

1 **Measuring Autonomous Vehicle Impacts on Congested Networks Using Simulation**

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5 Corresponding Author:

6 **David Stanek, PE**

7 Fehr & Peers

8 1001 K Street, 3rd Floor, Sacramento, CA 95814

9 Tel: (916) 329-7332; Fax: (916) 773-2015; Email: D.Stanek@fehrandpeers.com

10
11 Co-authors:

12 **Elliot Huang, PE**

13 City of Costa Mesa

14 77 Fair Drive, Costa Mesa, CA 92626

15 Tel: (714) 754-5000; Email: ELLOIT.HUANG@costamesaca.gov

16
17 **Ronald T. Milam, AICP**

18 Fehr & Peers

19 1013 Galleria Boulevard, Suite 255, Roseville, CA 95678

20 Tel: (916) 773-1900; Fax: (916) 773-2015; Email: R.Milam@fehrandpeers.com

21
22 **Yayun (Allen) Wang, PE**

23 Fehr & Peers

24 160 West Santa Clara Street, Suite 675, San Jose, CA 95113

25 Tel: (408) 278-1700; Fax: (408) 278-1717; Email: A.Wang@fehrandpeers.com

26
27 Word Count: 4,728 (7,478 with figures and tables)

28 Figures and Tables: 11

29 Submission Date: November 15, 2017

1 ABSTRACT

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

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

1 INTRODUCTION

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

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

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

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

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

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

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

8

9 **MODELING AUTONOMOUS VEHICLE OPERATIONS**

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

12

- 13 • Regulatory conditions governing adherence to traffic laws
- 14 • Network design and traffic control operation priorities
- 15 • Vehicle performance capabilities
- 16 • Driver behavior capabilities

17

18 **Regulatory Conditions**

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

23

24 *§ 227.32 Requirements for Autonomous Vehicle Test Drivers*

25 *(c) The autonomous vehicle test driver shall obey all provisions of the Vehicle Code and*
26 *local regulation applicable to the operation of motor vehicles whether the vehicle is in*
27 *autonomous mode or conventional mode.*

28

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

36

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

40

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

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

6 7 **Network Design and Traffic Control Operation Priorities**

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

14 15 **Vehicle Performance Capabilities**

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

23 24 **Driver Behavior Capabilities**

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

30 31 **ANALYSIS MODEL INPUTS**

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

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

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

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

12

13 **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,

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

3

4 **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

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

6

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

13

14 **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

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

16

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

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

3

4 **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

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

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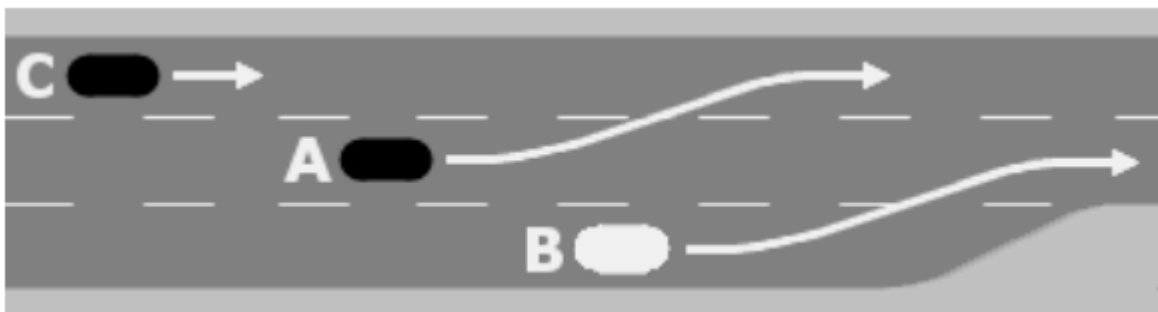
7 **Lane Change and Lateral Behavior**

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

13

- 14 • Minimum headway: reduced from 1.64 to 1.23 feet, a 25 percent reduction, to allow smaller
 15 acceptable distance between two vehicles after a lane change
- 16 • Safety distance reduction factor: reduced the safety factor by 25 percent to allow smaller
 17 acceptable safety distances for the lane-changing vehicle and trailing vehicle during the
 18 lane-change maneuver
- 19 • Maximum deceleration for cooperative braking: increased the default value of 9.84 feet per
 20 second squared (ft/s²) to the maximum value of 13.12 ft/s² to make trailing vehicles brake
 21 more cooperatively
- 22 • Cooperative lane change: this parameter was selected so that the trailing vehicle (Vehicle
 23 A) will change into adjacent lanes to facilitate the lane changing for the lane-changing
 24 vehicle (Vehicle B), as shown in Figure 1 (9)

