ANTICIPATING THE EMISSIONS IMPACTS OF SMOOTHER DRIVING BY CONNECTED AND AUTONOMOUS VEHICLES, USING THE MOVES MODEL

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ABSTRACT

Connected and autonomous vehicles (CAVs) are expected to have significant impacts on the environmental sustainability of transportation systems. This study examines the emission impacts of CAVs, presuming that CAVs are programmed to drive more smoothly than humans. This work uses the US Environmental Protection Agency's (EPA's) Motor Vehicle Emission Simulator (MOVES) to estimate CAVs' emissions based on driving schedules or profiles. CAV engine load profiles are anticipated to be smoother than those of human-controlled vehicles (HVs), because CAVs are designed to be more situationally aware (thanks to cameras and radar

communications) and enjoy faster reaction times and more sophisticated throttle and brake control than HVs. Human drivers tend to demonstrate significant and frequent speed fluctuations and have relatively long reaction times.

species of interest. For example, with gasoline vehicles, smoothing of the Federal Test Procedure (FTP) cycle delivers 5% fewer volatile organic compounds (VOC), 11.4% less fine particulate matter (PM2.5), 6.4% less carbon monoxide (CO), 13.5% less oxides of nitrogen (NOx), and 3% less sulfur and carbon dioxide (SO_2 and CO_2). Using Austin link-based cycles, average reductions were 10.9% for VOC, 19.1% for PM2.5, 13.2% for CO, 15.5% for NOx, and 6.6% for SO_2 and CO_2. While added travel distances by CAVs may more than cancel many of these benefits, it is valuable to start discussing a shift to gentle driving, to obtain these reductions via emerging technologies.

KEYWORDS: Autonomous Vehicles, Eco-Self-Driving, Smoothed Drive Cycles, MOVES Emissions Simulator

BACKGROUND AND INTRODUCTION

In addition to affecting human mobility and safety, connected and automated or fully autonomous vehicles (CAVs) are also expected to impact emissions, air quality, and energy use. Many elements of vehicular and fuel technologies are associated with the energy use and emissions, such as vehicle weights (Greene, 2008; Ford, 2012; Chapin et al., 2013; MacKenzie et al., 2014), fuel efficiencies and alternative fuels (Chapin et al., 2013; Liu et al., 2015; Reiter and Kockelman, 2016), and engine technologies (Paul et al., 2011; Folsom, 2012; Bansal et al., 2015; Reiter and Kockelman, 2016). CAVs are anticipated to be lighter than existing human-controlled vehicles (HVs) (Chapin et al., 2013; Anderson et al., 2014), and powered by alternative fuels or electricity (Chen and Kockelman, 2015; Chen et al., 2016) and more efficient engines (Anderson et al., 2014). CAV operational features are also likely to affect the energy used and emissions generated. Anderson et al. (2014) pointed out that CAVs would likely have fewer stop-and-go movements, given the connectivity of vehicle-to-vehicle (V2V), and vehicle-to-infrastructure (V2I), resulting in lower levels of fuel consumption and emissions. Fagnant and Kockelman (2014) simulated a fleet of shared autonomous vehicles (SAVs) to serve travelers in an idealized, small city and estimated that each SAV might replace 11 HVs while increasing total vehicle-miles traveled (VMT) – due to empty-vehicle driving (to reach the next trip-maker). However, a high rate SAV warm-starts (73 percent of trips began with a warm engine) and the use of smaller vehicles (as well as a need for fewer parking spaces, and their embodied emissions) let to overall estimates of lower emissions. Fagnant and Kockelman (2014) estimated that such SAV fleets could deliver an energy savings of 12 percent, along with a 5.6 percent reduction in greenhouse gas (GHG) emissions, relative to privately owend and operated HVs. AV platooning can also be expected to be associated with higher fuel efficiency and lower emission rates (Alam et al., 2010; Tsugawa, 2014). Wu et al., (2014) discussed the sustainability benefits of vehicle automation at singalzied intersections. Their results indicated 5 to 7 percent reductions in engery use and GHG emissions, up to 7 percent reductions in hydrocarbon (HC) emissions and 15 to 22 percent reductions in carbon monoxide (CO) emissions. Wadud et al., (2016) expect greater enery savings and emissions reductions at higher levels of vehicle automation. Chen et al., (2015) estiamted the energy and emissions benefits from an autmated-vehicle-based personal rapid transit system and revealed approximately 30 percent engery saving and reductions in GHG emissions.

CAV technlogies are also expected to improve fuel economy and reduce emissions per mile driven through more automated and optimized driving, thanks to more gradual acceleration and deceleration in driving cycles. A driving cycle is often represented as a vehicle's speed profile versus time. Figure 1 presents a driving cycle designed by the US Environmental Protection Agency (EPA) to represent highway driving conditions under 60 mph. In using HVs, driving patterns with gradual acceleration and deceleration are often referred to as "eco-driving" profiles (see, e.g., Anderson et al. 2014; (Barth and Boriboonsomsin, 2009; Chapin et al., 2013). Barth and Boriboonsomsin (2009) expect approximately 10 to 20 percent fuel savings and GHG emissions reductions, from humans driving conventional vehicles more thoughtfully, to reduce their energy use. Given the precision of fully automated driving, CAV driving profiles are likely to be much more fuel-efficient or at least smoother than human-controlled eco-driving profiles. Mersky and Samaras, (2016) simulated the automated following driving cycles to esimated the changes in engery use and found up to 10 percent engery savings. This paper estimates the energy and emissions impacts of CAVs, by presuming that CAVs can (and ultimately will be programmed to) deliver smooth driving cycles or engine loading profiles, effectively practicing Eco-Autonomous Driving (EAD).

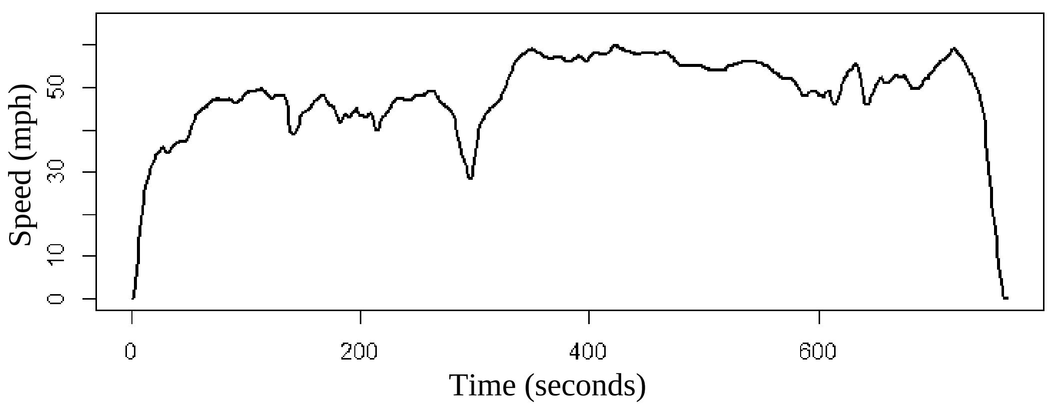


FIGURE 1 An EPA driving cycle for a conventional vehicle in highway driving conditions (EPA, 2013).

