Potential Energy and Emission Benefits of Vehicle Automation and Connectivity

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ABSTRACT

Driving behavior greatly impacts vehicle tailpipe emissions. Connected and automated vehicle (CAV) technologies are designed to smooth driving and relieve traffic congestion and are therefore expected to reduce fuel consumption and tailpipe emissions. Despite many first-generation CAV technologies such as cooperative adaptive cruise control (CACC) nearing market deployment or in early-stage adoption, changes from these technologies largely have not been incorporated into driving style and behavior of vehicle emission and energy models.

This paper presents the energy and emission impacts of CACC driving through a three-layered modeling framework with a case study of passenger cars on Interstate 91 near Springfield, Massachusetts. The framework closely integrates three separate model structures: 1) a driving behavior model to implement the car following algorithms of CACC systems, 2) a microscopic traffic simulation model to generate high-resolution (10 Hz) vehicle trajectories, and 3) the Motor Vehicle Emission Simulator (MOVES), the regulatory emissions inventory model for highway vehicles, to estimate the environmental effects. Our analysis confirms that CACC systems are likely to provide fuel efficiency and air quality benefits. Along with impacts from other CAV technologies, these CACC benefits could be included in energy and emission projections for future regulations and inventories.

INTRODUCTION

The US Department of Transportation has become increasingly interested in understanding the benefits of vehicle-to-vehicle (V2V) communications and vehicle automation systems. Many automotive manufacturers and technology firms have announced plans to deploy technologies that fall into at least SAE J3016 Level 1 or 2 of vehicle automation in the next few years.[1] DOT's Intelligent Transportation Systems Joint Program Office (ITS JPO) is sponsoring research to develop a multidisciplinary framework for evaluating benefits of CAVs across different impact areas, particularly safety, vehicle mobility and emissions/energy, as well as consumer choice and employment. A preliminary report on the CAV benefits framework was prepared by the DOT's Volpe Transportation Systems Center and publicly released in 2015.[2] Current research for ITS JPO continues to advance CAV benefits modeling across the primary impact areas.

This research builds on earlier published research focusing on the potential energy and emission benefits of CAV technologies like cooperative adaptive cruise control. The first publication[3] examines a scenario on an idealized highway network through traffic microsimulations of passenger cars with the oscillation parameters of the Wiedemann 99 car following model set to zero, which has been tested in previous literature as a rough representation of low level of vehicle automation. The second publication plugs in a CACC driving behavior model supplied by DOT's Turner-Fairbank Highway Research Center into the microsimulations on the idealized network and starts to experiment with different traffic volumes and market penetrations of CACC.[4] The third and most recent publication models the energy and emission impacts of the Wiedemann scenario without oscillations and CACC scenario on a real-world network, Interstate 91 northbound near Springfield, Massachusetts. It goes on to more explicitly lay out a three-layered modeling framework that integrates a CAV driving behavior model, a microscopic traffic simulation model, and the US Environmental Protection Agency's MOVES for evaluating the energy and emission impacts of CAV technologies.[5] Microsimulation vehicle trajectories were produced using PTV Vissim[6], and were then prepared for the most recent version of MOVES (MOVES2014a)[7] using Python.

METHODOLOGY & RESULTS

As described in our latest publication, we have developed three scenarios of passenger cars on I-91 northbound near Springfield:

