Department of Motor Vehicles recommends the following gap spacing (*7*).

> *Any time you merge with other traffic, you need a gap of at least 4 seconds, which gives both you and the other vehicle only a 2 second following distance. When it is safe, go back to following the “3-second rule”.*

The author’s observations of human drivers’ gap spacing revealed gaps of less than one second gap during peak period conditions. Use of a three-second gap would disrupt the

simulation severely such that it is not a meaningful analysis test. Instead, the authors developed a set of AV driver behavior parameter values generally based on current human drivers but adjusted for the faster reaction time of AVs as described below. In fact, the actual reaction time of AVs may lead to discomfort from human drivers and may result in lower than expected capacity. This effect was considered when setting the AVs driver behavior parameters.

Network Design and Traffic Control Operation Priorities

For this set of tests, the authors did not modify existing roadway network geometrics or traffic control operation to accommodate AVs. Given the potential for better operational and safety performance, AVs could be provided preferential lanes, signal phasing, or other advantages to encourage their use, similar to the way that high-occupancy vehicles have preferential lanes (*8*). For this research, however, AVs were incorporated into the model without any special operations priorities.

Vehicle Performance Capabilities

Vehicle performance of AVs was not adjusted compared to human driven vehicles. Since they are automated, AVs could have different performance characteristics, such as acceleration, deceleration, turning radius, etc. than other vehicles. However, no adjustment was made in the model to the vehicles identified as AVs in part due to the expectation that these vehicles would need to provide a 'comfortable ride experience' similar to that offered by human drivers. Additionally, the AV percentage is constant across all vehicles types: single-occupant vehicles, high-occupancy vehicles, and trucks.

Driver Behavior Capabilities

In contrast to the above areas, the simulation model does have different driver behavior capabilities for AVs compared with human driven vehicles. These adjustments are described in the following section. Actual AV driver behavior is under development and likely to vary among manufacturers. Based on theoretical changes to vehicle operation, modifications to the driver behavior models are proposed below.

ANALYSIS MODEL INPUTS

This section describes the driver behavior parameters that were used to model AVs in the microsimulation program Vissim. Vissim, developed by PTV Group, allows users to customize driver behavior parameters – car-following, lane changing, lateral behavior, and reaction to signal controls – to calibrate models to match the observed field conditions.

Car-following parameters define how vehicles interact longitudinally within the travel lane. Parameters include look-ahead and look-back distance, headway time, following distance, vehicle acceleration, and vehicle deceleration. The two car-following models included in Vissim are denoted Wiedemann 74 and Wiedemann 99. The current Wiedemann 74 car-following model is an improved version of Rainer Wiedemann's 1974 car following model, and is suitable to model urban traffic and merging areas. The Wiedemann 99 model contains more adjustable parameters, and is recommended for use when simulating freeway traffic. Lateral interaction of vehicles are

defined by the lane changing and lateral behavior parameters. Descriptions of the related driver behavior parameters are provided in the Vissim user manual (*9*).

PTV Group has provided guidance on how to model AVs in Vissim (*10*). As summarized in Table 1, the recommendations range from microscopic-level driver behavior changes to macroscopic-level travel behavior changes and are consistent with other research (*1-3*). Some of the recommended modifications can be accomplished through the internal model interface, while others can be done through external scripts (the COM interface) or through an external driving simulator program (*10*). Since the goal of this analysis is to evaluate the operational effects of AVs due to driver behavior changes, only the recommendations on driver behavior parameters that can be modified within the Vissim program were considered for this analysis (that is, items 1, 2, 3, 5, 10 and 11 in Table 1).