To simulate the EAD profile, this study employed two types of existing HV driving cycles: 1) EPA driving cycles used to test for compliance with Corporate Average Fuel Economy (CAFE) standards for light-duty vehicles (EPA, 2012), and 2) Austin-specific driving schedules developed by the Texas A&M Transportation Institute (TTI) to reflect local driving patterns of light-duty vehicles (Farzaneh et al., 2014). The EAD profiles were simulated by smoothing the existing driving cycles, given the anticipation that CAV driving profiles will contain fewer extreme driving events (like hard accelerations, sudden braking, and sharp or quick turns) than HV cycles. Then, this study used the US EPA's Motor Vehicle Emission Simulator (MOVES) to estimate emission rates (in grams per mile traveled) for various pollutants, including volatile organic compounds (VOC), fine particulate matter (PM2.5), carbon monoxide (CO), nitrogen oxides (NOx), sulfur dioxide (SO_2) and carbon dioxide (CO_2), based on the EAD profiles and HV cycles.

MOVES is the EPA's regulatory simulator for estimating on-road emissions from conventional vehicles such as passenger cars, buses, and trucks. It is used by planning organizations for project conformity analyses that are required for state implementation plans (SIPs), as well as for environmental analyses that gauge the impacts of potential transport planning decisions (EPA, 2014, 2015).The EPA and state environmental agencies have developed a database that provides basic emissions parameters for counties across the U.S. (EPA, 2015). Though this database is continually updated to provide the most accurate parameters for a given area, the EPA recommends that local data be developed and inserted into the MOVES simulator to provide the best estimate of on-road emissions at the project area, which Farzaneh et al. (2014) did for several Texas cities.

In this paper, CAV emissions impacts are limited to differences in basic driving profiles, as elected by independent CAVs driving at the same time in the same locations, with the same traffic control strategies and traffic variations that HVs face. In reality, many other CAV technologies and applications (like cooperative intersection coordination systems, platooning and coordinated adaptive cruise control) should also help save fuel and reduce emissions, but these are not evaluated in this paper. In addition, many factors that may affect the fuel consumption and emissions of vehicles, such as vehicle size and road grade (Boriboonsomsin and Barth, 2009) are not discussed here.

METHODLOGY

Envisioning Eco-Autonomous Driving (EAD) Cycles of Autonomous Vehicles

Smoothing Method

Many methods may be used to smooth driving cycles, such as a simple moving average, local polynomial regression, kernel density estimation, and smoothing splines (Simonoff, 2012). Most data smoothing efforts are designed to impute missing data points or remove random noise. In contrast, this study envisions generation of new CAV EAD cycles by smoothing existing HV cycles. These smoothed driving cycles present two key objectives and complexities:

1. CAVs' EAD profiles should have far fewer extreme driving events, such as hard accelerations and sudden braking, as compared to HV cycles. Intelligent and connected vehicles should be able to anticipate several seconds of downstream driving conditions, making timelier decisions and ultimately smoother responses to evolving traffic conditions. In such cases, a greater extent of smoothing (like a wider smoothing window) can be expected.

2. CAV movements on the road are influenced by other vehicles (when there is no free-flow and HVs are still in operation) and the traffic controls (like intersection signals and signs). Therefore, at the early stage of introducing CAVs on the roads, the CAV profiles will likely be similar to HV cycles at the microscopic level. In other words, the time-distance diagrams of both CAV (smoothed) and HV (unsmoothed) driving profiles should generally be similar to each other, to ensure that smoothed cycles do not make travelers late for meetings, late to green lights, or unyielding to (and thus colliding with) driveway-entering vehicles and the like. And the extent of smoothing (or level of smoothness) should not be extreme. This assumption implies largely unchanged driving patterns, from a macroscopic perspective.

However, CAV technologies are likely to eventually impact such patterns, as adoption and use rates rise; cooperative intersection management and smart CAV routing decisions will shorten travel times, everything else constant, but added VMT may make travel more congested. Such changes in load profiles are not examined here.

In order to approximate this “balance” between these two concerns, the method of smoothing spline was employed in this study to minimize the objective function:

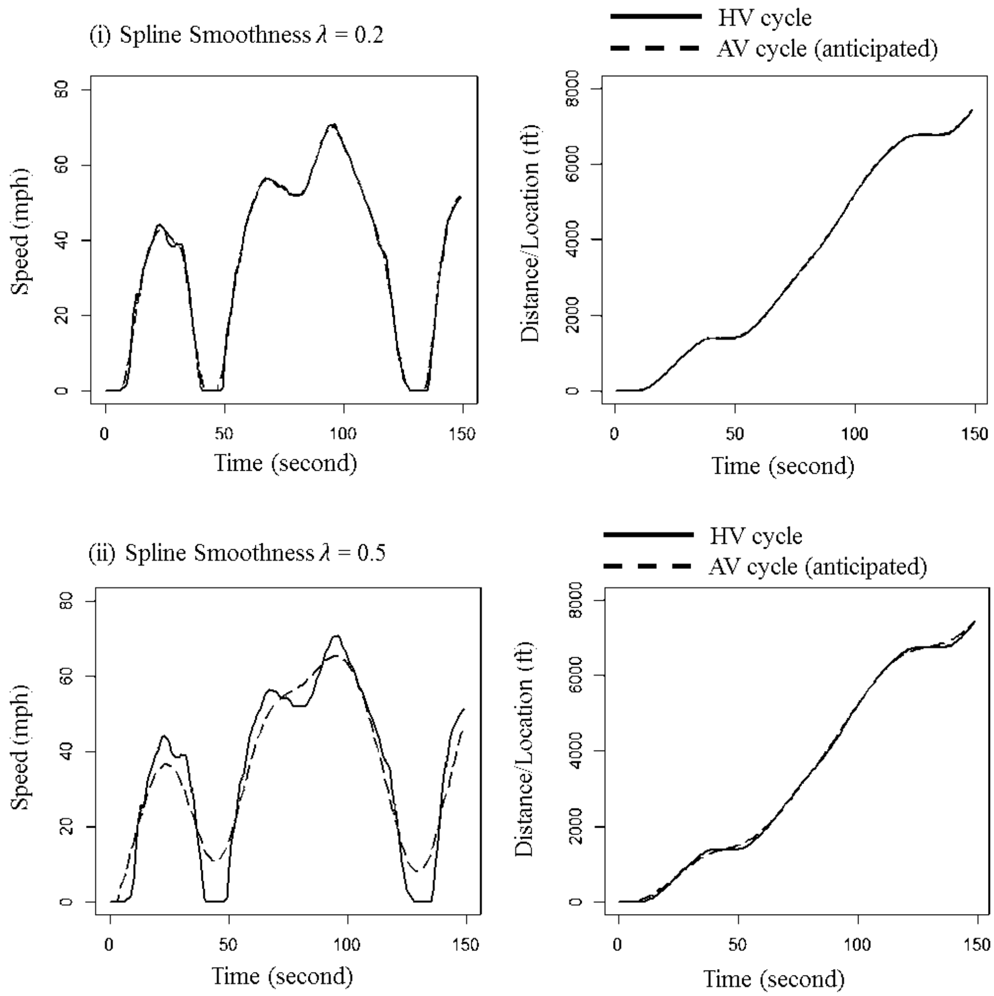
$$\underset{m}{arg\,min} \quad \frac{1}{n}\sum_{i=1}^{n}(y_i - m(x_i))^2 + \lambda \int dx(m''(x))^2$$

