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Energy Consumption Simulation for Connected and Automated Vehicles: Eco-driving Benefits versus Automation Loads

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Abstract

Eco-driving *benefits* and automation energy use *burdens* are important factors impacting the energy consumption of connected and automated vehicles (CAVs). However, challenges exist in evaluating the balance between these benefits and burdens under real-world driving conditions. Here we used a large dataset of 8064 real-world trips to establish analytical relationships between driving characteristics and fuel consumption for CAV sedans and sport utility vehicles (SUVs) with gasoline and battery electric powertrains. The regression-based model enables rapid estimation of eco-driving benefits using trip-level information (average speed and aggressiveness factor) with an accuracy similar to computationally intensive tools using second-by-second speed profiles. Three simulated scenarios reflecting different levels of smooth driving and avoidance of low-speed driving were considered. In the medium-level scenario, eco-driving reduces energy consumption by a median of 17% for gasoline vehicles and by 14% for battery electric vehicles (BEVs). Eco-driving benefits are more significant for trips with lower average speeds. Automation power consumption below approximately 1000 W is needed for eco-driving benefits to outweigh automation burdens. For trips with average speeds >60 km/h, even CAVs with an automation power consumption of 2000 W have fuel economies similar to non-automated vehicles.

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1. Introduction

Vehicle automation is a disruptive technology that is likely to reshape road transportation and urban mobility. Connected and automated vehicles (CAVs) promise safer, more convenient, and more accessible transportation. When combined with electrification and passenger pooling, CAVs offer substantial energy and emission mitigation benefits [1]. The Society of Automotive Engineers (SAE) has defined six levels of vehicle automation depending on the required level of human intervention: no automation (Level 0), driver assistance (Level 1), partial automation (Level 2), conditional automation (Level 3), high automation (Level 4), and full automation (Level 5). For Levels 1 and 2 human drivers are required to monitor the driving environment. For Levels 3 to 5, the automated system monitors the driving environment with a decreasing degree of human intervention [2]. Most new cars in the United States, Europe, Japan, and Korea are already partly automated, with adaptive cruise control, emergency braking, or lane-keeping and blind-spot assistance (Levels 1-3). Many vehicle manufacturers have announced their intention to commercialize CAVs by 2025, although the level of automation is usually not specified [1].

There are many factors that will affect the net energy and environmental impacts of CAVs including broader concerns on how CAVs will change travel patterns and the urban landscape [1]. Here we address the narrow but important question of to what extent the decreased fuel consumption from connected and automated driving (e.g., eco-driving and less idling) and the increased fuel consumption from additional energy use by the sensing, computing, and communication hardware offset each other on a per-vehicle per-kilometer basis. Given the large investment in CAV technology, it is critical to understand the uncertainty in the energy impacts of this emerging mobility technology. However, challenges exist in addressing the balance between eco-driving benefits versus automation loads of CAVs across real-world driving conditions and for different powertrains. We aim to establish a simulation model that addresses the combined effect of these two factors on CAV energy consumption based on the analytical relationships between trip characteristics (average speed and driving aggressiveness) and energy consumption. This is motivated by the following observations from the literature.

First, eco-driving techniques, including driving smoothly, driving at optimal speeds, and avoiding idling, reduces fuel consumption and carbon dioxide (CO_2) emissions. CAVs could be programmed to apply the best eco-driving practices in different conditions, maximizing the fuel-saving benefits. However, eco-driving benefits for CAVs with different powertrains are less understood with inconsistent results reported in studies [3, 4, 5]. A possible explanation may be the selection of test/driving routes because vehicle fuel consumption and eco-driving benefits depend on driving conditions. Wu et al. (2011) analyzed the effects of eco-driving and reported fuel reductions of up to 20% compared to baseline scenarios without eco-driving practices [6]. Wu et al. (2014) conducted field experiments and reported that the fuel consumption and CO_2 emission reduction benefits of CAV eco-driving at intersections were in the range of 5-7% depending on vehicle speed [7]. Stern et al. (2019) investigated emission reductions resulting from CAVs stabilizing traffic flow and dampening stop-and-go waves and reported emission reductions of 13-73% when stop-and-go waves were reduced or eliminated [8]. However, lower benefits were anticipated for CAV deployment in real-world driving with a broader range of traffic conditions [8]. The fact that eco-driving benefits are dependent on the traffic conditions necessitates energy analysis and modeling over a wide range of driving dynamics for different powertrains.