TABLE 1 Recommendations for Modeling Connected and Autonomous Vehicles in Vissim

	Connected and Autonomous Vehicle Behavior	Recommended Model Adjustment
1	Keep smaller standstill distances	W74: change W74ax parameter, W99: change CC0 parameter
2	Keep smaller distances at non-zero speed	W74: change W74ax, W74bxAdd, and W74bxMult parameters; W99: change CC0, CC1, and CC2 parameters
3	Accelerate faster and smoothly from standstill	W74: change acceleration functions, W99: change acceleration functions and CC8, CC9 parameters
4	Keep constant speed with no or smaller oscillation at free flow	COM Interface or External Driver Model/Driving Simulator Interface
5	Follow other vehicles with smaller oscillation distance oscillation	W74: reduce W74bxMult or set it to 0, W99: change CC2 parameter
6	Form platoons of vehicles	COM Interface or External Driver Model/Driving Simulator Interface
7	Following vehicles react on green signal at the same time as the first vehicle in the queue	COM Interface or External Driver Model/Driving Simulator Interface
8	Communicate with other AVs, i.e. broken down vehicle and others avoid it	COM Interface or External Driver Model/Driving Simulator Interface
9	Communicate with the infrastructure, i.e. vehicles adjusting speed profile to reach a green light at signals	COM Interface or External Driver Model/Driving Simulator Interface
10	Perform more co-operative lane change as lane changes could occur at a higher speed co-operatively	Switch to cooperative lane change, change maximum speed difference, and change maximum collision time
11	Smaller lateral distances to vehicles or objects in the same lane or on adjacent lanes	Same lane – change default behavior when overtaking on the same lane and define exceptions for vehicle classes
12	Exclusive AV lanes, with and without platoons	Define blocked vehicle classes for lanes, or define vehicle routes for vehicle classes, use COM for platooning

13	Drive as CAV on selected routes (or areas) and as conventional human controlled vehicles on other routes; i.e. Volvo DriveMe project	Use different link behavior types and driver behavior for vehicle classes; and/or (depending on complexity of CAV behavior) COM Interface
14	Divert vehicles already in the network onto new routes and destinations; i.e. come from a parking place or position in the network to pick up a rideshare app passenger on demand	COM Interface, Dynamic Assignment required (allows access to paths found by dynamic assignment, vehicles can be assigned a new path either when waiting in parking lot or already in the network, if path starts from vehicles current location)

Source: (*10*)

Car-following Parameters

Researchers (*1-2*) have tested three variations of the Wiedemann 99 car-following model for AVs: aggressive, intermediate and conservative. The aggressive profile assumed shorter headway time and more aggressive acceleration and deceleration than human-driven vehicles, and the conservative profile assumed the opposite. The preliminary simulation results showed that vehicle delay would decrease as driver behavior profile becomes more aggressive. Most of the modifications in the aggressive and intermediate profiles are consistent with the recommendations presented in Table 1. After reviewing the specific values, this analysis adopted most of the car-following parameters tested in the intermediate profile to provide a noticeable but not drastic change from regular driving behavior. One exception to this approach was the headway time (CC1), which was re-calculated to achieve a 0.5-second headway (front bumper to front bumper) between subsequent vehicles since AVs are expected to have faster reaction times than human drivers. The list below summarizes the changes made to the default Wiedemann 99 model to simulate the expected behavior of AVs.

- Standstill Distance: reduced from 4.92 to 4.1 seconds to allow smaller gaps between stopped vehicles
- Headway Time: reduced from 0.9 to 0.25 seconds, to achieve a 0.5-second headway (front bumper to front bumper) between subsequent vehicles at the speed of 50 miles per hour
- Car Following Distance/Following Variation: reduced from 13.12 to 9.84 feet, a 25 percent reduction, to allow for shorter vehicle gaps
- Threshold for Entering Following: increased from 8 to 12 seconds to allow trailing vehicles to enter following mode and react to the leading vehicle behavior earlier
- Speed Dependency of Oscillation: set to zero, which assumes the speed oscillation is independent of the distance to the preceding vehicle

The complete list of parameters in the default Wiedemann 99 car-following model and the proposed values for AV driver behavior are presented in Table 2. PTV Group also recommended changes to standstill acceleration and acceleration at 50 miles per hour to account for aggressive acceleration and deceleration by AVs. Since no empirical data exists on the recommended values,

these parameters were not modified because they could have negative effects on passenger comfort.