where the first term is the mean square error (MSE) (with y_i = the value of y at i^{th} data point x_i in the original driving cycle, i = 1, 2, …, n; and $m(x_i)$ = the predicted value of m at the i^{th} data point x_i in the smoothed cycle); $m''(x)$ = the second derivative of m with respect to x (i.e., the curvature of m at x); λ = a smoothness factor to penalize MSEs. As $\lambda \rightarrow +\infty$, the MSE is not a concern and there is only a linear function resulted from the smoothing process. In contrast, as $\lambda \rightarrow 0$, the curvature is negligible and remains the same as un-smoothed. To address both these ideas and the two objectives or complexities listed above, an appropriate smoothness factor λ was chosen to construct smoothing cycles.

To determine the most appropriate smoothness factor, various λ values were tested, as shown in Figure 2. Larger values of λ, like λ = 0.8, are associated with smoother but less realistic driving cycles that significantly deviate from the original cycle.

To better appreciate the effects of the chosen λ, the distributions of the smoothed and original cycles’ accelerations and decelerations were also compared. Figure 3 presents the distributions of acceleration/deceleration values before smoothing (when λ=0) and after the smoothing. For comparison, typical distributions of acceleration/deceleration are shown in the figure as well, indicated by means (solid line) and means plus one standard deviation (dashed lines). The means and standard deviations were calculated for specific speed ranges (with bin width = 0.5 mph) using large-scale trajectory data from the Austin region.

The trajectory data were obtained from the Transportation Secure Data Center (TSDC) of the National Renewable Energy Laboratory (NREL) (TSDC, 2014). The data were originally collected in TTI’s 2006 Austin/San Antonio GPS-Enhanced Household Travel Surveys. This study extracted 241 hours of second-by-second driving speed records collected from 231 vehicles in Austin, Texas in 2005 - 2006. (More details about the calculation of distributions of acceleration/deceleration along speeds can be found in Wang et al. 2015. Note that the distributions can vary from one region to another). Figure 3 shows how, with a high smoothness factor (λ=0.8), the accelerations/decelerations are close to zero across speeds. To ensure that AV cycles remain similar to existing HV cycles (in order stop at red lights, and slow when vehicles merge in front of a CAV), this study chose λ=0.22999 as the smoothing factor, since this value allows most acceleration/deceleration data points to lay within the mean + one standard deviation of the typical distributions in the Austin region. In the study by Wang et al. (2015), the acceleration/deceleration data points were regarded as extreme driving events for falling beyond the mean-value lines plus one standard deviation, reflecting the unpredictable maneuvers of HVs. As CAVs become more common in traffic streams, such unpredictable maneuvers are likely to fall dramatically (thanks to inter-vehicle communications).



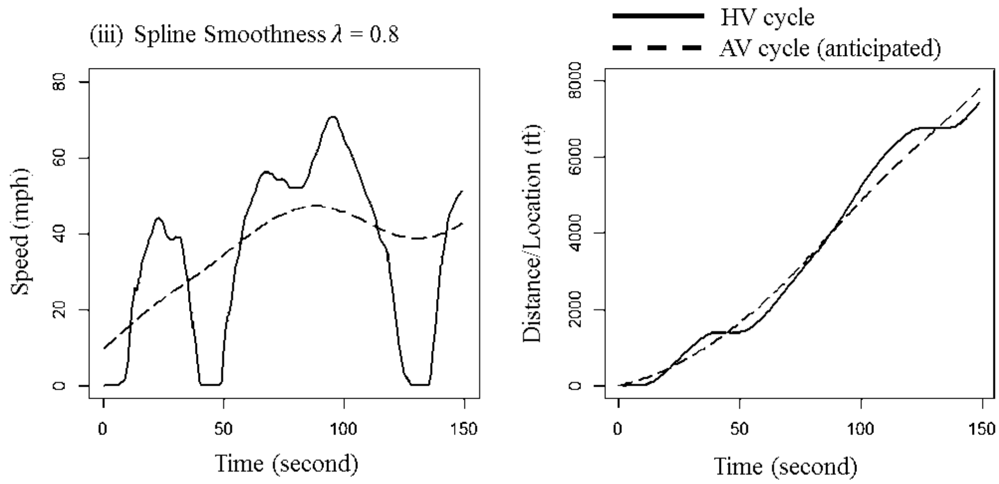


FIGURE 2 Driving cycle example (smoothed CAV cycle vs. original HV cycle).