25



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FIGURE 1 Cooperative lane change

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

2

3 **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

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

5

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

14

15 **CASE STUDIES AND FINDINGS**

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

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

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

5
 6 **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

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

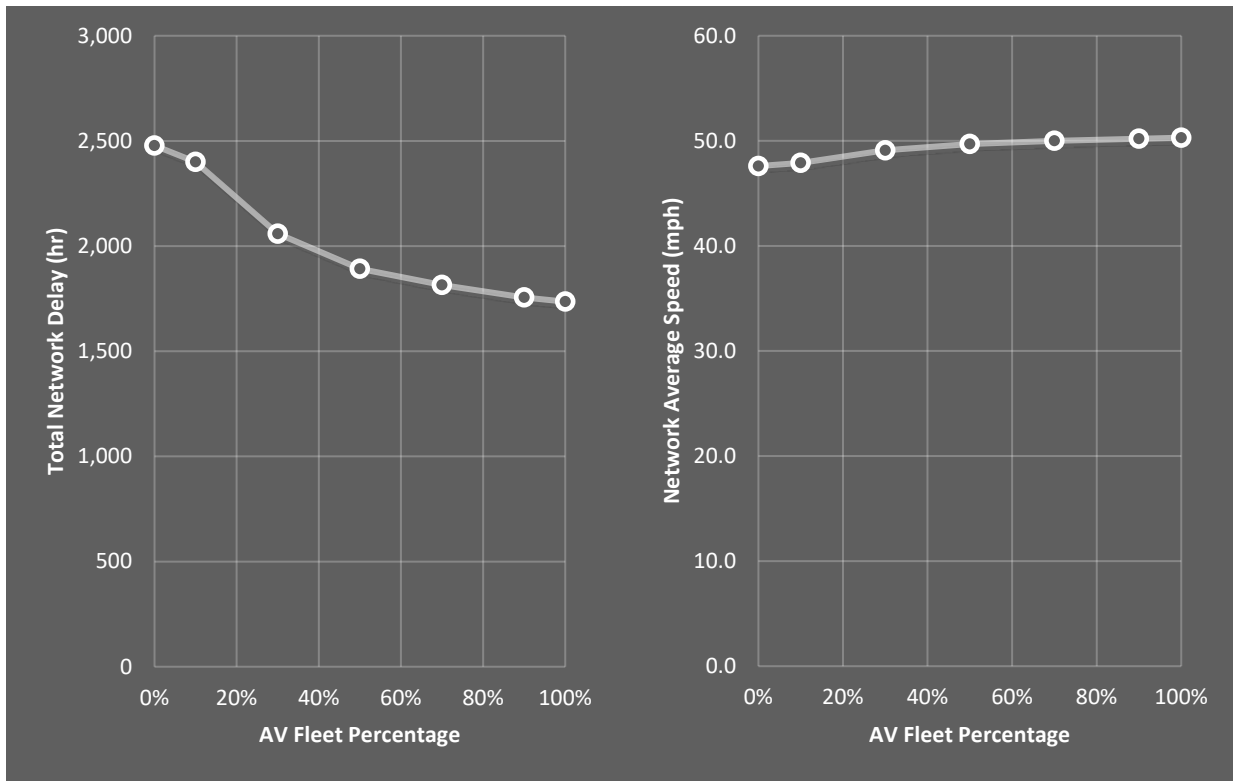
8
 9 The AV driver behavior parameters set was created as listed above in Tables 2 through 6.
 10 The vehicle fleet was modified by converting varying percentages of human-driven vehicles to
 11 AVs. The changes to the vehicle fleet were applied network wide. The change in each performance
 12 measure compared to the no AV scenario is provided in Table 7. The total network delay and
 13 average network speed as a function of AV percentage is plotted in Figure 2.