TABLE 2 Car Following Parameters – Wiedemann 99 Model

Parameter	Default Value	Proposed Value for AVs
CC0 - Standstill distance (ft)	4.92	**4.10**
CC1 - Headway time (gap between vehicles) (seconds)	0.9	**0.25**
CC2 - Car-following distance/following variation (ft)	13.12	**9.84**
CC3 - Threshold for entering following (seconds)	-8	**-12**
CC4 - Negative following threshold (ft/s)	-0.35	-0.35
CC5 - Positive following threshold (ft/s)	0.35	0.35
CC6 - Speed dependency of oscillation (1/(ft/s))	11.44	**0**
CC7 - Oscillation during acceleration (ft/s^2)	0.82	0.82
CC8 - Standstill acceleration (ft/s^2)	11.48	11.48
CC9 - Acceleration at 50 miles per hour (ft/s^2)	4.92	4.92

Note: All modified parameters are highlighted in **bold**.

Although there are fewer adjustable parameters in the Wiedemann 74 model, the logic for modifying the parameters to simulate the AV driver behavior is similar. Due to a lack of empirical data on the recommended values, the three parameters used to calculate the desired following distance were reduced by 25 percent to be consistent with the changes to the Wiedemann 99 model parameters. The default and modified parameter values for the Wiedemann 74 car-following model are presented in Table 3.

TABLE 3 Car Following Parameters – Wiedemann 74 Model

Parameter	Default Value	Proposed Value for AVs
Average standstill distance (ft)	6.56	**4.92**
Additive part of safety distance	2	**1.5**
Multiplicative part of safety distance	3	**2.25**

Note: All modified parameters are highlighted in **bold**.

AVs will be able to observe and follow more activities on the road than human drivers (*6*). The related parameters in Vissim are the look-ahead distance, look-back distance, and number of observed vehicles. Modifications to these parameters were made based on the data provided by Bohm and Häger (*2*). As shown in Table 4, the look-ahead and look-back distances were assumed

to be twice as the default values for human-driven vehicles, and the number of observed vehicles was changed from 2 to the maximum value of 10.

TABLE 4 Car Following Parameters - General

Parameter	Default Value	Proposed Value for AVs
Look ahead distance	0 to 820 feet	**0 to 1640 feet**
Look back distance	0 to 490 feet	**0 to 980 feet**
Observed vehicles	2	**10**
Smooth close-up behavior	Checked	Checked

Note: All modified parameters are highlighted in b**old**.

Lane Change and Lateral Behavior

AVs are expected to perform more cooperative lane change maneuvers than human-driven vehicles (*3*). Based on the recommendations in Table 1, the following lane change parameters were modified. Since no empirical data exists, the modifications were made based on the assumption of a 25 percent reduction to the default parameters to be consistent with the car-following parameter changes.

- Minimum headway: reduced from 1.64 to 1.23 feet, a 25 percent reduction, to allow smaller acceptable distance between two vehicles after a lane change
- Safety distance reduction factor: reduced the safety factor by 25 percent to allow smaller acceptable safety distances for the lane-changing vehicle and trailing vehicle during the lane-change maneuver
- Maximum deceleration for cooperative braking: increased the default value of 9.84 feet per second squared (ft/s^2) to the maximum value of 13.12 ft/s^2 to make trailing vehicles brake more cooperatively
- Cooperative lane change: this parameter was selected so that the trailing vehicle (Vehicle A) will change into adjacent lanes to facilitate the lane changing for the lane-changing vehicle (Vehicle B), as shown in Figure 1 (*9*)