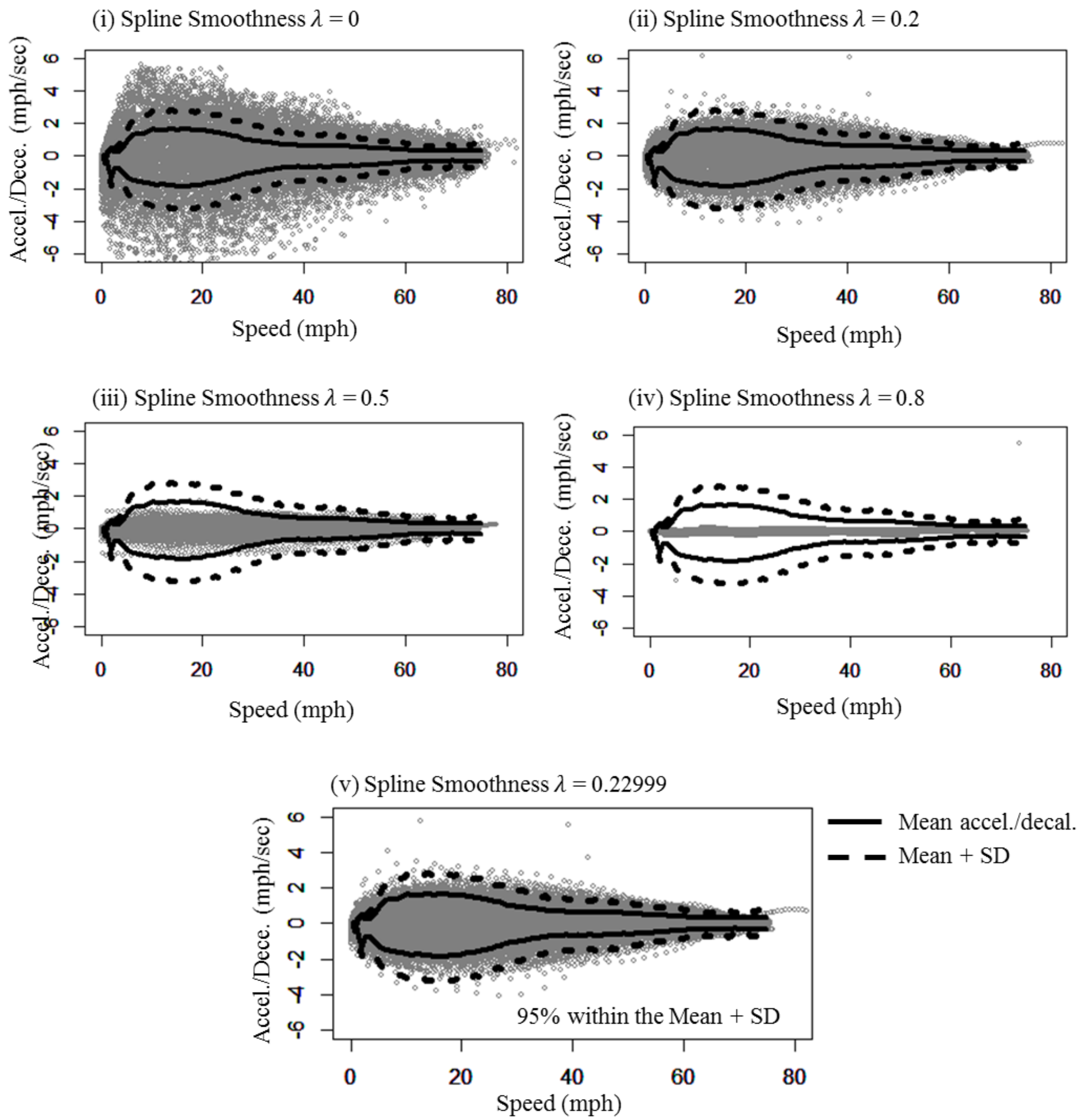


FIGURE 3 Distributions of acceleration and decelerations: before smoothing and after smoothing, assuming different smoothing factors.

Envisioned CAV Driving Profiles using EPA Cycles

The EPA has designed various driving cycles to represent a variety of driving conditions, such as highway versus city driving, aggressive driving behavior, and air-conditioner in use. Five EPA cycles are usually used in testing light-duty vehicles' compliance with CAFE standards (Davis et al., 2009; Berry, 2010). This study uses these same five, well-established cycles to envision future CAV cycles in various driving contexts. Table 1 summarizes basic information about these cycles, and Figure 4 presents these cycles in their original time-speed schedule (blue solid line) vs. a smoothed time-speed profile (red dashed line). The smoothed cycles are envisioned to be the driving profiles for CAVs operating in the trip conditions listed in Table 1

TABLE 1 EPA Cycles

EPA Cycle	Travel Description	Max. Speed	Avg. Speed	Max. Accel.	Simulated Distance	Duration	Test Temp.
FTP (Federal Test Procedure)	Low speeds in stop-and-go urban traffic	56 mph	21.2 mph	3.3 mph/sec	11 mi.	31.2 min.	68°F–86°F
HWFET (Highway Fuel Economy Driving Schedule)	Free-flow traffic at highway speeds	60 mph	48.3 mph	3.2 mph/sec	10.3 mi.	12.75 min.	68°F–86°F
US06 (Supplemental FT)	Higher speeds; harder acceleration & braking	80 mph	48.4 mph	8.46 mph/sec	8 mi.	9.9 min.	68°F–86°F
SC03 (Supplemental FTP)	A/C use under hot ambient conditions	54.8 mph	21.2 mph	5.1 mph/sec	3.6 mi.	9.9 min.	95°F
UDDS (Urban Dynamometer Driving Schedule)	City test w/ colder outside temp.	56 mph	21.2 mph	3.3 mph/sec	11 mi.	31.2 min.	20°F

Source: EPA (2013).