Second, as the speed, acceleration, and idling of CAVs under real-world driving conditions can differ significantly compared to laboratory test driving conditions, a large-scale dataset is required to better represent a wide range of real-world driving dynamics. More importantly, mass adoption of CAVs is expected to reshape traffic flow and driving dynamics; therefore, it is critical to not only represent current real-world driving dynamics but also characterize how changes in speed and aggressiveness correlate to fuel consumption. Berry (2010) analyzed driving dynamics of a total of ~9000 real-world trips, among which 155 trips were used to simulate energy consumption, and introduced a novel linear correlation between aggressiveness factor (i.e., a metric that accounts for the deviation from steady driving) and energy consumption [9]. However, the compounding effect of speed and aggressiveness on energy consumption is not clearly characterized by Berry (2010) [9]. Without a universal definition of aggressiveness factor across different speed ranges, the study instead applied three functions to describe aggressiveness for city, highway, and neighborhood driving. Additionally, the limited number of trips (i.e., 155 trips) might not be sufficient to develop a reliable correlation between energy consumption, speed, and aggressiveness.

Third, CAVs require an integrated hardware system (cameras, radar, lidar, computers), software, onboard data storage, and digital connections to other vehicles and roadside devices and sensors. Some studies have analyzed the degradation in vehicle fuel economy and driving range because of the energy requirement from the automation system [10, 11, 12] but did not consider the combined effects of automation power consumption and eco-driving. Lin et al. (2018) examined possible architectures of automation systems and found that a 1000-2000 W automation power consumption reduces the all-electric-range (AER) of a battery electric CAV by up to 12%, while 400 W automation power consumption reduces the AER by 2% [10]. For a typical gasoline vehicle, each additional 400 W power demand reduces the fuel economy by approximately one mile per gallon [11]. Hamza et al. (2019) estimated that a 3000 W automation power consumption would shorten the all-electric range (AER) of EVs by 27-47% [12]. Other studies [13, 14] considered the combined effects by assuming that the factors are independent, and therefore their combined effect is multiplicative. Gawron et al. (2019) estimated a ~10% increase in greenhouse gas (GHG) emissions due to automation power consumption for Level 4 CAV and a ~20% decrease in life cycle GHG emissions from automated driving (e.g., eco-driving) resulting in a ~10% net reduction in GHG emissions when combined [13]. While an assumption of independent variables has been applied, the validity of such an assumption in different driving conditions and across powertrains is unclear and needs further investigation. The energy efficiencies of engine and electric motor are a function of the total output rather than a constant, and the effect of power consumption-related factors tend to be dependent on each other.

To address these research gaps, we present the first assessment of the balance between eco-driving benefits versus automation power consumption on CAVs energy use based on simulations over ~8000 real-world driving trips. Previous research [15, 16] showed that the balance between the two factors is the key determinator of the life cycle energy and GHG benefits of CAVs; we provide here an improved approach to be used in future life cycle assessments. Two vehicle powertrains (gasoline and battery electric) and two vehicle segments (sedan and sport utility vehicle, SUV) were considered, which results in four vehicle options: gasoline sedan, battery electric sedan, gasoline SUV, and battery electric SUV. A regression-based analytical model was developed that allows for quick estimation of the fuel savings from eco-driving, i.e., changes in speed and aggressiveness to improve fuel economy, compared with the baseline fuel consumption. The baseline fuel consumption is that of nonautonomous conventional driving estimated for the real-world driving profiles listed in Table 2. The combined impact of eco-driving and automation power consumption on energy consumption was evaluated for a series of driving and automation energy use scenarios with different vehicle options. We focus on energy implications at the vehicle level as impacts at larger scales (transportation system level, urban system level, society level) are more uncertain and difficult to quantify [17]. The results provide key insights into the net energy benefits of CAVs under various real-world driving conditions on a per-vehicle per-kilometer basis, which will help to better quantify larger-scale implications and life cycle environmental impacts of the system.

2. Method

2.1. Vehicle Specification and Fuel Consumption

The Future Automotive Systems Technology Simulator (FASTSim) model developed by the National Renewable Energy Laboratory [18] was adopted with customized inputs to simulate vehicle fuel consumption. FASTSim is a physics-based model that conducts vehicle simulation through speed-versus-time drive profiles. At each time step, the model accounts for drag, acceleration, rolling resistance, powertrain efficiency and power limits, and regenerative braking. The model was validated and reported to have an accuracy of 5-10% [19]. FASTSim is available in Microsoft Excel and Python format. The Python version can be customized for specific analysis considering different powertrain, additional energy consumption, and driving behaviors and can batch process thousands of simulations. We used the Python version in the present study and conducted batch simulations of four vehicles over 8064 real-world driving trips.

