A FRAMEWORK FOR EVALUATING ENERGY AND EMISSION IMPACTS OF CONNECTED AND AUTOMATED VEHICLES THROUGH TRAFFIC MICROSIMULATIONS

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ABSTRACT

Connected and automated vehicles (CAV) may deliver energy efficiency and air quality benefits by reducing traffic congestion and facilitating smoother driving behavior. This paper proposes a three-layered modeling framework for assessing the energy and emission impacts of first-generation CAV technologies, such as cooperative adaptive cruise control (CACC). The framework tightly integrates 1) a CAV driving behavior model with 2) a microscopic traffic simulation model to create vehicle trajectory data and then evaluates those trajectories in 3) a fleet-based modal emissions model.

In a case study to test this framework, we utilized the microscopic model for simulation of intelligent cruise control (MIXIC) to represent vehicles driving with CACC systems in PTV Vissim, traffic microsimulation software, on Interstate 91 (I-91) northbound near Springfield, Massachusetts with real-world traffic speed and volume data. High-resolution (10 hertz), simulated passenger car trajectories were processed into operating modes according to vehicle-specific power, speed, and acceleration and then run through the Motor Vehicle Emission Simulator (MOVES) to quantify the hourly emissions and energy consumption on the I-91 network. We compared the results of baseline driving using the default Wiedemann 99 car following model in Vissim against a scenario where all vehicles are CACC-enabled and another scenario where the Wiedemann oscillation parameters were set to zero. Our findings suggest that CACC driving will produce notable reductions in fine particulate matter (PM2.5) and carbon monoxide (CO) over the baseline but will not have an effect on fuel economy. The Wiedemann scenario without oscillations showed little to no benefit.

Keywords: Automated vehicles, mobility benefits, energy, emissions, traffic simulation, MOVES

INTRODUCTION

Connected and automated vehicles (CAV) are poised to transform surface transportation systems in the United States. While much of the CAV research focuses on future road safety and network performance, environmental effects are often overlooked. There is growing concern that automation may induce travel demand and therefore increase fuel consumption and air pollution from the passenger vehicle fleet. Near-term CAV technologies like cooperative adaptive cruise control (CACC) have the potential to deliver energy efficiency and air quality benefits. This paper lays out a modeling framework for evaluating fuel economy and tailpipe emission impacts from vehicle automation and connectivity, including an initial case study of passenger cars on Interstate 91 northbound near Springfield, Massachusetts. This framework is designed to assess low-level automation, specifically Society of Automotive Engineers (SAE) J3016 Level 1 (*1*) that assist the human driver in tasks such as acceleration and deceleration or steering.

Background

In 2014, the US Department of Transportation's Intelligent Transportation Systems Joint Program Office (ITS JPO) initiated a project to develop a framework for the potential benefits of automated vehicles across various impact areas and different spatial and temporal resolutions, with an initial report being published in 2015 (*2*). This paper focuses on analysis within two areas of the broader framework: vehicle operations and energy/emissions.

Other research published in these specific impact areas of CAV modeling can be categorized into three groups:

1) Modeling vehicle automation in traffic microsimulation software;
2) Evaluating link-level energy and emissions of microsimulation vehicle trajectories, particularly through the Motor Vehicle Emission Simulator (MOVES) (*3*); and
3) Quantifying emissions and energy impacts of CAV technologies.

Modeling vehicle automation in traffic microsimulations

Automated car following via adaptive cruise control (ACC) and cooperative adaptive cruise control (CACC) systems have been extensively modeled through microscopic traffic simulations for the last two decades. In 2002, VanderWerf et al. (*4*) characterizes CACC systems as ACC systems with vehicle-to-vehicle (V2V) communication and a reduced time gap between vehicles. VanderWerf et al. demonstrated that microsimulations could be used to model the trajectories of vehicles equipped with ACC and CACC systems and concluded ACC would be unlikely to change traffic flow and increase highway capacity whereas CACC could increase capacity. Further work by van Arem, van Driel, and Visser (*5*) developed a stochastic traffic flow model called MIXIC to analyze the impact of CACC systems on vehicle speeds and the number of shockwaves. They found that high penetrations of CACC, upwards of 60 percent, led to greater traffic stability and throughput. Shladover, Su, and Lu (*6*) used the microsimulation software AIMSUN (*7*) to explore the impacts on lane capacity under different market penetrations of ACC and CACC according to preferred time gaps between vehicles based on a consumer acceptance study by Nowakowski et al. (*8*).

PTV Vissim (*9*) offers the conventional Wiedemann 74 and the Wiedemann 99 models for default car following, as explained by Aghabayk et al. *(10)*. Besides MIXIC, other independent psychophysical car following models for CAVs have been created for implementation in microsimulations, such as the Intelligent Driver Model (IDM) from Treiber et al. (*11*) and an enhanced IDM from Kesting et al. (*12*). The most recent studies have begun to analyze mixed traffic scenarios of automated and human-driven vehicles on specific real-world road networks. For example, Shelton et al. (*13*) used a dynamic traffic assignment (DTA) model to calibrate a microscopic traffic network on Interstate 35 in Austin, Texas and then adjusted Vissim's Wiedemann 99 parameters for CACC driving.

Evaluating link-level energy and emissions of microsimulation vehicle trajectories
The connection between traffic microsimulations and emissions models is well established. Some of the first microsimulation-emissions model integrations were described separately by Barth, Malcolm, and Scora (*14*) in 2001 and by Ahn et al. (*15*) in 2002. Barth, Malcolm, and Scora integrated Quadstone Paramics traffic simulation software (*16*) with the Comprehensive Modal Emissions Model (CMEM), which assesses tailpipe emissions and fuel consumption from second-by-second (1 Hz) vehicle trajectories. Later work in a paper by Barth and Boriboonsomsin (*17*) analyzed the impacts of eco-driving, though not specifically ACC or CACC systems, with the Paramics-CMEM tool. Ahn et al. paired the INTEGRATION microscopic model with a fitted regression model, later named VT-Micro (*18*), which used emissions test data from eight light-duty vehicles on a chassis dynamometer.