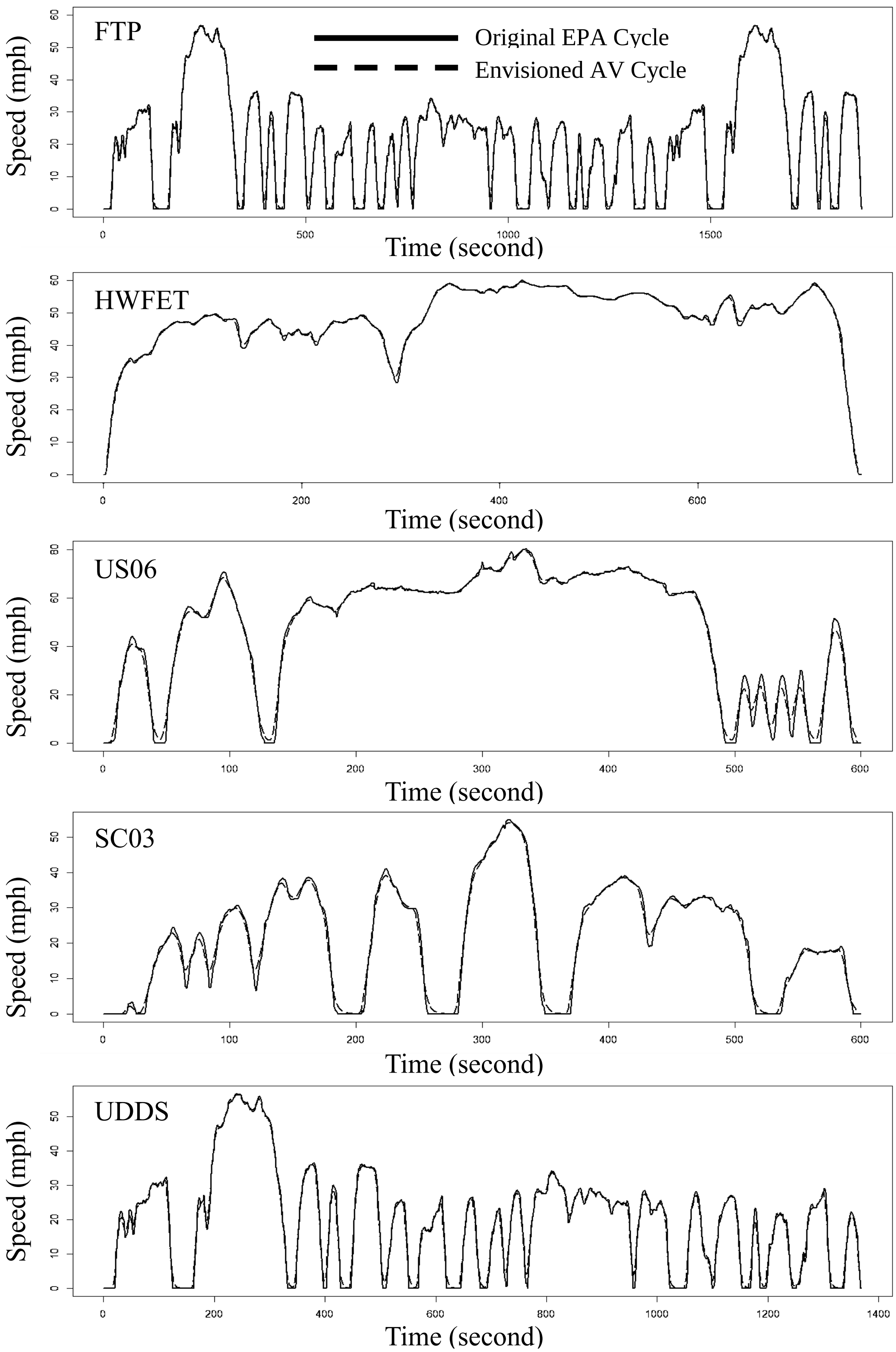


FIGURE 4 EPA driving cycles before (solid line) and after (dashed line) the smoothing.

Envisioned CAV Driving Profiles using Austin Cycles

This research also relies on the Austin-specific driving cycles, extracting them from the Database of Texas-Specific Vehicle Activity Profiles for use with MOVES (Farzaneh et al., 2014). These extracted cycles do not represent a complete automobile trip, but rather travel along any specific type of roadway (like a collector vs. an arterial roadway). These links may be combined to approximate a complete trip or driving cycle, but here the emissions analysis was conducted at the link level. For regional analysis, emissions on each coded network links are summed, to reflect their proportions in any region's road network.

In total, 36 links were extracted from the database, covering two types of light-duty vehicles (passenger car and light-duty truck), two types of roadways (urban restricted and unrestricted road), and nine link-level average speed bins. Using the smoothing method introduced above, the links' driving cycles were smoothed to envision the driving profiles of CAVs running in the Austin region. Figure 3 presents the distributions of acceleration/deceleration (i) before and (ii) after the smoothing. Figure 3(v) gives the distributions of acceleration/deceleration in envisioned CAV driving profiles.

Preparing Data Inputs for MOVES

Several studies have employed MOVES to estimate on-road emissions. Instead of using real data to estimate travel times, queue length, and other parameters, microsimulation data can provide the needed MOVES inputs. This method was employed by Xie et al. (2012) to estimate emissions on a freeway segment in Greenville, South Carolina. The researchers used PARAMIC software to simulate the freeway operations and outputs used in MOVES for emissions modeling. Xie et al. (2012) modified the fuel table to estimate the environmental benefits of using alternative fuels. Their results showed alternative fuels changed emissions rates as expected, but the scope of their study was limited to one freeway segment. Abou-Senna and Radwan (2013) employed MOVES to look at how traffic volume, vehicle speed, grade, and temperature affected CO_2 emission rates. Their results reconfirmed that increasing factors like grade and traffic volume on a link leads to higher emission rates.

The MOVES model's key configurations include:

1. Geographic Bounds of the county where the project is located. Here, Travis County was selected.

2. Vehicles/Equipment that generate the emissions, and the fuels they use. Here, passenger cars and light-duty trucks powered by diesel fuel, ethanol (E-85), and gasoline were considered.

3. Road Types modeled in MOVES are off-network, rural roads, and urban roads, with urban and rural roads classified as having either restricted or unrestricted access. Only urban road emissions were simulated here.

4. Pollutants and Processes studied here are VOC, CO, CO_2, NOx, and PM2.5, as noted early in this paper.

After finishing the configuration of the MOVES model, the user enters project-specific data into the Project Data Manager. Relevant inputs specified for this project are described below (with other inputs specified using MOVES' default values):

1. Links – the user specifies the road type, length, volume, average speed, and grade of each link being modeled in the project analysis. The road type, length, and average speed for each link considered was provided in the Texas drive cycle database referenced earlier. The grades of all roads were considered to be zero. Though this is a very simplistic assumption, analyzing the emissions impacts of smoothing cycles can still be performed effectively because the input parameters remain the same for both unsmoothed and smoother driving cycles. Only urban restricted and urban unrestricted roads were considered in this analysis to minimize MOVES run times. The volume of the link, which is the total traffic volume in one hour, was considered to be 145,000 vehicles for urban restricted roads and 10,000 for all urban unrestricted roads included in the analysis. Since link volumes are not readily available in a database for each link on a network, a conservative estimate was used for both urban restricted roads and urban unrestricted roads.

2. Link Source Types – each link considered must have the vehicle mix specified. Only light vehicles were considered in this analysis due the lack of available data highlighting the actual vehicle mixes in this analysis.

3. Link Drive Schedules – the speed vs. time profiles (drive cycles) extracted from the Texas drive cycle database were used as the model of driving behavior for vehicles in the project area.

RESULTS

This section presents emissions estimates based on smoothed driving cycles (for light-duty CAVs), using MOVES, as compared to the original HV-based driving schedules. Results using the EPA's national driving cycles are presented first, followed by some Austin-specific driving cycle results.

Emission Estimates from EPA Cycles

The emission rates of a specific type of pollutants were estimated for light-duty passenger vehicles. The HV emission estimations were based on the original EPA schedules and the CAV emissions were estimated according to the corresponding smoothed EPA schedules.

Figure 5 presents the estimates of volatile organic compounds (VOC) emissions. The estimates are generally reasonable. For example, 1) the SC03 cycle with air-conditioning on in high temperature of 95°F and FTP cycle with frequent acceleration and brake events at low speeds lead to the high emission rates in both gasoline and diesel vehicles; and 2) the HWFET cycle representing free-flow freeway traffic is associated with the least emission rates, with other factors held constant. CAV emission levels are expected to be lower than those of HVs. Among both gasoline and diesel passenger vehicles, all five cycles are estimated to have lower VOC emission rates after the spline smoothing. Noticeably, the HWFET cycle is associated with the smallest emissions reductions, perhaps because this cycle does not contain many hard brakes and accelerations. The US06 cycle is linked with greatest emissions reductions (6.25% to 6.65%), as the original US06 cycle contains many rapid acceleration and hard-braking events that may occur only rarely in CAV operations. FTP cycle is associated with the second greatest reductions (4.99% to 5.23%) in VOC emissions.