Table 1 provides details of the four vehicles considered: gasoline sedan and SUV, and battery electric sedan and SUV. The gasoline and battery electric sedans are based on compact-sized sedan models currently available in the market. The battery electric sedan has a 33.5 kWh battery pack. The gasoline SUV is a full-size SUV currently available in the market. The battery electric SUV is a simulated vehicle with the same dimensions and coast-down coefficients (i.e., rolling, rotating, and aerodynamic) as the gasoline SUV and has a 75 kWh battery.

Real-world driving cycles were derived from a large-scale global positioning system (GPS)-based travel survey in Beijing, China [22]. While the survey was designed to be demographically representative, our primary intention in the present study was not to represent a typical driving pattern of a certain location but to cover a wide range of real-world driving profiles in urban settings. There are a limited number of high-speed

TABLE 1 Vehicle parameters [20, 21].

	Gasoline vehicle		Battery electric vehicle	
	Sedan	SUV	Sedan	SUV
Frontal areal (m^2)	2.694	3.568	2.694	3.568
Curb weight (kg)	1355	2020	1641	2573
Maximum engine power (kW)	184	205	/	/
Maximum electric motor power (kW)	/	/	230	256
Battery usable capacity (kWh)	/	/	33.5	75
Rolling coast-down coefficient (N)	102.13	205.50	102.57	205.50
Rotating coast-down coefficient (N/(m/s))	3.1446	3.5646	3.6303	3.5646
Aerodynamic coast-down coefficient ($N/(m/s)^2$)	0.43399	0.58989	0.42241	0.58989

TABLE 2 Trip statistics for GPS-based real-world driving profiles.

		Duration (seconds)		Average trip speed (km/h)	
Dataset	Number of trips	Mean	Standard deviation	Mean	Standard deviation
Beijing	7831	1723	1418	24.5	22.7
California	233	1074	787	43.3	21.0
Combined	8064	1705	1408	25.0	22.5

samples in this dataset, so driving profiles from California were added [23]. A trip is defined here as driving between stops (i.e., zero speed) longer than five minutes. A screening process was applied to eliminate trips with durations less than 5 minutes, average speeds less than 5 km/h, and initial or final speeds of more than 2 m/s (caused by temporary signal loss). Statistics for the 8064 trips remaining after screening are given in Table 2.

2.2. Eco-driving Scenarios

Eco-driving actions that are most relevant to CAVs on urban roads include smoother (reduced acceleration/deceleration) and faster driving (reduced low-speed ranges) [3]. Note that speeding up at high-speed ranges, e.g., on highways, usually increases fuel consumption; therefore, it is not considered to be eco-driving. Reduced acceleration and deceleration are achievable with eco-driving technologies, for example, adaptive cruise control, intelligent speed adaption, active haptic gas pedal feedback, and also system-wide traffic management technologies. Faster driving on urban roads is possible when CAVs enable shorter intervehicle distances and thus improved road capacity and traffic flow [3]. CAVs with a high level of automation (Level 4 or Level 5) can control their driving behavior to achieve better fuel economy without human intervention.

Given the limited data on real-world eco-driving, we chose to simulate three levels of eco-driving using a method similar to that described by Michel et al. (2016) [3]. The degree of eco-driving was represented by applying modifications to the second-by-second speed profile following the three steps below. First, by increasing the speed at lower speed ranges by using two empirical speed-up functions derived from Michel et al. (2016) [3]. Second, by removing short stops or idling which presumably reflect stops at intersections, a threshold of 5 seconds was set, and stops shorter than 5 seconds were removed by smoothing the speeds before and after the stop. The second step does not change the average speed, or the time required to enter an intersection. Third, by smoothing speed changes. A moving average over n seconds was applied to smooth the speed profile as shown in Equation 1

$$f_{smoo}\left(v(t)\right)=\frac{\sum_{t-\frac{n-1}{2}}^{t+\frac{n-1}{2}}v(i)}{n} \qquad \text{Eq. (1)}$$

where $v(t)$ and $v(i)$ are the speeds at time t and i, respectively, km/h. Fourth, by capping the acceleration using a threshold.

Following these steps, three scenarios with increasing levels of eco-driving were developed, as shown in Table 3. The low-level eco-driving scenario includes smoother driving. The medium-level scenario includes smoother driving and increased speeds for low-speed ranges and was used as the base case. The high-level scenario includes smoother driving and increased speed the same as the base case but with a higher degree of eco-driving. The longer the smoothing window, n, the smoother the speed profiles.