Contemporary integrations usually employ emission rate data from the US Environmental Protection Agency's MOVES, the regulatory emissions inventory model for highway vehicles built on modal 1 Hz data from portable emissions measurement systems introduced by Frey et al. (*19*) and others. Song, Yu, and Zhang (*20*) described the early shortcomings of emission estimates from MOVES using large, multi-gigabyte files of simulated vehicle trajectory data from Vissim. Similar to our current work, Abou-Senna et al. (*21*) developed a custom software package called VIMIS that translated Vissim output data into MOVES project-level input files, mainly operating mode distributions from vehicle trajectories as an external process from the MOVES graphical user interface (GUI).

Quantifying emissions and energy impacts of automation technologies
Tu et al. (*22*) have conducted a study with similar methodology to our research, though they make emission and energy estimates of CACC by pairing INTEGRATION with VT-Micro. Liu, Kockelman, and Nichols (*23*) used MOVES to calculate the emissions and energy benefits of smoothing standard drive cycles, such as the Federal Test Procedure (FTP) commonly used for fuel economy testing.

Integrating Vissim and MOVES for automated vehicle modeling
Our previous research on the Vissim-MOVES integration for emissions and energy modeling of CAVs produced two publications. First, Reed et al. (*24*) analyzed an idealized, straight highway segment to find the environmental benefits of traffic smoothing through a modified Wiedemann 99 car following model where all the traffic oscillations have been set to zero. Second, Eilbert et al. (*25*) utilized a version of the CACC MIXIC car following model adapted from a Federal Highway Administration (FHWA) project in Vissim to study emissions and energy impacts on an idealized two-mile highway segment. We found that a limited number of CACC-equipped vehicles could be added to the idealized network to maintain comparable fuel consumption and criteria pollutant emissions as the baseline Wiedemann 99 scenario with a throughput of about 2,500 vehicles per lane per hour.

METHODOLOGY

This section describes our modeling framework from configuring the microsimulations to analyzing the energy and emissions impacts from MOVES. In this study, we devised three scenarios for comparison:

1) Baseline driving behavior with Vissim's default Wiedemann 99 car following, meant to emulate current human drivers;
2) CACC driving behavior according to an adjusted MIXIC model car following model developed for FHWA; and
3) Modified baseline driving behavior where the Wiedemann 99 traffic oscillation parameters have been set to zero.

The CACC MIXIC model used in the second scenario was adapted from unpublished work by Su et al. (*26*) and supplied as a dynamic link library (DLL) by FHWA's Turner-Fairbank Highway Research Center, where several driving behavior models are being developed, calibrated, and tested. By importing the DLL with a specified driver model, we could override the default car following behavior in Vissim. Additionally, we edited the DLL source code to turn off the flags for platooning, lane change, and a managed lane. Turner-Fairbank also has a publicly available version of the MIXIC DLL for download (*27*).

Given that CACC systems fall within Level 1 automation, the human driver is expected to perform all aspects of the dynamic driving task besides acceleration and/or deceleration behind a lead vehicle. Steering and tactical components of driving (i.e. merging and turning) would still be the responsibility of the driver. Like constant-speed cruise control, we imagine CACC would be enabled through a button on the vehicle dashboard or steering wheel and vehicle control would be transferred to the human driver upon touching the brake pedal.

In the third scenario (*24*), the following five Wiedemann 99 parameters were set to zero and expected to smooth driving behavior:

- Following variation (CC2),
- Negative following threshold (CC4),
- Positive following threshold (CC5),
- Speed dependency of oscillation (CC6), and
- Oscillation acceleration (CC7).

Traffic Microsimulations

For this research, we selected a traffic microsimulation model with flexibility to use a new driving behavior model. We chose PTV Vissim to run 15 random seeds at 10 Hz for each of the three scenarios. Each of these 45 simulations generated a standardized text output (.fzp) file of vehicle trajectory data containing the following fields:

- Time stamp (tenths of a second),
- Vehicle type,
- Vehicle number,
- Link and lane number,
- Speed (miles per hour),

- Acceleration (feet/second^2),
- Headway (feet) to the leading vehicle, and
- Delay time (seconds).

From the Vissim manual (*9*), headway is defined as the distance to the preceding vehicle before the time step and delay time is the difference between the simulated and ideal driving time. Random seeding allows Vissim users to compare results across scenarios. Our study used 15 random seeds and each seed had its own unique settings about when and how vehicles entered the network. The only difference between our three scenarios was the car following model, so we compared the CACC and Wiedemann without oscillations scenario results against the baseline by seed number.

Network Modeled

To test the modeling framework on a real-world road network, Interstate 91 northbound (NB) near Springfield, Massachusetts was chosen (*29*). This I-91 NB network is a freeway segment with five on-ramps and seven off-ramps over roughly three miles and consisting of mostly three lanes. Much of the analysis below focuses on the I-91 freeway links between Route 5 and Interstate 291, which present optimal road conditions for CACC simulations. The satellite image in Figure 1a below shows the superimposed I-91 links labeled 100 to 104.