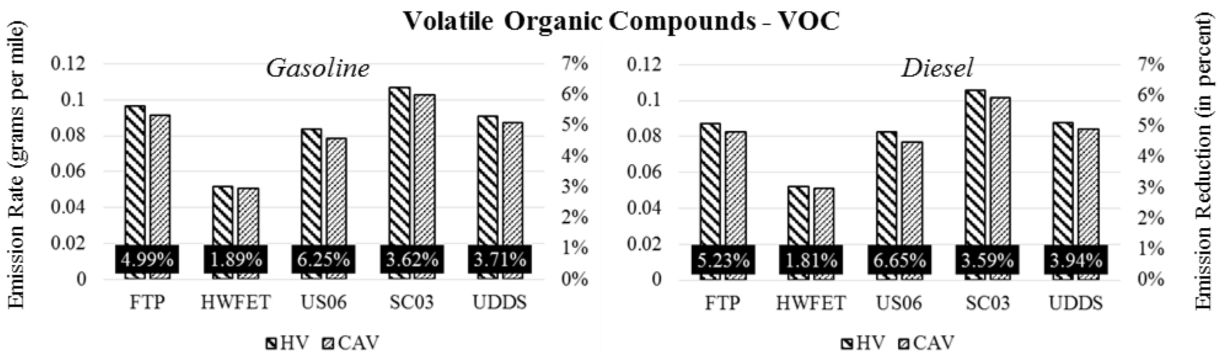


FIGURE 5 Emission Estimates for VOC

Figure 6 shows estimated emissions of particulate matters (PM), carbon monoxide (CO), nitrogen oxides (NOx), and carbon dioxide (CO_2). Variations are found in these emission species. US06 cycle leads to greater emission rates than FTP and HWFET cycles for emissions of PM 2.5 and CO, owing to the hard brakes and accelerations in US06 cycle. UDDS SC03 cycles are found to have the greatest emission rate of PM2.5, and CO, respectively, for gasoline vehicles. The reason may be related to the testing temperature: UDDS was tested at extreme cold temperature, 20°F, and SC03 cycle was to simulate the driving in hot weather, 95°F. For emissions of NOx, US06 cycle leads to greatest emission rates among both gasoline and diesel vehicles. FTP cycle has relatively great CO_2 emission rates, which may be related to the low-speed driving, and frequent acceleration or brake events.

Regarding the emission reductions from HVs and CAVs, FTP and UDDS cycles seem to have great reductions (> 10%) in emissions of PM 2.5 and NOx. US06 cycle is expected to have great reductions (around 7%) in emissions of CO. Again, HWFET cycle with least hard brake and acceleration events is related to the smallest reductions across all emission species.

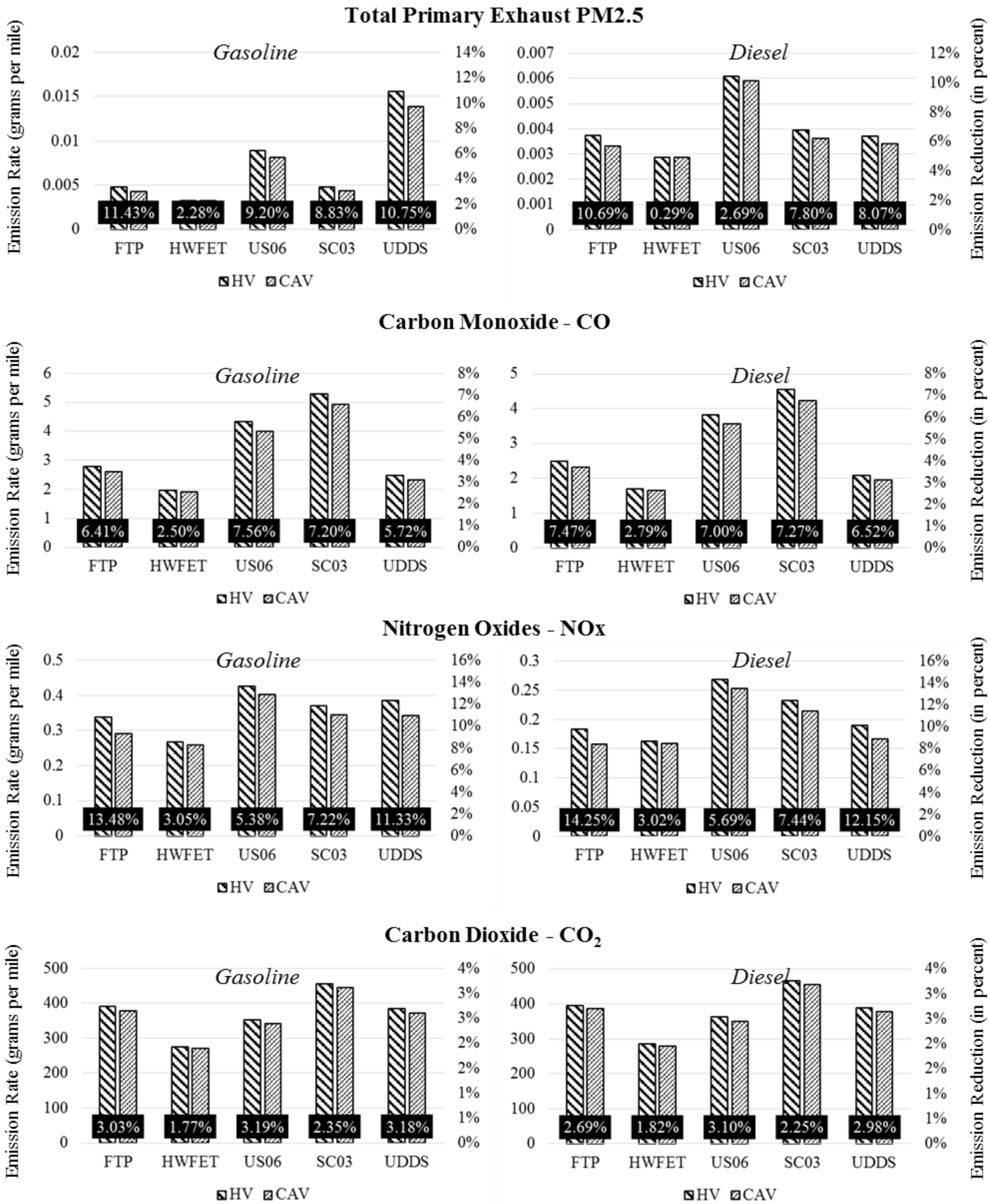


FIGURE 6 Emission Estimates for PM2.5, CO, NOx, and CO_2

Overall, smoothed EPA cycles were associated with lower emission rates, indicating that CAVs are likely to be more environmentally friendly than HVs. However, these reductions are not guaranteed, and vary according to emission types, fuel types, and driving contexts.