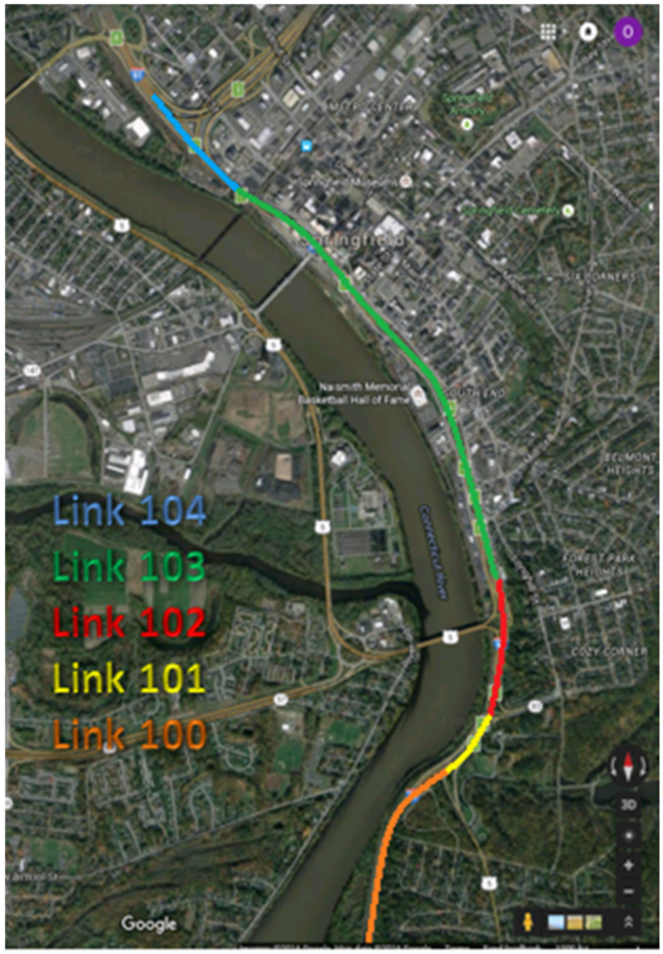
1. Baseline driving behavior with Vissim's default Wiedemann 99 car following model, meant to emulate human drivers;
2. CACC driving behavior according to an adjusted MIXIC model car following model developed for FHWA; and
3. Modified baseline driving behavior where the Wiedemann 99 traffic oscillation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

The MIXIC model is a stochastic traffic flow model that was originally developed by van Arem, van Driel, and Visser[8] to mimic driving with CACC systems. The second scenario utilizes an enhanced CACC MIXIC model adapted from Su et al.[9], where flags for platooning, lane change, and a managed lane were turned off in the source code. The third scenario set the following Wiedemann 99 parameters to zero:

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

For comparison, all other microsimulation network parameters were unchanged between scenarios. The network consists of five highway links on Interstate 91 northbound, labeled 100 through 104, from Route 5 to Interstate 291 near Springfield, Massachusetts. Figure 1 below shows a satellite image of the links from the I-91 northbound network. Measured traffic volumes and speeds collected by the Massachusetts Department of Transportation were entered into Vissim as inputs. Our last publication provides a more detailed description of the I-91 network and the microsimulations.[5]