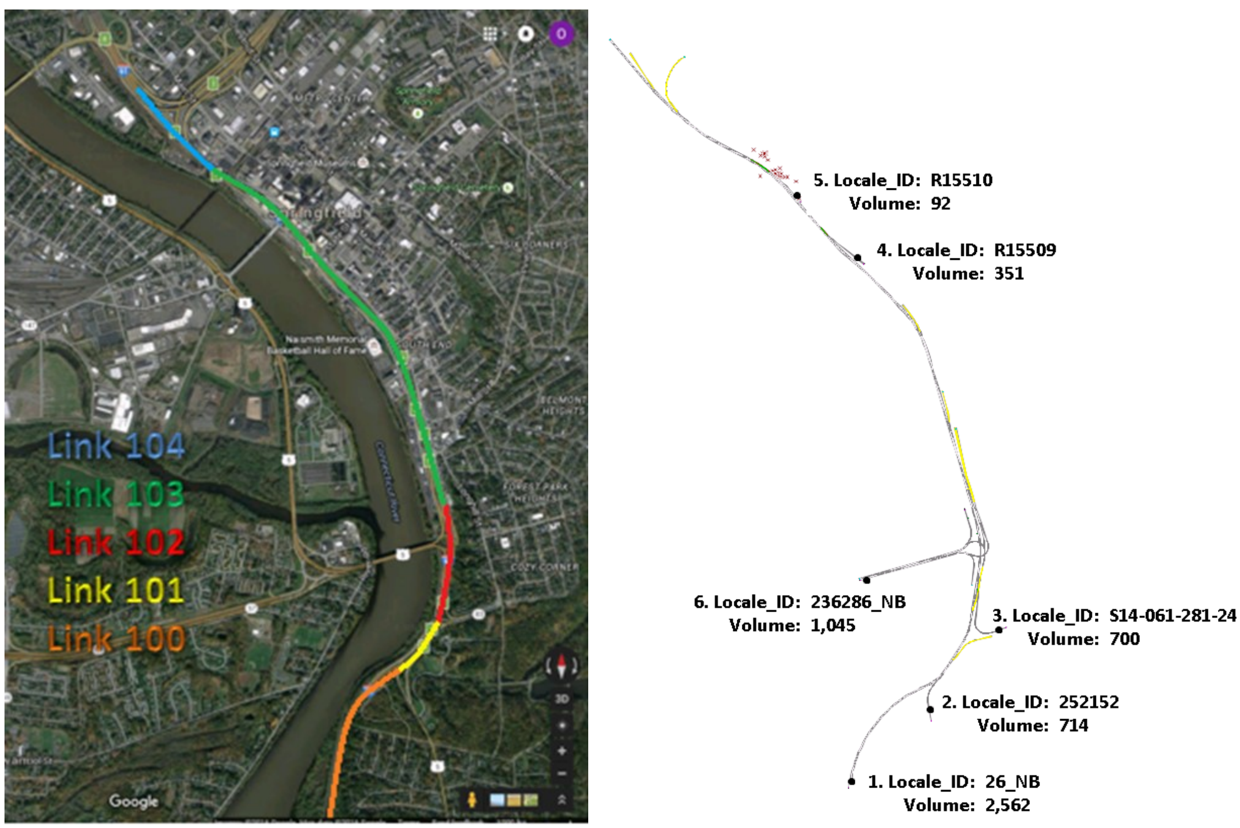

FIGURE 1 (a) I-91 in Springfield, Massachusetts and (b) the Vissim network implementation with observed weekday morning traffic volumes entering the network

Network Calibration

Traffic volumes on the I-91 NB network were defined in the microsimulation using vehicle counts from the Massachusetts Department of Transportation (MassDOT) Transportation Data Management System (*33*). We used the most recent counts from weekday mornings, specifically 07:00-08:00. Utilizing these MassDOT records, the volumes were specified in Vissim using the corresponding field sensor data laid out in Figure 1b. The MassDOT volume data indicates that more than 2,500 vehicles entered the network from I-91 (Node 1) and that about 1,000 vehicles entered from the west on Route 5 (Node 6) and about 700 vehicles entered from the east on Route 5 (Node 2). Volumes entering from Massachusetts-83 (Node 3) were not available and estimated from other nearby ramps to be 700 vehicles. On-ramps from local roads had roughly 350 vehicles (Node 4) and 90 vehicles (Node 5) entering the network, respectively.

A cumulative speed distribution was developed in miles per hour (mph) for the I-91 network from a nearby speed sensor (I-91 northbound from Route 5 southbound, MassDOT Data Locale ID 2797). The desired I-91 speed measurements were collected in April 2017 in the following speed bins: 0-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74, 75-79, 80-84, and 85-119 mph. For simplicity, the first and last speed bins were dropped and then cumulative percentages were calculated by speed bin and assigned to the midpoint speed of the bin. Figure 2 below shows the midpoint speed-cumulative percentage pairs plotted for the I-91 network with a normal cumulative distribution of speeds for reference. The measured I-91 speed distribution was then used as an input to the traffic microsimulations across the three scenarios and all 45 runs.