Emissions Estimates from Austin-area Cycles

The emissions were estimated in 36 Austin-specific cycles that represent the local driving patterns. Given the variety of pollutant types, fuel types, vehicle types, various cycles, etc., simple regression models were constructed to present and explain the results. The correlates of emissions reductions for a specific pollutant were explored. The response or dependent variable is the percentage reduction in any specific pollutant species. Explanatory or independent variables (X_1, X_2, etc.) include fuel type, vehicle type, temperature, and link-level average speed values. All explanatory variables, except link-level average speed values, are indicator (X = 0 or 1) variables, and just two ambient temperature conditions (cold, 40°F in January, and hot, 75°F in September) were simulated. Table 2 shows the descriptive statistics of variables in the regression models. The models for different pollutants had exactly the same descriptive statistics.

TABLE 2 Summary Statistics of Emissions-Related Variables

(i) Explanatory Variables

Variable		Mean or Proportion	S.D. or Freq.	Min	Max
Vehicle Type	Passenger Car	50%	216	0	1
	Light-Duty Truck	50%	216	0	1
Fuel Type	Gasoline	33%	144	0	1
	Diesel	33%	144	0	1
	Ethanol	33%	144	0	1
Temperature	Cold	50%	216	0	1
	Hot	50%	216	0	1
Link Mean Speed (mph)		30.18	21	2.5	69.5

(ii) Emission Reeducations

Emission Species	Average Drop	S.D.	Min	Max
Volatile Organic Compounds - VOC	10.89%	9.09%	-4.56%	30.77%
Fine Particulate Matter - PM2.5	19.09%	17.31%	-23.81%	59.66%
Carbon Monoxide - CO	13.23%	16.50%	-16.93%	40.04%
Nitrogen Oxides - NOx	15.51%	11.50%	-7.41%	38.63%
Sulfur Dioxide – SO_2	6.55%	5.45%	-4.12%	16.77%
Carbon Dioxide - CO_2	6.55%	5.45%	-4.11%	16.76%

Note: all variables except Link Mean Speed and Emission Reduction are indicator variables. No. of observations = 432 for each emission type.

Figure 7 presents the distributions of percent reductions (Y) in emissions of VOC, PM2.5, CO, NOx, SO_2, and CO_2. The positive percentages indicate the emissions reductions from HV to CAV cycles. The magnitudes of percent reductions are generally consistent with the estimates from EPA cycles. As shown in Figure 10, in most cases, the estimated emissions decreased during the shift from HV to CAV cycles (i.e., positive percentages). The mean emission reductions are 10.89% for VOC, 19.09% for PM2.5, 13.23% for CO, 15.51% for NOx, and 6.55% for SO_2 and CO_2.

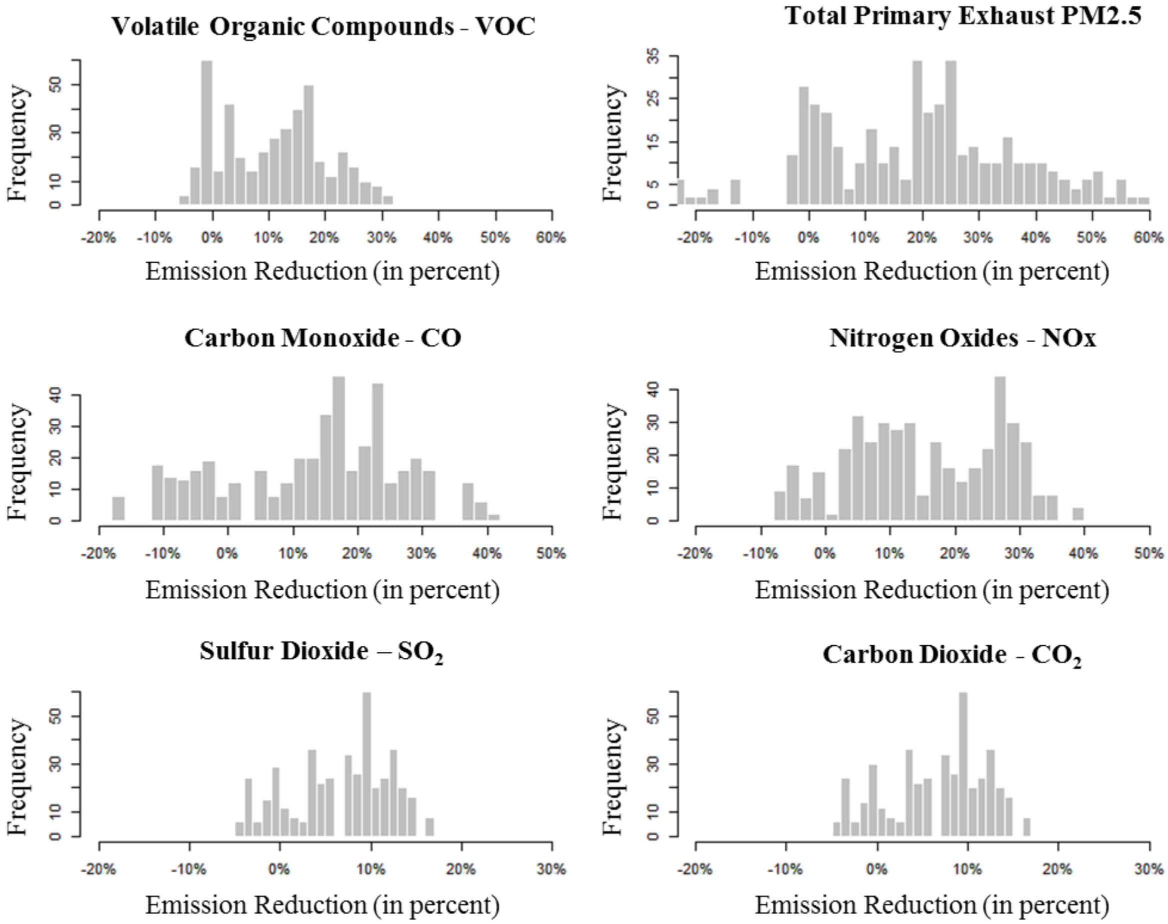


FIGURE 7 Distributions of emissions reductions (in percentages) of VOC, PM2.5, CO, NOx, SO_2, and CO_2.

Table 3 delivers the regression models, showing the correlates of emission reductions (from HV to CAV EAD cycles) with the factors shown in Table 2. The coefficients refer to the changes in emission reductions (%) from HV to CAV cycles, with one unit change in explanatory variables, when controlling for other variables. The findings from the models include the following:

- VOC: Greater reductions in VOC emissions are expected for passenger cars, 1.925 percentage points more than for passenger trucks. Diesel vehicles showed smaller emission reductions, 4.636 percentage points less than vehicles powered by ethanol. Higher average link speeds lead to greater reductions in VOC emissions, while a one-unit increase in speeds results in a reduction in VOC of 0.273 percentage points less.

- PM2.5: Gasoline vehicle are associated with a greater reduction (4.367 percentage points more) in emissions of PM2.5, and diesel vehicle are linked with a smaller reduction (8.307 percentage points less), as relative to the vehicles powered by ethanol. The road links with higher average speeds are expected to have a greater emission reduction. A one-unit increase (1 mph) in average speed corresponds to a 0.302 percentage point reduction in PM2.5 emissions.