Figure 1. Satellite image of I-91 Springfield network with superimposed links

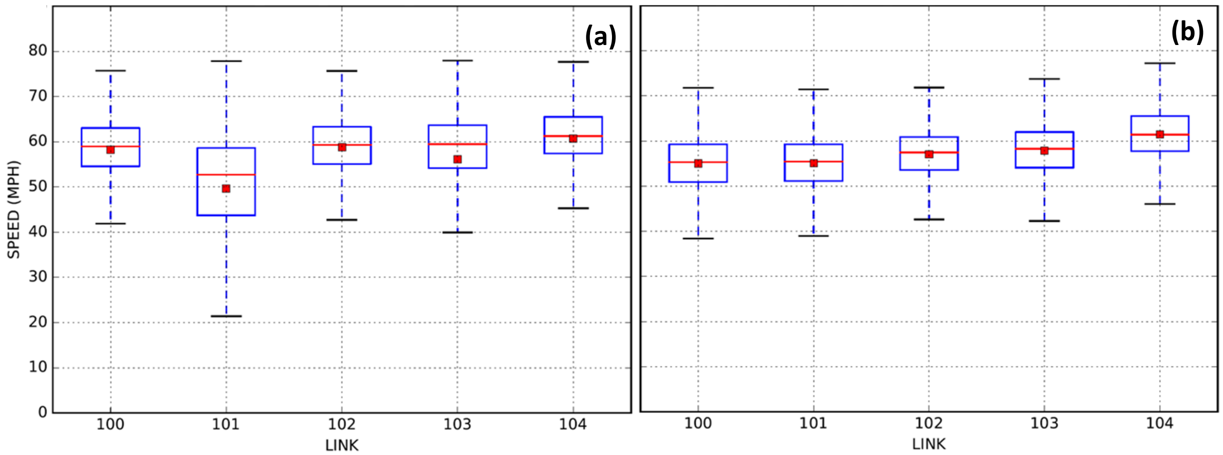


To account for any network variability within Vissim, we ran 15 random simulation seeds at 10 Hz for each of the three scenarios. Each of these 45 simulations generated a standardized text output (.fzp) file of vehicle trajectory data containing the following fields:

- 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).

We examined the network performance based on summary statistics of speed, acceleration, headway, and acceleration by link, as discussed at greater length in our last publication.[5] Using an example from the first random Vissim simulation, Figure 2a presents baseline box plots of speed and Figure 2b presents box plots of speed from the CACC scenario.

Figure 2. Speed box plots from the first simulation on I-91 network for **(a)** the baseline and **(b)** the CACC scenario



Our findings suggest that average speed generally does not change much between the baseline and CACC scenarios, but the range of speeds, especially on more congested links like 101, narrows substantially. Similar trends played out for the other network performance metrics, where CACC driving reduced headway, delay, and fluctuations in acceleration across links compared to the baseline. The Wiedemann scenario with the oscillation parameters set to zero, on the other hand, had little to no effect on the performance metrics.

Using Python, the vehicle trajectories were assigned an operating mode based on the vehicle-specific power (VSP), speed, and acceleration to eventually determine energy and emission estimates in MOVES. For each time step t, VSP_t was calculated from an equation in the latest MOVES technical documentation for emission rates of light-duty vehicles[10], as shown in Equation 1 below:

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

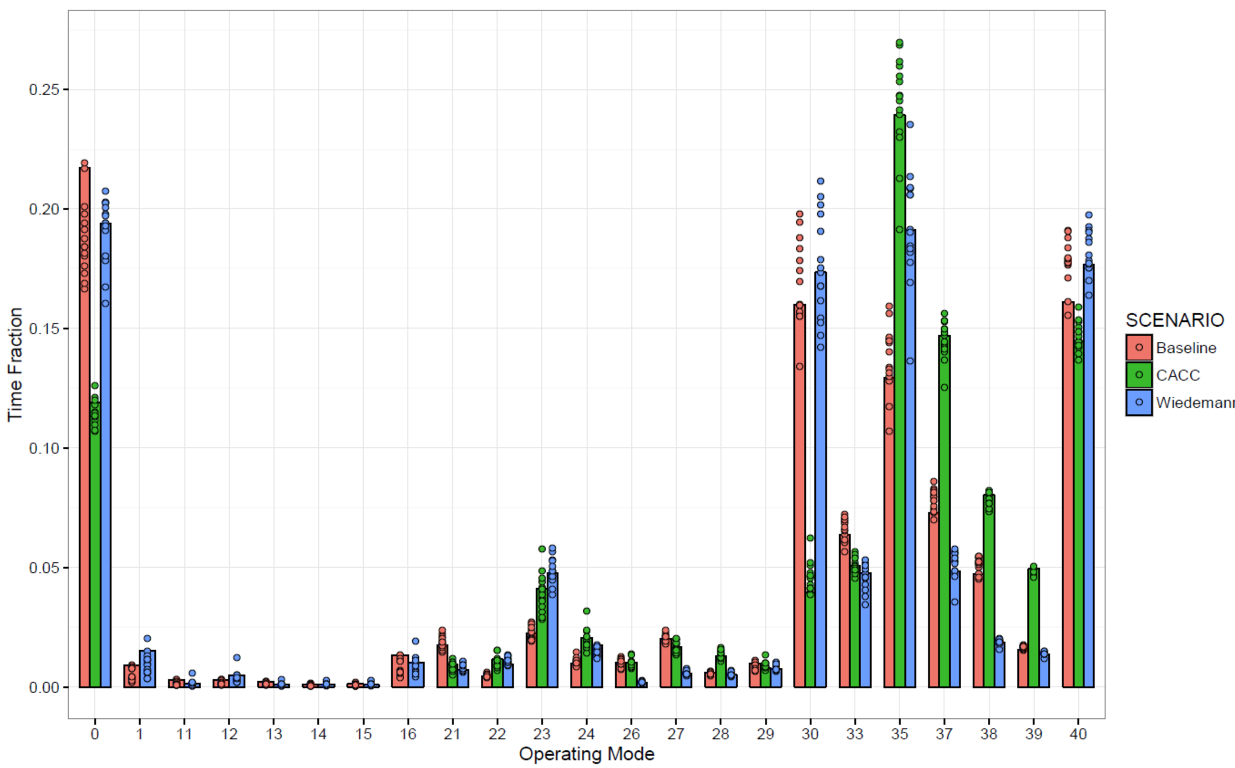
where v_t is speed at every time step, a_t is acceleration at every time step, A is the tire rolling resistance coefficient, B is the rotational resistance coefficient, C is the aerodynamic drag coefficient, and m is the vehicle mass. Default road load coefficients A, B, and C along with the vehicle mass m for a passenger car were taken from the *sourceusetypephysics* table in the MOVES2014a database 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.