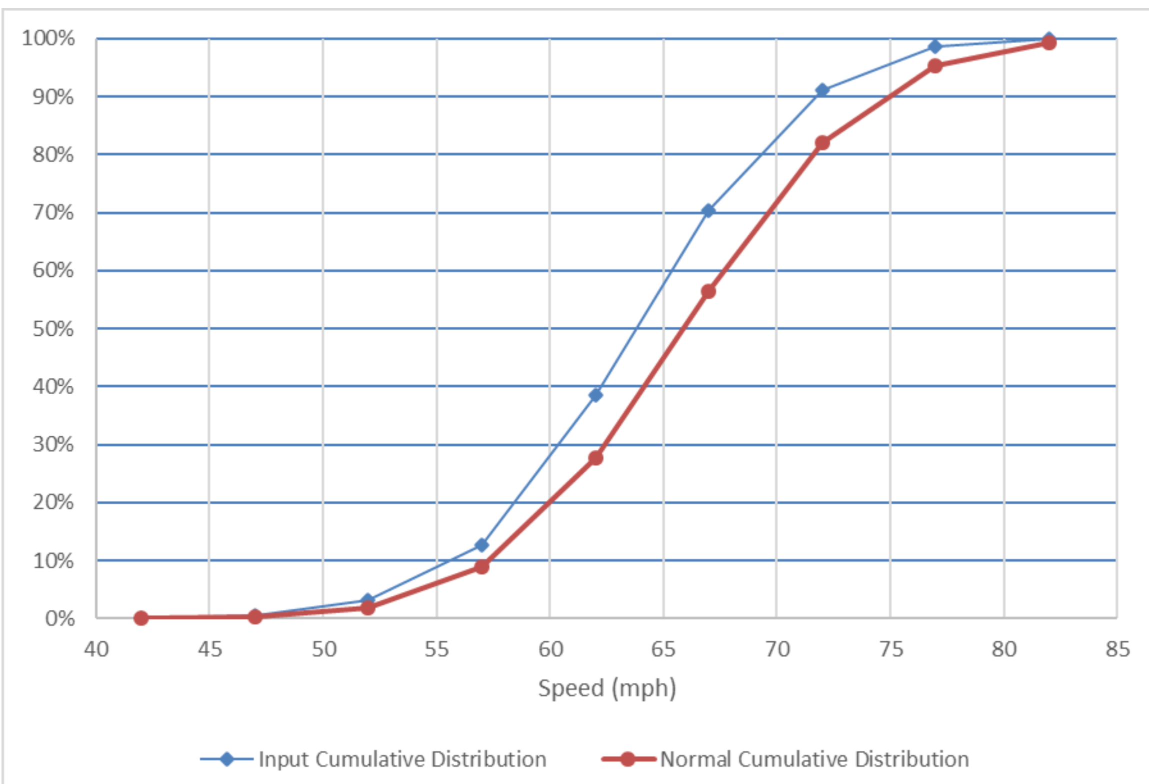

FIGURE 2 A cumulative speed distribution derived from I-91 speed measurements and a normal cumulative distribution for reference

Energy and Emissions Modeling

In our modeling, the energy consumption and tailpipe emissions—particularly carbon monoxide (CO), nitrogen oxides (NOx), particulate matter of 2.5-micron diameters or less, volatile organic compounds (VOC), and carbon dioxide (CO_2)—is based on project-scale analysis with the latest release of EPA's Motor Vehicle Emission Simulator (MOVES2014a), which uses high-resolution vehicle trajectories to estimate impacts. Much like the traffic microsimulations, the I-91 northbound network was modeled through a series of MOVES project-scale inputs including link number, length, volume, average speed, and operating mode distribution.

For initial MOVES testing, we chose to model the network as a custom domain for one weekday morning hour in January 2020, adapted from the original run specifications proposed in Reed et al. (*24*). MOVES run specifications are stored within an XML file and are conventionally given the extension .mrs. By directly editing the .mrs files, we avoided having to change parameters in the MOVES GUI.

Other project-scale inputs were specified for the I-91 network where known and the rest of the inputs were replicated from national-scale default data. Only three project-scale input tables utilized network data, namely the link, linksourcetypehour, and opmodedistribution tables. The linksourcetypehour table was network-specific, but it did not change between scenarios and random seeds. The link and opmodedistribution tables were edited and inserted dynamically using Python to circumvent entering them individually via the MOVES Project Data Manager.

Operating Mode Distributions

MOVES assigns each time step *t* of a vehicle trajectory into one of 23 operating modes through binning of three time-dependent variables: vehicle-specific power (VSP_t), vehicle speed (v_t), and vehicle acceleration (a_t). VSP is the tractive power exerted by the vehicle for propulsion normalized by the vehicle mass (*34*), as defined in Equation 1 below:

$$VSP_t = \frac{Av_t + Bv_t^2 + Cv_t^3 + mv_t a_t}{m}, \tag{1}$$

where *A* is the tire rolling resistance coefficient, *B* is the rotational resistance coefficient, *C* is the aerodynamic drag coefficient, and *m* is the vehicle mass. Default road load coefficients *A*, *B*, and *C* as well as vehicle mass *m* for a passenger car were pulled from the MOVES2014a sourceusetypephysics table for our calculations of VSP_t:

- A = 0.15461 kW-s/m (kilowatts-seconds per meter),
- B = 0.00200193 kW-s/m^2 (kilowatts-seconds per meter squared),
- C = 0.000492646 kW-s/m^3 (kilowatts-seconds per meter cubed), and
- m = 1.4788 metric tons.

Speeds v_t in meters per second (m/s) and accelerations a_t in meters per second squared (m/s^2) were used to calculate VSP_t for every 10 Hz step in each .fzp file. After calculating VSP_t, operating modes were assigned according to the designations given in the MOVES technical documentation of light-duty emission rates (*30*), as reproduced in Table 1 below. Operating mode distributions summarizing the fraction of time spent in each operating mode were developed by link for the 45 simulations on the I-91 network.