- CO: Passenger cars are related to greater CO emission reductions (1.655 percentage point more) when moving from HV to CAV cycles, as relative to passenger trucks. Diesel vehicles demonstrated smaller emission reductions, 2.131 percentage points less than vehicles powered by ethanol. Higher average link speeds are expected to result in a greater reduction in CO emissions. The regression shows that a one-unit increase in average link speed results in a 0.505 percentage points greater emission reduction in CO.

- NOx: Passenger cars demonstrated greater NOx emission reductions from the HV to CAV cycles, 1.363 percentage points more than passenger trucks. Diesel vehicles showed smaller emission reductions, 4.042 percentage points less than vehicles powered by ethanol. Higher average link speeds are expected to result in a lower reduction in NOx emissions, while a one-unit increase in speeds results in a reduction in NOx of 0.048 percentage points less.

- SO_2 and CO_2: These two types of emissions were found to have similar correlates of emission reductions. Only the link average speed has a significant correlation with these emission reductions. Higher link average speeds are expected to result in a lower reduction in SO_2 and CO_2 emissions. A one-unit increase in speeds results in a reduction in SO_2 and CO_2 emissions of 0.069 percentage points less.

TABLE 3 Regression Results for Y = % Emission Reductions, as a Function of Vehicle, Fuel Type, Starting Engine Temperature, and Average Speed

Emission Species	Variable	β	Std Error	p-value	R-Square
Volatile Organic Compounds VOC	Constant	2.641**	5.74	<.0001	0.643
	Passenger Car (base: Passenger Truck)	1.925**	7.33	<.0001	
	Gasoline (base: Ethanol)	-0.588	-1.58	0.1146	
	Diesel (base: Ethanol)	-4.636**	-12.47	<.0001	
	Cold (base: Hot)	-0.188	-0.72	0.4737	
	Link Mean Speed (mph)	0.273**	21.81	<.0001	
Fine Particulate Matter PM2.5	Constant	9.983**	7.87	<.0001	0.253
	Passenger Car (base: Passenger Truck)	-0.862	-1.19	0.2342	
	Gasoline (base: Ethanol)	4.367**	4.27	<.0001	
	Diesel (base: Ethanol)	-8.307**	-8.12	<.0001	
	Cold (base: Hot)	0.550	0.76	0.4477	
	Link Mean Speed (mph)	0.302**	8.75	<.0001	
Carbon Monoxide CO	Constant	-2.011**	-2.95	0.0034	0.646
	Passenger Car (base: Passenger Truck)	1.655**	4.25	<.0001	
	Gasoline (base: Ethanol)	0.038	0.07	0.9455	
	Diesel (base: Ethanol)	-2.131**	-3.87	0.0001	
	Cold (base: Hot)	0.080	0.21	0.8373	
	Link Mean Speed (mph)	0.505**	27.20	<.0001	
Nitrogen Oxides NOx	Constant	14.054**	15.21	<.0001	0.103
	Passenger Car (base: Passenger Truck)	1.363*	2.59	0.0101	
	Gasoline (base: Ethanol)	0.116	0.16	0.8768	
	Diesel (base: Ethanol)	-4.042**	-5.42	<.0001	
	Cold (base: Hot)	-0.275	-0.52	0.6017	
	Link Mean Speed (mph)	0.048	1.92	0.0555	
Sulfur Dioxide SO_2	Constant	4.480**	10.09	<.0001	0.076
	Passenger Car (base: Passenger Truck)	-0.392	-1.55	0.1225	
	Gasoline (base: Ethanol)	-0.089	-0.25	0.8043	
	Diesel (base: Ethanol)	0.247	0.69	0.4903	
	Cold (base: Hot)	0.046	0.18	0.8562	
	Link Mean Speed (mph)	0.069**	5.69	<.0001	
Carbon Dioxide CO_2	Constant	4.479**	10.10	<.0001	0.076
	Passenger Car (base: Passenger Truck)	-0.391	-1.550	0.1231	
	Gasoline (base: Ethanol)	-0.089	-0.250	0.804	
	Diesel (base: Ethanol)	0.248	0.690	0.4898	
	Cold (base: Hot)	0.046	0.180	0.8562	
	Link Mean Speed (mph)	0.069**	5.690	<.0001	

Note: ** = significant at 99% confidence level; * = significant at 95% confidence level.

CONCLUSIONS AND FUTURE STUDY

This study seeks to anticipate some of the emission impacts of CAVs. CAV driving profiles are envisioned to be smoother than those of HVs, because CAVs are expected to be faster and more precise than human drivers, in terms of reaction times and maneuvering. Human drivers tend to create significant, frequent speed fluctuations (i.e., hard brakes and rapid accelerations) and have relatively long reaction times (e.g., 1.5 seconds). CAV technologies may rarely suffer from such fluctuations, allowing for smoother driving profiles, referred to here as Eco-Autonomous Driving (EAD) cycles. Hard braking and rapid acceleration events are associated with increased emissions, so, by smoothing HVs' existing driving cycles, this work anticipates the emission benefits of CAVs.

National EPA cycles and Austin, Texas cycles were smoothed to obtain EAD emissions estimates using MOVES. Various emission species were considered here, including volatile organic compounds (VOC), fine particulate matter (PM2.5), carbon monoxide (CO), nitrogen oxides (NOx), sulfur dioxide (SO_2), and carbon dioxide (CO_2). Differences in HV vs. CAV emissions estimates suggest valuable air quality from CAVs – assuming CAVs are driven no more than HVs would be.

The results from EPA cycles suggest that, in general, if HVs are replaced by AVs, greater emission benefits (up to 14% emission reductions) are anticipated in driving conditions where there are many hard acceleration and braking events, and for drivers with aggressive driving styles. The results from Austin cycles indicate the mean emission reductions are 10.89% for VOC, 19.09% for PM2.5, 13.23% for CO, 15.51% for NOx, and 6.55% for SO_2 and CO_2. Regression models revealed that passenger cars were found to be associated with lower emission reductions for , VOC, PM2.5, CO, and NOx than passenger trucks. Diesel vehicles are linked with smaller emission reductions for these six types of emissions. The road links with higher average speeds have greater emission reductions for all emission species.

The results are solely based estimates from MOVES models. Other emission modeling tools, such as UC Riverside's Comprehensive Modal Emissions Model (CMEM) (Scora and Barth, 2006), may be employed in continuing efforts. At this point, the discussion of emission impacts of AVs is limited to the differences between the anticipated EAD profiles of CAVs and existing HV driving cycles. CAV profiles are envisioned to be smoother than HV cycles as compared to HV cycles. Other CAV-based technologies (like platooning of vehicles and CACC) may also save fuel and reduce emissions further.

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