To measure driving aggressiveness, the present study used an Aggressiveness Factor (AF) that accounts for the degree of deviation from steady-speed driving. The mathematical representation of AF was taken from Berry (2010) [9]. Berry (2010) used three different mathematical functions to describe AFs in city, highway, and neighborhood driving [9]. We applied a single mathematical function of AF for city driving, which allows for a direct comparison of AF for all driving profiles and a consistent correlation function structure. AF is the difference in energy demand at the wheels between following a drive profile (E_{wheel}) and driving at a steady average speed (E^*_{wheel}) normalized by travel distance (D) (Equations 2-4). As the degree of eco-driving increases, AF decreases toward zero.

$$E_{wheel}=\int\left(Av+Bv^2+Cv^3+Mav\right)^+ dt \qquad \text{Eq. (2)}$$

$$E^*_{wheel}=\int\left(A\tilde{v}+B\tilde{v}^2+C\tilde{v}^3\right)dt=\left(A+B\tilde{v}+C\tilde{v}^2\right)\int\tilde{v}dt \qquad \text{Eq. (3)}$$

TABLE 3 Three eco-driving scenarios assumed in this study.

	Speed-up function[1]	Remove short stops[2]	Smoothing window (seconds)	Acceleration threshold (m/s²)
Low	None	All	5	1.5
Medium	Function 1	All	5	1.5
High	Function 2	All	15	1.2

Notes: [1]Speed-up functions 1 and 2 are empirical functions from Michel et al. [3].
[2]Threshold for short stops is 5 seconds for all three scenarios.

$$AF = \frac{1}{D}\left[E_w - E_w^*\right] = \frac{\int\left(Av + Bv^2 + Cv^3 + Mav\right)^+ dt}{\int v dt} - \left(A + B\tilde{v} + C\tilde{v}^2\right) \qquad \text{Eq. (4)}$$

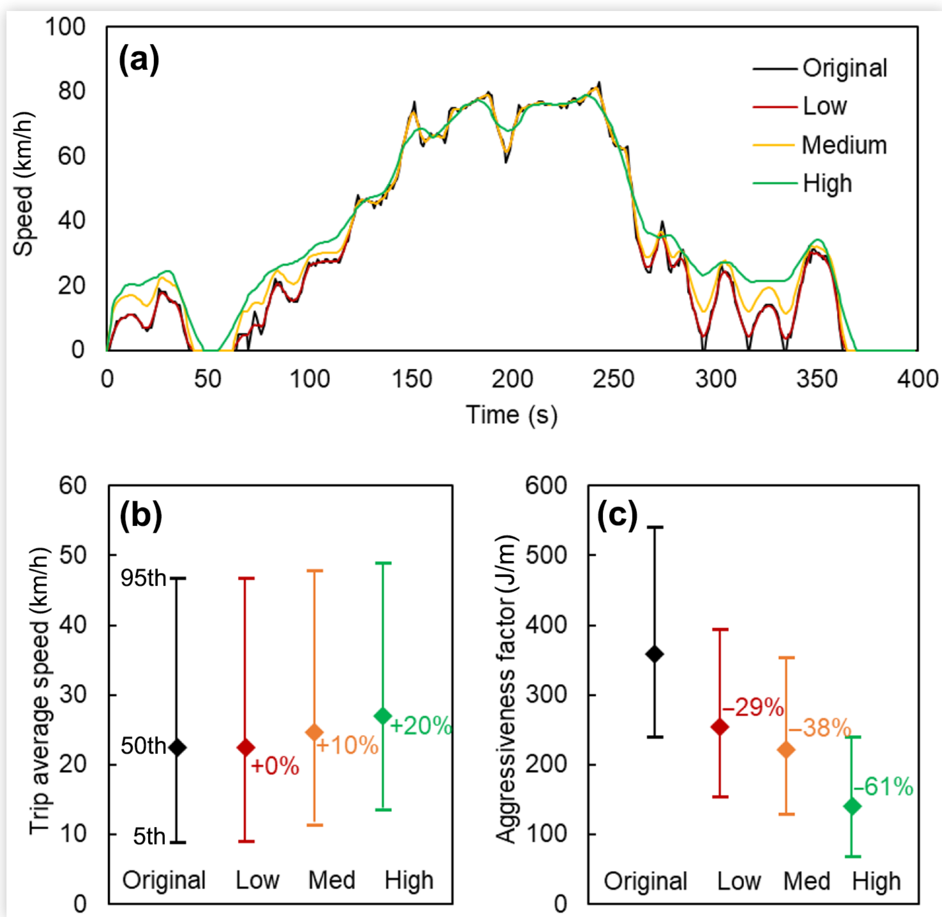
where A (N), B (N/(m/s), and C (N/(m/s)^2) are coast-down coefficients, corresponding to rolling, rotating, and aerodynamic resistive coefficients, respectively. The coast-down coefficients are vehicle-specific parameters and are listed as "target coefficients" in the Environmental Protection Agency fuel database [21]. a (m/s^2), v (m/s), and $\tilde{v}$ (m/s) are instantaneous positive acceleration, speed, and trip average speed, respectively. M (kg) is the vehicle mass. These vehicle-specific parameters are summarized in Table 1.