Operating modes were then designated for every vehicle at each time step in an external Python tool for processing vehicle trajectory data according to the VSP-speed matrix from the MOVES2014a light-duty emission rates report.[10] Once designated, link-level operating mode distributions were developed based on the time spent in each operating mode over the duration of the simulation. Operating mode distributions are particularly useful for understanding the underlying causes for energy and emission benefits.

As an example, we present a plot of the operating mode distribution of Link 101 in Figure 3 below, where we express the variability in the microsimulations by displaying the first random seed as a bar and the other seeds as dots. We find that braking (op mode 0) and driving in op mode 30 at moderate speed (25-50 mph) and high power (30+ kW per metric ton) drop drastically from the baseline to the CACC scenario. While the Wiedemann scenario without any oscillations did reduce time in some higher op modes compared to the baseline, it showed increases in op modes 30 and 40, which have the highest VSP bins.

Figure 3. Operating mode distribution of Link 101 on the I-91 network (bar represents the first simulation and the dots represent the other 14 simulations)



To expedite the energy and emission estimates, the external Python tool also automatically created a MOVES project-scale input database for the *link*, *linksourcetypehour*, and *opmodedistribution* tables. The *link* table contains link-specific road type, length, traffic volume, and average speed and the *linksourcetypehour* table indicates the hourly allocation of vehicle source use type, which was network-specific but did not vary by link or simulation. None of the other project-scale inputs were changed for our energy and emissions analysis. We decided to model the I-91 network as a custom domain for a weekday morning hour in January 2020, similar to the MOVES run specifications in our first publication.[3] For each of the 45 microsimulations, the standard MOVES run specifications (stored in an .mrs XML file) were edited to include the appropriate input database. Each modified .mrs file was then placed in a

MS-DOS batch file and run from the command line rather than the MOVES graphical user interface, which can be tedious to repeatedly run. The external Python tool processed the 17.5 gigabytes of 10 Hz Vissim-generated vehicle trajectories through MOVES project-scale analysis with a single button click.

For comparison, we generated plots of the link-level energy and emission impacts across the 45 microsimulations on the I-91 network normalized per vehicle, as shown in Figure 4 below. Our analysis presents results for energy consumption/carbon dioxide (CO_2), particulate matter with diameters of 2.5 microns or less (PM2.5), nitrogen oxides (NOx), volatile organic compounds (VOC), total gaseous hydrocarbons (THC), and carbon monoxide (CO). Impacts varied more by link than pollutant for the three scenarios. On average, some links saw emission and energy benefits, namely on Link 101 and 104, for the CACC scenario over the baseline, and other links saw dis-benefits, namely Link 100 and 103. CACC systems appear to perform well in congestion and not as well on links prior to congestion. The Wiedemann scenario without oscillations had mixed results, where it was often as likely to produce benefits as dis-benefits. We found marginal energy/CO_2 and NOx reductions for Link 100 and 103.