14
 15 **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%

16
 17 Increasing AV fleet percentage yields a decrease in network delay and an increase in
 18 network speeds. In the 100 percent AV scenario, the results show a 30 percent decrease in network
 19 delay and 6 percent increase in network speeds. A notable feature of these results is the diminishing
 20 return in network performance as the AV fleet percentage increases. The operational
 21 improvements gained going from 0 to 50 percent AVs is more than the operational improvements

1 gained going from 50 to 100 percent AVs. A 30 percent share of AVs provided more than half the
 2 reduction in network delay from the 100 percent AV scenario.
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4 **FIGURE 2 Effect of AV percentage for Case Study 1**

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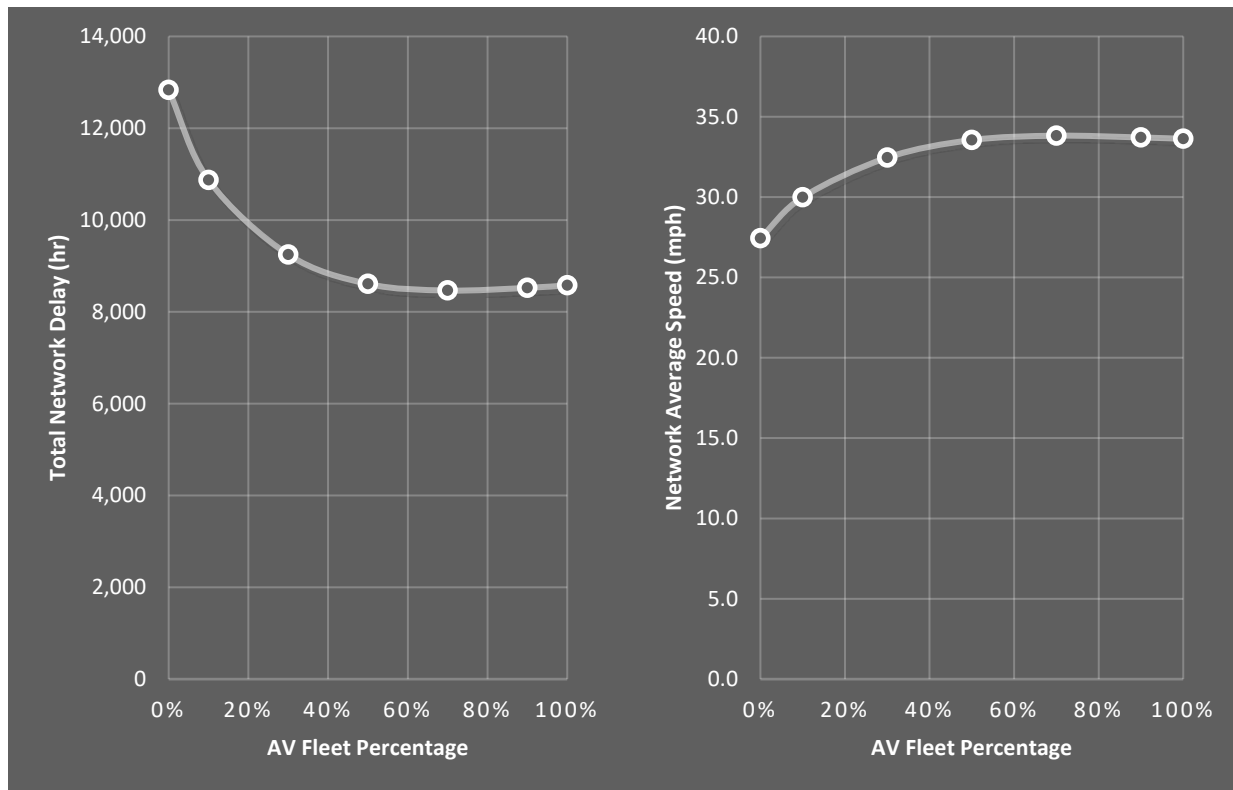
The second case study is a calibrated existing conditions network for a segment of the State Route 55 freeway corridor in southern California. This network consists of approximately 10 miles of freeway mainline, 6 interchanges at arterials, 2 interchanges at other freeways, and 14 ramp terminal intersections. 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.

1 **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%

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4 **FIGURE 3 Effect of AV percentage for Case Study 2**

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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

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

4 5 **CONCLUSIONS AND RECOMMENDATIONS**

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

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

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

29

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