TABLE 1 MOVES operating mode designations based on VSP, speed, and acceleration (*34*)

Operating Mode	Operation Mode Description	Vehicle-Specific Power (VSP_t, kW/metric ton)	Vehicle Speed (v_t, mph)	Vehicle Acceleration (a_t, mph/s)
0	Deceleration/Braking			$a_t \leq -2.0$ OR ($a_t < -1.0$ AND $a_{t-1} < -1.0$ AND $a_{t-2} < -1.0$)
1	Idle		$-1.0 \leq v_t < 1.0$	
11	Coast	$VSP_t < 0$	$1 \leq v_t < 25$	
12	Cruise/Acceleration	$0 \leq VSP_t < 3$	$1 \leq v_t < 25$	
13	Cruise/Acceleration	$3 \leq VSP_t < 6$	$1 \leq v_t < 25$	
14	Cruise/Acceleration	$6 \leq VSP_t < 9$	$1 \leq v_t < 25$	
15	Cruise/Acceleration	$9 \leq VSP_t < 12$	$1 \leq v_t < 25$	
16	Cruise/Acceleration	$12 \leq VSP_t$	$1 \leq v_t < 25$	
21	Coast	$VSP_t < 0$	$25 \leq v_t < 50$	
22	Cruise/Acceleration	$0 \leq VSP_t < 3$	$25 \leq v_t < 50$	
23	Cruise/Acceleration	$3 \leq VSP_t < 6$	$25 \leq v_t < 50$	
24	Cruise/Acceleration	$6 \leq VSP_t < 9$	$25 \leq v_t < 50$	
25	Cruise/Acceleration	$9 \leq VSP_t < 12$	$25 \leq v_t < 50$	
27	Cruise/Acceleration	$12 \leq VSP_t < 18$	$25 \leq v_t < 50$	
28	Cruise/Acceleration	$18 \leq VSP_t < 24$	$25 \leq v_t < 50$	
29	Cruise/Acceleration	$24 \leq VSP_t < 30$	$25 \leq v_t < 50$	
30	Cruise/Acceleration	$30 \leq VSP_t$	$25 \leq v_t < 50$	
33	Cruise/Acceleration	$VSP_t < 6$	$50 \leq v_t$	
35	Cruise/Acceleration	$6 \leq VSP_t < 12$	$50 \leq v_t$	
37	Cruise/Acceleration	$12 \leq VSP_t < 18$	$50 \leq v_t$	
38	Cruise/Acceleration	$18 \leq VSP_t < 24$	$50 \leq v_t$	
39	Cruise/Acceleration	$24 \leq VSP_t < 30$	$50 \leq v_t$	
40	Cruise/Acceleration	$30 \leq VSP_t$	$50 \leq v_t$	

Batch MOVES Runs

Running MOVES many times can be tedious. We automated this process with Python by creating a new input database with the link and opmodedistribution tables for every run using the vehicle trajectory data produced by Vissim for the I-91 northbound network. For each of the 45 simulation runs, a unique input database with link statistics, such as traffic volumes, average speeds, and operating mode distributions, was created and dropped into a new .mrs file. The .mrs file was then executed through a MS-DOS batch file instead of the MOVES GUI. This Python-based tool was able to evaluate energy and emission results for the 17.5 GB of vehicle trajectory data over 45 microsimulations on the I-91 network with a single button click.

RESULTS

After running the traffic microsimulations and processing the resulting vehicle trajectory data in MOVES, we compared the link-level network performance and impacts to fuel consumption and tailpipe emissions across scenarios.

Microsimulation Performance

Summaries of vehicle speed, acceleration, delay time, and headway results from the first random seed of traffic microsimulations for I-91 northbound network are presented as box plots below in Figure 3. Interestingly, we found that the second scenario with CACC driving does not increase average vehicle speeds over the baseline scenario except for Link 101, but it will narrow the range of speeds, particularly for links with higher congestion, as shown in Figure 3a. The third scenario where the Wiedemann 99 oscillation parameters are set to zero does not show appreciable difference in speeds from the baseline. In Figure 3b, CACC driving appears to smooth accelerations across all links besides Link 100 while setting the Wiedemann oscillations to zero generated more constant speeds except for Link 101.

Delay and headway must be non-negative, so those plots begin at zero. Figure 3c shows that CACC driving leads to some small reductions in delay time over the baseline, especially for Link 101 and 104, but increased delay time slightly for Link 100, possibly due to the merging with Route 5 ahead in the next link. The Wiedemann scenario without oscillations offered only marginal improvements to baseline delay time if at all, only Link 104 shows a modest improvement. Headway had mixed results in Figure 3d. CACC driving yields an observable reduction in maximum headway for Link 100, 102, and 103 but not for Link 101 nor 104, potentially due to the MIXIC model leaving more following distance than Wiedemann for merging situations. The CACC and baseline scenarios did not show any perceptible difference in mean headways. The Wiedemann scenario had little effect on headway and even faintly increased maximum headway for the first three links.