The energy and emission results were also aggregated into plots for the entire network, as shown in Figure 5 below. Average CACC scenario results generated benefits from the baseline, particularly for PM2.5 and CO, which always yielded benefits across the 15 random seeds. However, the Wiedemann scenario had little to no benefits from the baseline, and in some instances lead to dis-benefits on average. Average energy/CO2 and PM2.5 estimates in the Wiedemann scenario were actually greater than the baseline.

To provide better context for these network-level impacts, we calculated the range of potential benefits for the CACC and Wiedemann scenarios in Table 1 below. Minimum and maximum percent reductions from the baseline are given for the pollutants mentioned above in addition to brakewear and tirewear (PM2.5). Our findings show that CACC driving on I-91 may result in up to 39% reduction in total PM2.5 and up to 34% reduction in CO on a per vehicle basis from the baseline. Even in the worst cases across all pollutants, CACC systems will cause a 6% increase over the baseline. Even though the Wiedemann scenario shows benefits as much as 15-20% compared to the baseline, the results are less definitive because the ranges and averages are so close. Not only do independent driving behavior models better represent CAV technologies like CACC systems in real-world networks, they also yield more energy and emission benefits than modifying Vissim's default Wiedemann 99 car following algorithms.

Figure 4. Volume-normalized link-level energy and emission results by I-91 link for each of the 45 simulations for **(a)** energy/CO2, **(b)** PM2.5, **(c)** NOx, **(d)** VOC, **(e)** THC, and **(f)** CO