An example of a comparison between the original speed profile and three eco-driving scenarios (low, medium, high) speed profiles is given in Figure 1. The low eco-driving scenario decreases the AF by 29% (median value) via smoother driving but does not change the trip average speed. The medium scenario decreases the AF by 38% and increases the trip average speed by 10% compared with the original speed profiles. The high-level scenario decreases the AF by 61% and increases the trip average speed by 20%.

2.3. Automation Equipment and Energy Use

Automation equipment, including cameras, radar, lidar, GPS, and computers, affect energy consumption in multiple ways, including added electricity demand, aerodynamic drag, and weight. The added electricity demand for sensing, computing, and data transmission is the most decisive factor [16]. To address its impact, we use three sensitivity cases, 200 W, 1000 W, and 2000 W, which cover the typical range discussed in the literature. For gasoline vehicles, the conversion efficiency from mechanical power to electric power using an alternator is ~67% [16]. To provide 1 unit of accessory power, gasoline vehicles require 1.5 units (1/67%) of mechanical power from the engine, while battery electric vehicles (BEVs) require 1 unit of electric power from the battery. The impact of increased aerodynamic drag and weight from CAV equipment is minor

FIGURE 1 Three eco-driving scenarios (low, medium, high) and the original speed profile. Panel (a) shows an example of speed profiles; the original profile used for illustration is a segment of a typical peak hour driving cycle in Beijing, China from Ma et al. (2019) [24]. Panels (b) and (c) show the range of average speeds and aggressiveness factors (AFs) for ~8000 trips.



(<0.5% [16]) and is not included in the present study. We focus on the operational effects of automation subsystems because the increased energy burden associated with the materials and manufacturing of sensing, computing, and communication subsystems is relatively small [16].

3. Results and Discussion

3.1. Energy Consumption for Baseline Non-automated Vehicles

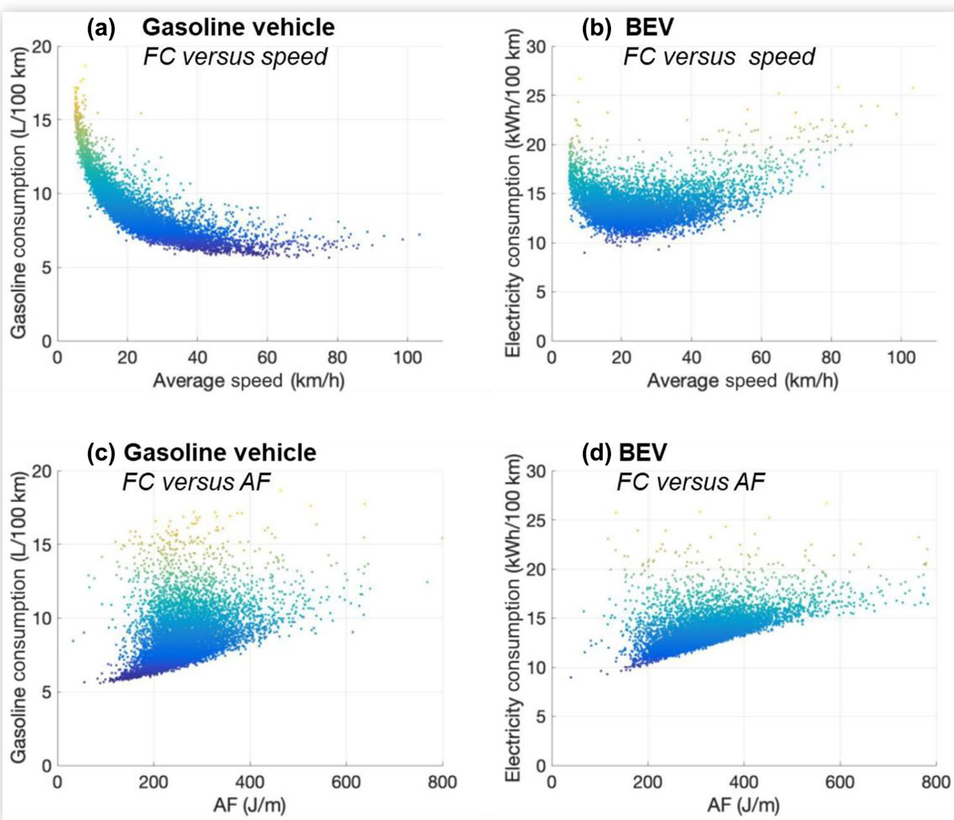
Distance-based fuel consumption for baseline gasoline vehicles and BEVs is closely related to average speed and driving aggressiveness, as shown in Figure 2. For the gasoline vehicle, fuel consumption decreases rapidly as average speed increases for low speeds (e.g., <30 km/h), is essentially unchanged for average speeds of 30-70 km/h, and increases slightly at high speeds (>70 km/h). For the BEV, fuel consumption decreases as speed increases at low speeds, but the turning point where fuel consumption starts to increase (~25 km/h) is much lower than for the gasoline vehicle. This is explained by the difference in the powertrain system efficiency profiles. The efficiency of gasoline engines drops off markedly at low speeds. As speed rises, fuel consumption decreases with the increased energy efficiency gains until the aerodynamic losses gradually offset the gains from increased engine efficiency and become dominant at high speeds. In contrast, the efficiency of an electric motor does not drop off sharply at lower speeds, so the breakeven when aerodynamic losses outweigh motor efficiency gains occurs at lower speeds.