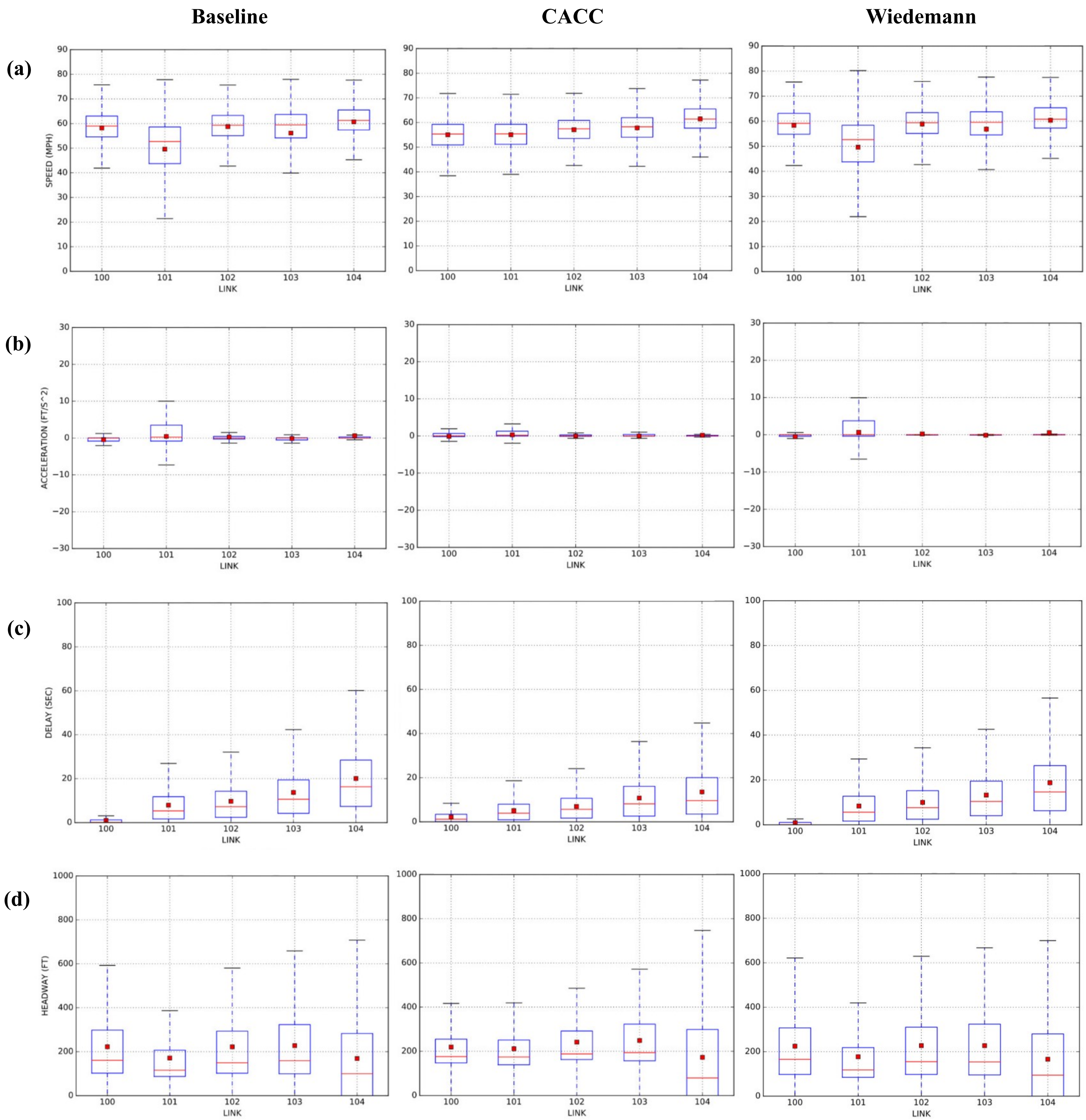

FIGURE 3 Box plots of (a) vehicle speed (mph), (b) acceleration (ft/s^2), (c) delay time (sec), and (d) headway (ft) for the first random seed as an example on the I-91 network by link and scenario (red dot represents the mean)

Another way to examine the link-level performance is through operating mode (or op mode) distributions, as shown in Figure 4. For each link-specific operating mode distribution, the first random seed is represented by the bar plot and other 14 seeds are represented by the scatterplot to highlight the variability between simulations. As one might expect, most of the time on these highway links is spent driving at speeds above 50 mph (op modes 33-40) and in midrange VSP bins or braking (op mode 0).

Each op mode distributions has different characteristics. In Figure 4a, Link 100 is characterized by the CACC scenario having less braking and less time in op mode 35 but recognizably more time in the highest two operating modes than the baseline. The Wiedemann scenario without oscillations spent nearly half of its time in op mode 35 and has some reductions from the baseline in op modes 33, 37, and 38. Link 101 appears to be the most congested link with high fractions of braking and some idling (op mode 1) for the baseline and Wiedemann scenarios, as shown in Figure 4b. The CACC scenario shows drops in braking and op mode 30 compared to the baseline, although it has increases in op modes 35-39. The Wiedemann scenario has slightly less braking than the baseline but higher fractions in op modes 30, 35, and 40, where much of the driving on Link 101 is spent. Links 102-104 in Figure 4c-4e follow similar patterns, though the CACC scenario in Link 102 and 104 contains marginally more braking and somewhat less time spent in op mode 40 than the baseline. Like in Link 100, the Wiedemann scenario spent nearly 50 percent of time in op mode 35 for these last three links but has a similar distribution as the baseline.

Energy and Emission Impacts

MOVES stores tailpipe exhaust emission and fuel consumption rates by operating mode and number of other factors, such as fuel type, model year, and regulatory class. MOVES emission and fuel consumption rates are well correlated to VSP, so generally speaking the rates will be highest in the op modes with the highest VSP and speed bins (*34*). In its simplest form, to calculate hourly emissions and energy estimates for each op mode, MOVES multiplies the hourly op mode time fraction by the appropriate op mode-specific hourly emission or fuel consumption rate from the default database and then sums the emissions or fuel consumption across the set of all op modes.

The results follow the same trends across all pollutants and energy use. The hourly emission and energy estimates were normalized by the number of vehicles because each of the 45 microsimulations had different link throughputs. As example output, Figure 5a shows the normalized hourly results by link for energy consumption reported in one million British Thermal Units per vehicle per hour (MMBTU/veh/hr) and Figure 5b shows fine particulate matter (PM2.5) reported in grams per vehicle per hour (g/veh/hr). As summarized in these link-specific plots, CACC driving generated PM2.5 and energy reductions over the baseline for Link 101 and 104, likely due to higher levels of congestions; however, CACC driving caused increases for Link 100 and 103. Results between the CACC and baseline scenarios were quite similar for Link 102.

The last scenario where the Weidemann oscillations were set to zero did not show much difference in PM2.5 from the baseline, except for Link 100 that showed minor reductions. One could argue that the Wiedemann scenario also had energy benefits on Link 103, but they are marginal. Most differences between the Wiedemann scenario and the baseline were muddled.