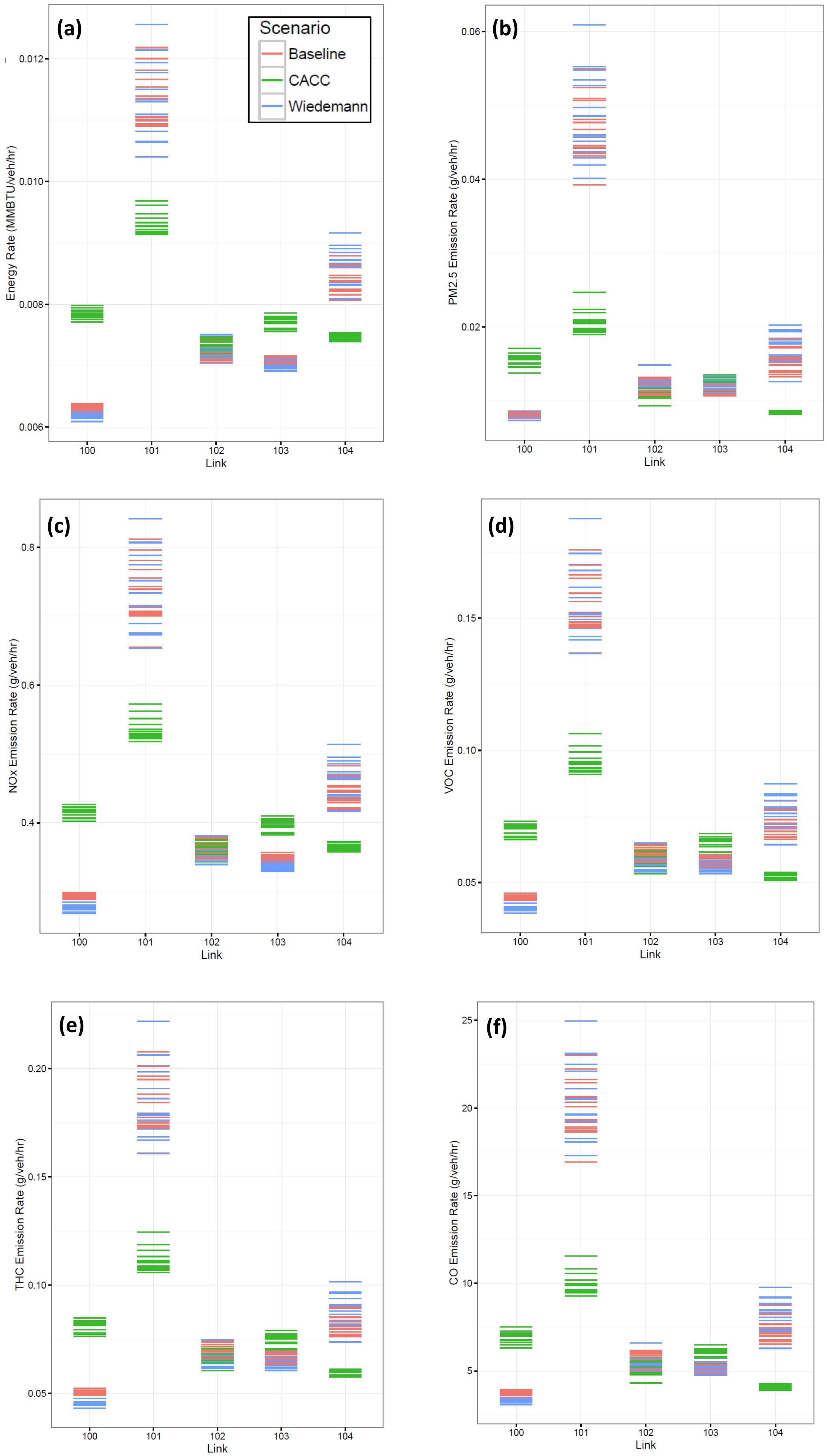


Figure 5. Volume-normalized network-level energy and emission results for each of the 45 simulations for **(a)** energy/CO2, **(b)** PM2.5, **(c)** NOx, **(d)** VOC, **(e)** THC, and **(f)** CO