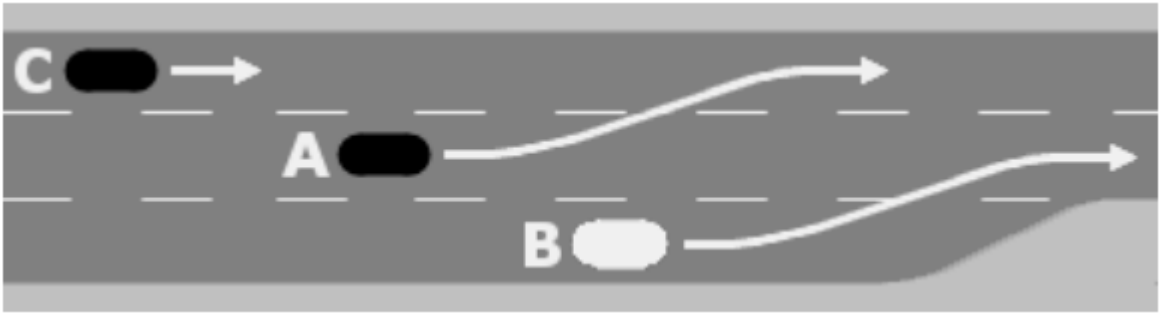

FIGURE 1 Cooperative lane change

The complete list of lane change parameters applied to AVs is presented in Table 5.

TABLE 5 Lane Change Parameters

Parameter	Default Value	Proposed Value for AVs
General behavior	Free lane selection	Free lane selection
Maximum deceleration - own vehicle (ft/s^2)	-13.12	-13.12
Maximum deceleration - trailing vehicle (ft/s^2)	-9.84	-9.84
-1 ft/s^2 per distance - own vehicle and trailing vehicle (ft)	200	200
Accepted deceleration - own vehicle (ft/s^2)	-3.28	-3.28
Accepted deceleration - trailing vehicle (ft/s^2)	-1.64	-1.64
Minimum headway - front/rear (ft)	1.64	**1.23**
Safety distance reduction factor	0.6	**0.45**
Maximum deceleration for cooperative braking (ft/s^2)	-9.84	**-13.12**
Cooperative lane change	Not checked	**Checked**
Maximum speed difference (mph)	6.71	6.71
Maximum collision time (seconds)	10	10

Note: All modified parameters are highlighted in b**old**.

The lateral behavior parameters define how vehicles interact with vehicles in the same lane, when the travel lane is wide enough and overtaking is allowed (*9*). Since most freeway lanes in the case studies are only wide enough for one vehicle, these parameters will mainly affect the urban streets in the networks. The two parameters modified in this analysis are the minimum lateral standstill distance and the minimum lateral distance while driving. Similar to the lane change behavior modifications, both parameters were reduced by 25 percent, which assumes that automated vehicles would have better detection system and thus can operate with less clearance distance, as shown in Table 6.

CASE STUDIES AND FINDINGS

This section describes how the driver behavior parameters discussed previously were applied to micro-simulation models. In this assessment, the driver behavior parameters were applied to two calibrated existing conditions networks to identify the operational effects of varying the level of AVs. AV percentages of 0, 10, 30, 50, 70, 90, and 100 percent were tested. Network wide performance measures were collected for each simulation run and then compared to identify overall trends related to the AV fleet percentage.

The first case study is a calibrated existing conditions model of a freeway and arterial network in northern California. To analyze the transportation impacts of improvements to the Interstate 80/State Route 65 freeway system interchange, the study area encompassed about 20

freeway miles, 15 freeway interchanges, 3 parallel arterial corridors, and 32 study intersections. This network experienced moderate congestion during the AM and PM peak periods in 2012. For this test, the AM peak period model was selected since it has more congestion with bottlenecks on both freeway facilities (*11*).