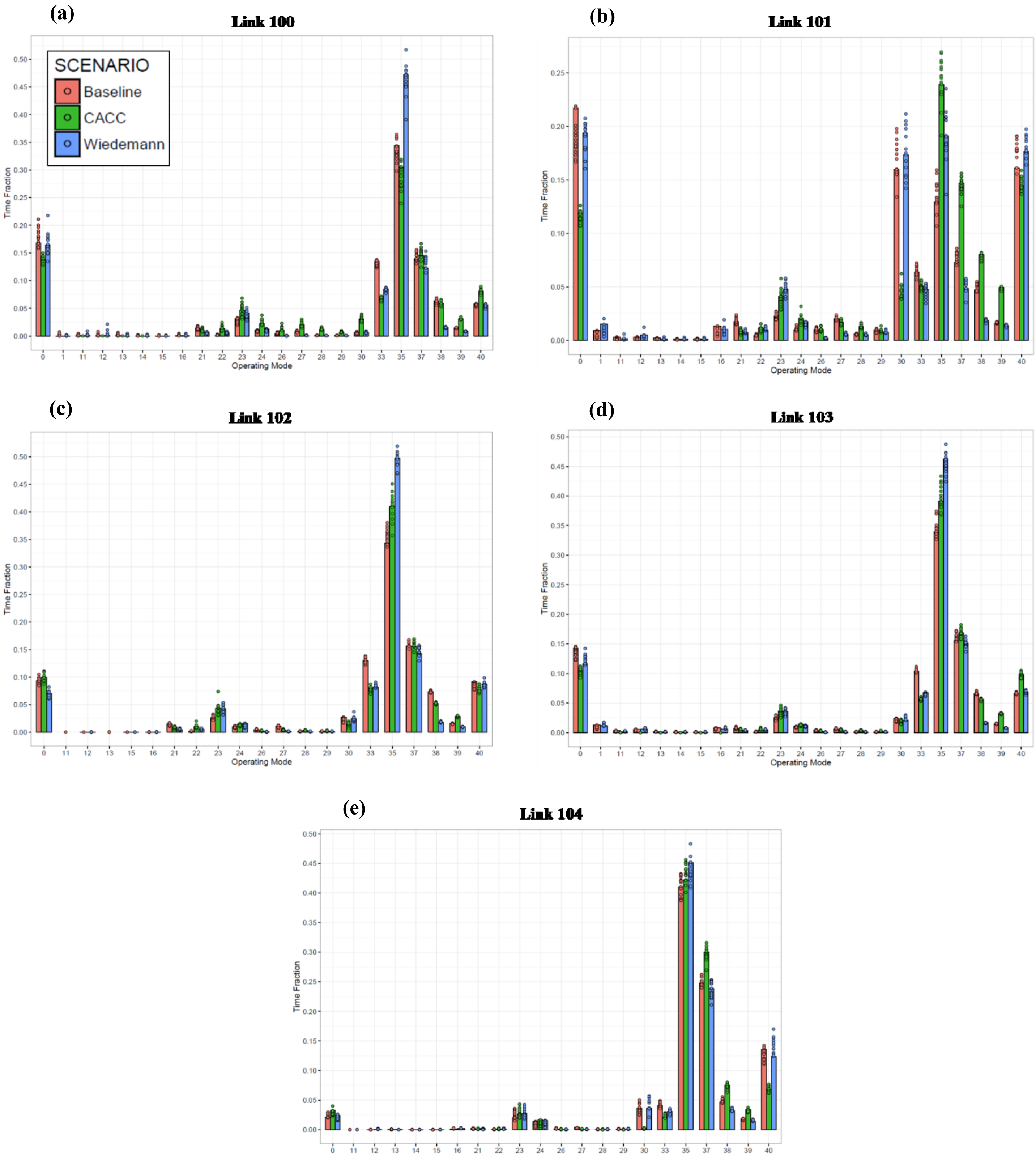

FIGURE 4 Operating mode distributions for the five highway links in I-91 northbound network (bar represents the first random seed and points represent the other 14 seeds)