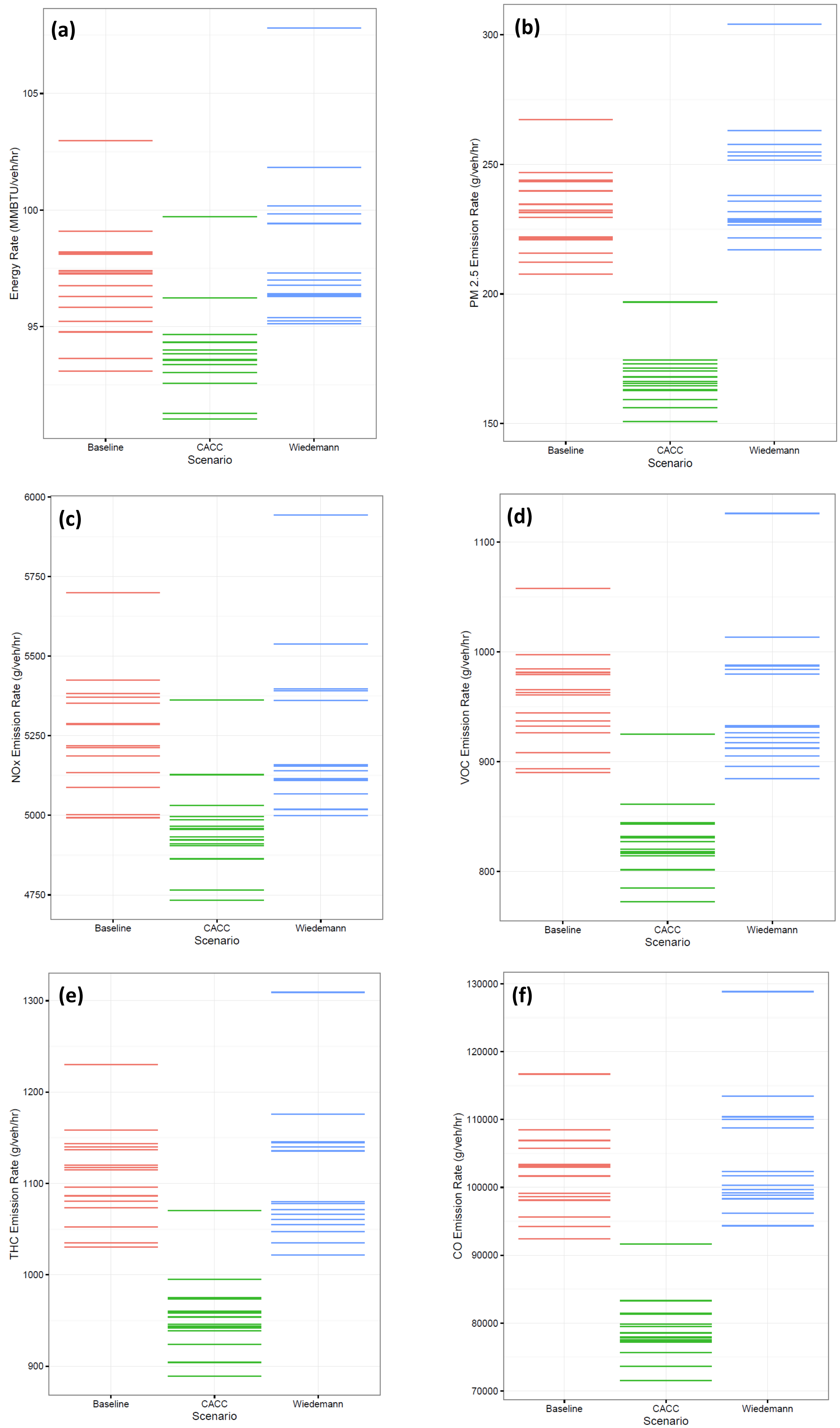


Table 1. Minimum and maximum potential energy and emission benefits (percentage reductions) on the I-91 network for the CACC and Weidemann scenarios from the baseline

	CACC from Baseline		***Wiedemann from Baseline***	
	Min	**Max**	**Min**	**Max**
THC	-2.2%	22.1%	-18.7%	15.4%
CO	2.5%	33.9%	-30.2%	17.6%
NOx	-5.6%	10.4%	-11.2%	10.6%
VOC	-2.2%	21.2%	-18.2%	14.8%
Energy/CO_2	-4.7%	4.7%	-7.5%	5.9%
PM2.5	6.8%	39.2%	-36.8%	17.3%
Brakewear (PM2.5)	11.3%	38.2%	-21.3%	24.6%
Tirewear (PM2.5)	-2.1%	3.0%	-5.5%	2.9%

DISCUSSION & CONCLUSION

Although this paper analyzes CACC systems, the techniques presented here are relevant to other technologies that fall under SAE J3016 Level 1 or Level 2 of vehicle automation. CAV technologies such as dynamic speed harmonization, platooning, and queue warning could easily fit within the three-layered modeling framework proposed in this paper. It would just be a matter of finding an existing driving behavior model for the given CAV technology or implementing the appropriate vehicle control algorithms to override the default driving behavior model in the traffic microsimulation software. As these technologies reach production and become more prevalent, the particular driving behavior models can be calibrated and validated against field tests of instrumented vehicles.

As government agencies write new emission standards and develop new emission inventories, they should explore ways to incorporate CAV technologies into future projections. The current version of MOVES cannot easily alter default driving behavior for regulatory analysis. Much of MOVES driving behavior is based on default drive cycles of a single vehicle for a given speed range and road type. We suggest adding a feature to allow users to input custom operating mode distributions at a county and/or national scale.

While this paper lays out a modeling framework for evaluating the potential energy and emission benefits of near-term CAV technologies, it does not analyze broader social, economic, and infrastructure impacts. Our analysis does not consider shared vehicles and trips, changes to vehicle miles traveled due to connectivity and automation, or the effect of CAVs on parking. Future research may include switching to electric drivetrains and therefore divert some fuel consumption and air quality impacts from mobile to stationary sources. We plan to model congestion by varying traffic volumes and penetrations of CAVs in our next phase of work.

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