TABLE 6 Lateral Parameters

Parameter	Default Value	Proposed Value for AVs
Collision time gain (seconds)	2	2
Minimum longitudinal speed (mph)	2.24	2.24
Time before direction changes (seconds)	0	0
Overtake same lane vehicle - minimum lateral distance standing (ft)	0.66	**0.495**
Overtake same lane vehicle - minimum lateral distance driving (ft)	3.28	**2.46**

Note: All modified parameters are highlighted in b**old**.

The AV driver behavior parameters set was created as listed above in Tables 2 through 6. The vehicle fleet was modified by converting varying percentages of human-driven vehicles to AVs. The changes to the vehicle fleet were applied network wide. The change in each performance measure compared to the no AV scenario is provided in Table 7. The total network delay and average network speed as a function of AV percentage is plotted in Figure 2.

TABLE 7 Network Wide Performance for Case Study 1

AV Fleet Percentage	Network Total Delay (Percent Difference)	Network Average Speed (Percent Difference)
0%	0%	0%
10%	-3%	1%
30%	-17%	3%
50%	-24%	4%
70%	-27%	5%
90%	-29%	5%
100%	-30%	6%

Increasing AV fleet percentage yields a decrease in network delay and an increase in network speeds. In the 100 percent AV scenario, the results show a 30 percent decrease in network delay and 6 percent increase in network speeds. A notable feature of these results is the diminishing return in network performance as the AV fleet percentage increases. The operational improvements gained going from 0 to 50 percent AVs is more than the operational improvements

gained going from 50 to 100 percent AVs. A 30 percent share of AVs provided more than half the reduction in network delay from the 100 percent AV scenario.