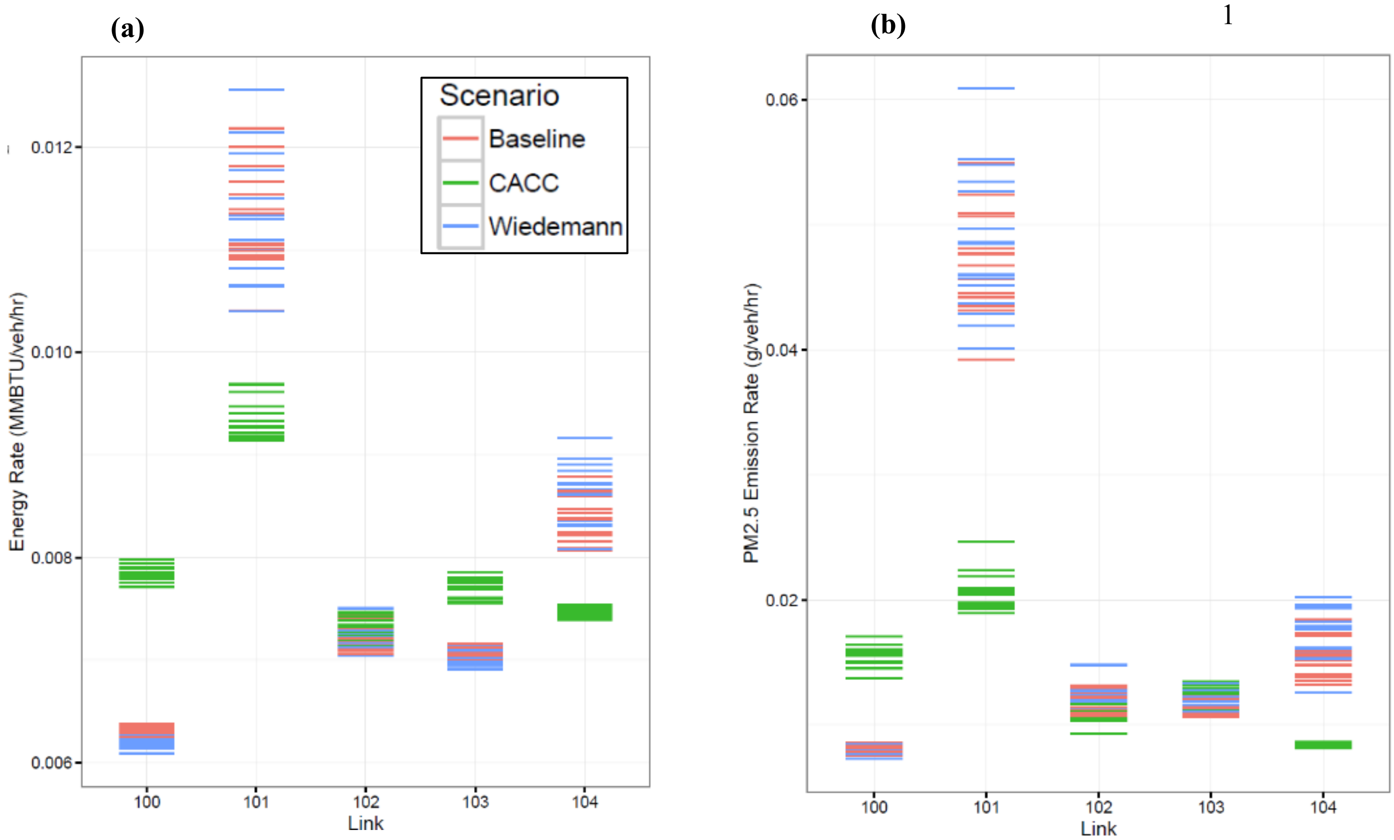

FIGURE 5 Example plots of link-level (a) energy and (b) PM2.5 estimates by scenario for 45 microsimulations on the I-91 northbound network

CONCLUSION AND DISCUSSION

This proposed three-layered modeling framework combines the following tools to estimate the energy consumption and tailpipe emission impacts of connected and automated vehicles:

1. driving behavior model for specific CAV technologies,
2. microscopic traffic simulation model, and
3. modal emissions model.

Despite modest changes to network performance metrics, especially delay and headway, CACC systems produces substantial changes to operating mode distributions and subsequent emissions from the baseline Wiedemann 99 driving behavior.

Pairing the energy and emission results by seed, we were able to calculate the percent reductions for each scenario from the baseline on the I-91 Springfield network. Table 2 below shows the mean percent reductions and standard deviations for the CACC and Wiedemann without oscillations scenarios for carbon monoxide (CO), nitrogen oxides (NOx), fine particulate matter (PM2.5), and volatile organic compounds (VOC) as well as carbon dioxide (CO_2) and energy consumption. Our findings suggest that CACC driving will lead to sizable CO, PM, and VOC benefits along with slight NOx benefits but will not improve fuel efficiency over the baseline. The Wiedemann scenario, however, leads to negligible or no benefits from the baseline.

TABLE 2 Mean and standard deviation of energy, CO, NOx, PM2.5, and energy/CO_2 benefits (percent reductions) on the I-91 network for the CACC and Weidemann scenarios from the baseline over the 15 random seeds

	CACC from Baseline		***Wiedemann from Baseline***	
Pollutant	**Mean**	**Std Dev.**	**Mean**	**Std Dev.**
CO	20.12%	±3.85%	-0.84%	±6.64%
NOx	2.53%	±2.20%	1.59%	±3.21%
PM2.5	25.24%	±4.05%	-3.35%	±7.55%
VOC	10.41%	±2.89%	1.71%	±4.61%
Energy/CO_2	-0.23%	±1.38%	0.25%	±1.97%

Based on our results above, using an independent driving behavior model for simulating specific CAV technologies appears to be preferable over changing the default microsimulation parameters to mimic CAV driving. While this paper only examines CACC systems, the modeling framework enables the assessment of other SAE J3016 Level 1 automation technologies or combinations thereof (*1*), such as:

- Dynamic speed harmonization,
- Platooning,
- Lane keeping assistance, and
- Cooperative lane change.

Driving behavior models also can be calibrated and validated against field tests of instrumented vehicles as the CAV technologies become available. Using MOVES, this study has developed a streamlined process to evaluate energy and emission impacts of multiple microsimulations of CAVs with high-resolution, 10 Hz vehicle trajectory data through an external Python tool.

If government agencies are to start incorporating CAV technology impacts into federal and state policy, MOVES modeling will be needed. Our current analysis is on the project scale; however, as currently designed, MOVES cannot easily evaluate changes to driving behavior at the national or county scale to reflect adoption of CAV technologies. With large amounts of real and simulated vehicle trajectory data available now and in the near future, it may be appropriate to reconsider the default drive cycles, which are developed using a single vehicle without automation or connectivity for a given speed range and road type. We recommend adding a feature to MOVES that allow users to input custom operating mode distributions for larger scale analysis of CAVs.

Although this research presents some promising outcomes, it does not address issues associated with higher levels of driving automation, SAE Level 3 and above. Changes in vehicle ridesharing and ownership, routing and mode choice, and even land use due to self-driving and driverless vehicles will undoubtedly lead to other environmental effects. Continuing in our research, we plan to examine higher levels of congestion, test different CAV market penetrations, and utilize more network-specific data in MOVES to refine this modeling framework.

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