3.2. Relationships between Fuel Consumption and Both Trip Mean Speed and Aggressiveness Factor

To quantitatively explain how eco-driving affects fuel consumption, the present study used a multiple linear regression model to develop the relationship between fuel consumption and explanatory variables (i.e., speed and AF) by fitting a linear equation.

$$\widehat{FC} = \beta_0 + \beta_v v + \beta_{AF} AF \quad \text{Eq. (5)}$$

FIGURE 2 Fuel consumption (FC) versus average speed and aggressiveness factor (AF) for the gasoline sedan (Panels a and c) and the battery electric sedan (Panels b and d).



where $\widehat{FC}$ is fuel consumption, L/100 km or kWh/100 km; β_0 is a constant; β_v and β_{AF} are regression coefficients; v is speed, km/h; and AF is aggressiveness factor, J/m.

The data profiles are divided into four categories according to trip mean speed, i.e., 5-10 km/h (565 trips), 10-25 km/h (4063 trips), 25-60 km/h (3311 trips), and >60 km/h (125 trips). The selection of speed intervals is determined by considering an approximately linear relationship between fuel consumption and speed within a category and a statistically representative sample size for each category. The multiple linear regression was performed separately for each category.

Figure 3 shows an example of the fitting, and Table 4 summarizes regression coefficients for all vehicle options and speed categories. A positive regression coefficient indicates a positive correlation between the variable (i.e., mean speed or AF) and fuel consumption. The adjusted coefficient of determination (R^2) indicates decent goodness of fit for most cases ($R^2 > 0.73$ for cases with trip mean speed > 10 km/h). We note

FIGURE 3 Analytical characterization of fuel consumption as a function of average speed and *AF*. Results for SUVs are shown here for illustration.