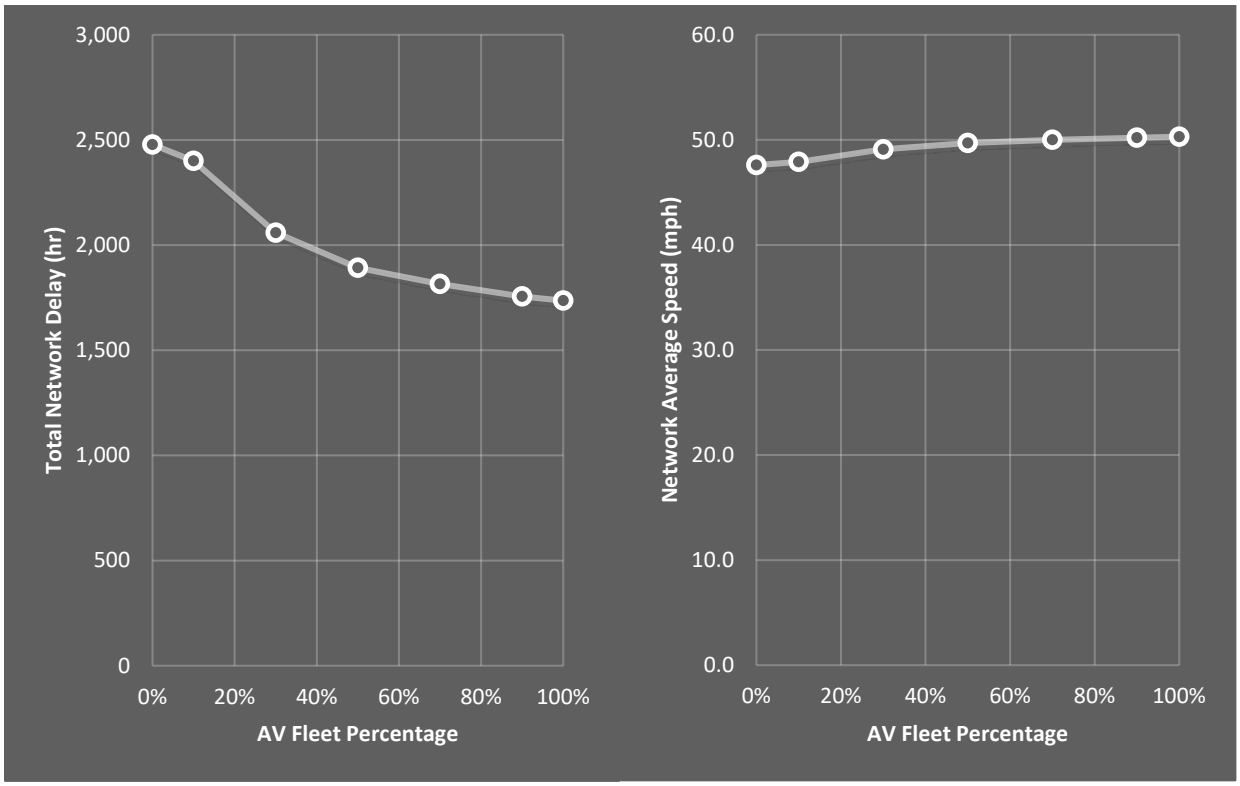

FIGURE 2 Effect of AV percentage for Case Study 1

The second case study is a calibrated existing conditions network for a segment of the State Route 55 freeway corridor in southern California. This network consists of approximately 10 miles of freeway mainline, 6 interchanges at arterials, 2 interchanges at other freeways, and 14 ramp terminal intersections. This network had moderate to high congestion in the northbound direction during the PM peak hour in 2011 (*12*). The AV driver behavior profile was applied to the network in a similar manner as the first case study. The change in each performance measure compared to the no AV scenario is provided in Table 8. The total network delay and average network speed as a function of AV fleet percentage is plotted on Figure 3.

The same general trend from the first case study is seen in the second case study. In the 100 percent AV scenario, the results indicate a 33 percent decrease in network delay and 23 percent increase in network speeds. The percent increase in network speed is higher in the second case study compared to the first case study; however, the larger change is likely due to the second network is initially more congested. The diminishing returns of network performance is also seen in the second case study. Most of the network delay decrease occurs at the 30 percent AV penetration level. Only an additional 5 percent delay reduction occurs when AVs are increased from 30 to 100 percent.

TABLE 8 Network Wide Performance for Case Study 2

AV Fleet Percentage	Network Total Delay (Percent Difference)	Network Average Speed (Percent Difference)
0%	0%	0%
10%	-15%	9%
30%	-28%	18%
50%	-33%	22%
70%	-34%	23%
90%	-34%	23%
100%	-33%	23%