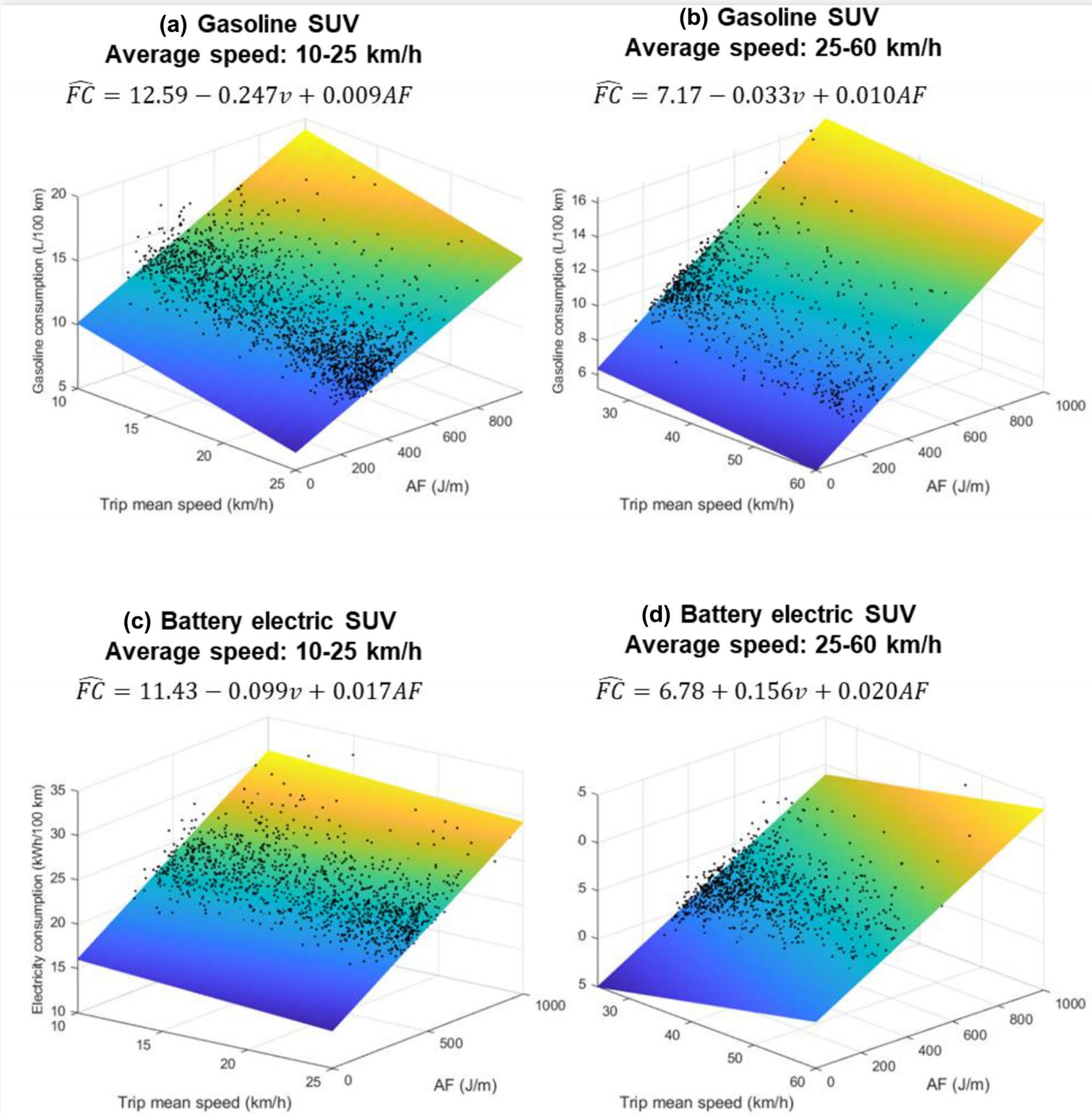


TABLE 4 Regression model parameters for fuel consumption as a function of average speed and *AF*.