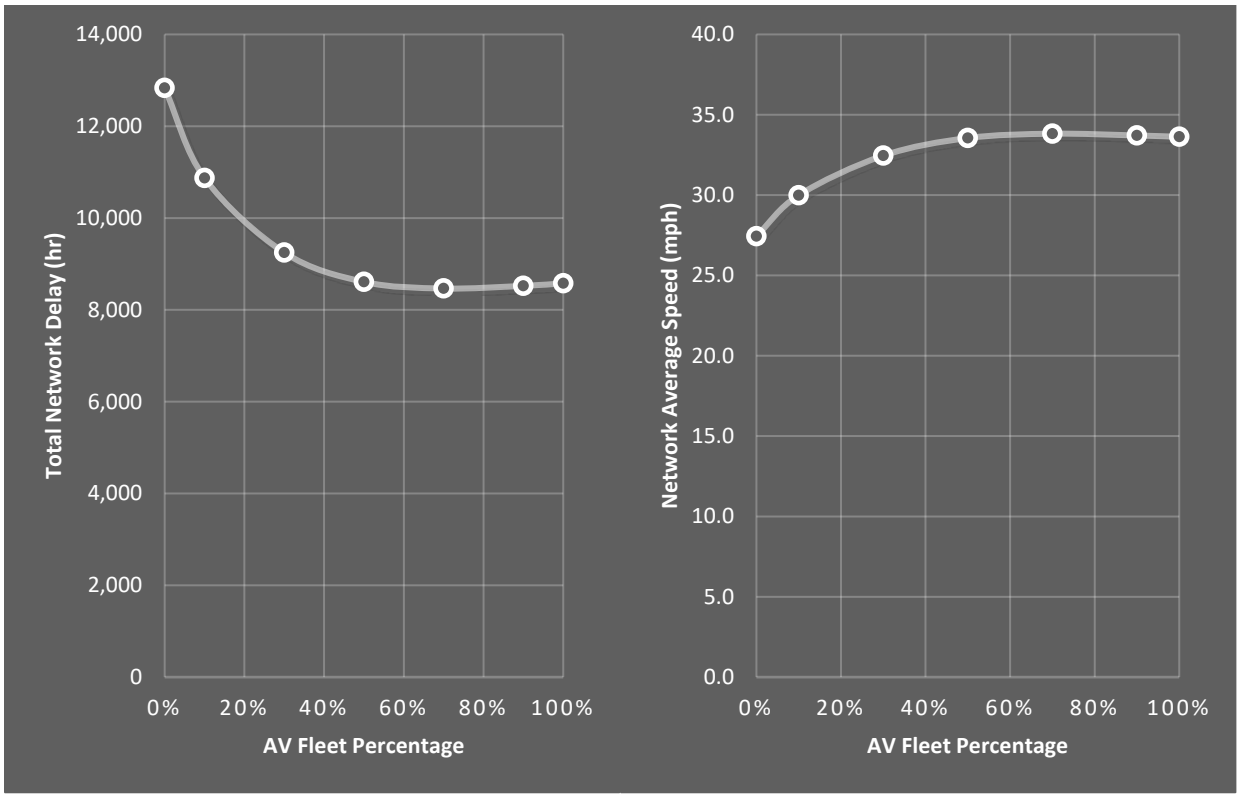

FIGURE 3 Effect of AV percentage for Case Study 2

One final note on applying the AV driver behavior parameters warrants discussion. In many instances, simulation networks are calibrated by changing driver behavior parameters to match observed data, particularly at bottleneck locations. As a result, the driver behavior profiles described previously will not apply, at least not directly, since they are relative to the Vissim default parameters. Therefore, judgment is required when applying the AV parameters to previously calibrated links to arrive at a reasonable AV driver behavior. The analyst might start from the calibrated values and adjust from there. Alternatively, the analyst may find that further

decreasing the calibrated following distance will result in some unrealistic vehicle behavior. The case studies applied both approaches depending on the parameter and the potential for further adjustment.

CONCLUSIONS AND RECOMMENDATIONS

Estimating AV driver behavior is not a trivial task, especially since most of the AV systems under development for vehicles are not publicly available. The parameters provided in this paper serve as a starting point, and the direct application could vary on a case-by-case basis as transportation analysts gain more knowledge about AV behavior and operating regulations. Further, the parameters used in the case studies lack research on how human drivers will react when followed closely by AVs.

While this paper only includes two case studies, the AV effects were similar despite different levels of congestion severity. In both cases, a substantial delay reduction was achieved at the 30 percent AV penetration level. However, the 17 to 28 percent level of delay reduction was substantially less than predicted in experimental conditions. According to researchers at the University of Illinois at Urbana-Champaign, test track results showed that a vehicle stream with as few as 5 percent of AVs (and carefully controlled) could eliminate the typical shockwaves created by human drivers *(13)*. These types of differences deserve additional research to accurately assess capacity effects given that traditional long-range transportation planning uses 20 to 30 year forecasting periods. The potential for small numbers of AVs to dramatically influence traffic flow could reduce the need for continued roadway capacity expansion in some corridors.

As more information becomes available about AV driver behavior, improvements to transportation analysis tools will be needed. For simulation analysis, new driver behavior models with inputs specific to AVs such as level of automation can be developed. For the *Highway Capacity Manual* methods, a capacity adjustment factor similar to the current one for heavy vehicles could be developed for AVs based on simulation model analysis and eventually empirical data. When these future applications have been developed, the impact of AVs on congested networks will be able to be measured more accurately.

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