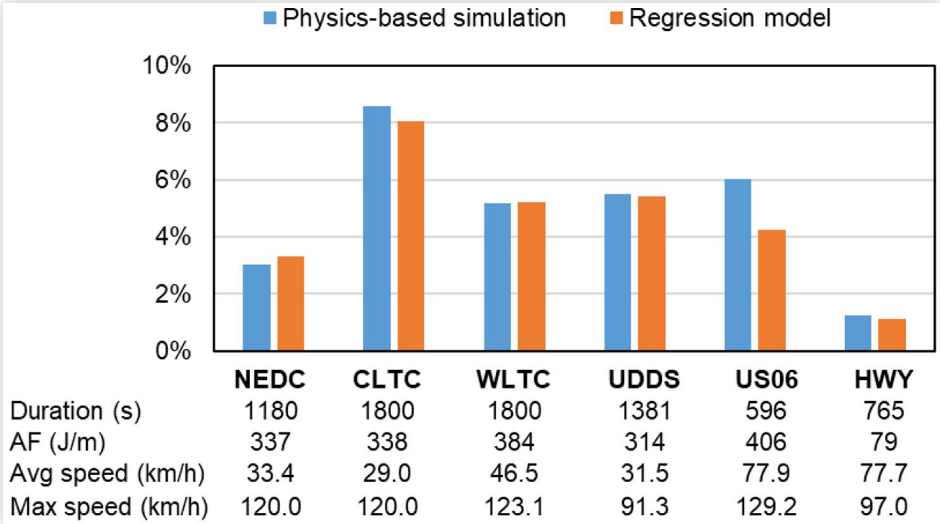
	Average trip speed (km/h)	Trip count	Adjusted R^2	β_0 (95% CI)	β_v (95% CI)	β_{AF} (95% CI)
Gasoline sedan	[5, 10)	565	0.809	17.8 (17.4, 18.1)	−0.927 (−0.967, −0.887)	0.010 (0.009, 0.011)
	[10, 25)	4063	0.868	10.3 (10.3, 10.4)	−0.209 (−0.212, −0.206)	0.010 (0.009, 0.010)
	[25, 60)	3311	0.902	6.04 (5.99, 6.10)	−0.033 (−0.034, −0.032)	0.010 (0.010, 0.010)
	>60	125	0.933	2.93 (2.66, 3.20)	0.026 (0.023, 0.030)	0.009 (0.009, 0.010)
Battery electric sedan	[5, 10)	565	0.721	22.3 (21.6, 23.0)	−1.007 (−1.084, −0.929)	0.021 (0.020, 0.023)
	[10, 25)	4063	0.840	11.4 (11.3, 11.5)	−0.099 (−0.104, −0.095)	0.017 (0.017, 0.018)
	[25, 60)	3311	0.731	6.78 (6.53, 7.03)	0.156 (0.151, 0.161)	0.020 (0.020, 0.020)
	>60	125	0.823	−7.16 (−9.89, −4.43)	0.364 (0.330, 0.396)	0.030 (0.026, 0.034)
Gasoline SUV	[5, 10)	565	0.623	20.2 (20.0, 20.8)	−1.003 (−1.075, −0.930)	0.010 (0.009, 0.011)
	[10, 25)	4063	0.779	12.6 (12.5, 12.7)	−0.247 (−0.252, −0.242)	0.009 (0.009, 0.009)
	[25, 60)	3311	0.899	7.17 (7.10, 7.24)	−0.033 (−0.034, −0.031)	0.010 (0.009, 0.010)
	>60	125	0.956	2.87 (2.46, 3.28)	0.047 (0.041, 0.052)	0.010 (0.009, 0.010)
Battery electric SUV	[5, 10)	565	0.629	22.04 (21.1, 23.0)	−0.787 (−0.893, −0.682)	0.013 (0.012, 0.014)
	[10, 25)	4063	0.863	14.8 (14.7, 15.0)	−0.102 (−0.107, −0.096)	0.013 (0.013, 0.013)
	[25, 60)	3311	0.748	9.89 (9.63, 10.2)	0.120 (0.115, 0.125)	0.012 (0.012, 0.012)
	>60	125	0.830	1.55 (−1.60, 4.70)	0.249 (0.208, 0.291)	0.015 (0.012, 0.018)

that linearity is more evident at higher speeds (e.g., >60 km/h), and therefore, 125 trips are sufficient to generate a reliable analytical correlation.

The regression model can be used to quickly estimate the fuel-saving benefits from eco-driving that reflect vehicle-specific and cycle-specific characteristics. For a given vehicle powertrain (gasoline vehicle or BEV) and segment (sedan or SUV), three simple parameters are required to estimate eco-driving fuel savings: original trip average speed, and changes in trip average speed and AF resulting from eco-driving. Large-scale driving data for CAVs are unavailable, and we chose to validate the model using the hypothetical eco-driving scenario defined in Table 3. Figure 4 compares the fuel-saving results over certification test cycles estimated using the regression model proposed in the present study and those based on the physics-based FASTSim model. The certification test cycles used were the New European Driving Cycle (NEDC) and its successor the Worldwide harmonized Light-duty vehicles Test Cycle (WLTC) developed by the United Nations Economic Commission for Europe (UN ECE); China Light-duty vehicle Test Cycle (CLTC) developed by the China Automotive Technology and Research Center (CATARC); the Urban Dynamometer Driving Schedule (UDDS), the Supplemental Federal Test Procedure (US06), and the Highway Fuel Economy Test (HWFET) developed by the US Environmental Protection Agency.

Results show that the eco-driving fuel-saving ratios (i.e., percentage of reduced fuel consumption due to changes in speed and driving aggressiveness) estimated using the regression model closely match the fuel-saving ratios estimated using the physics-based FASTSim model for most test cycles with average speeds of 29-78 km/h. The only exception, US06, has a larger estimation discrepancy possibly due to its rapid speed fluctuations at high speeds where our dataset may not include enough cases to accurately reflect such high aggressiveness at high speeds. Fuel-saving ratios tend to be more

FIGURE 4 Comparison of eco-driving fuel savings estimated using the FASTSim model and the regression model developed in the present study (medium-level eco-driving for the gasoline SUV).



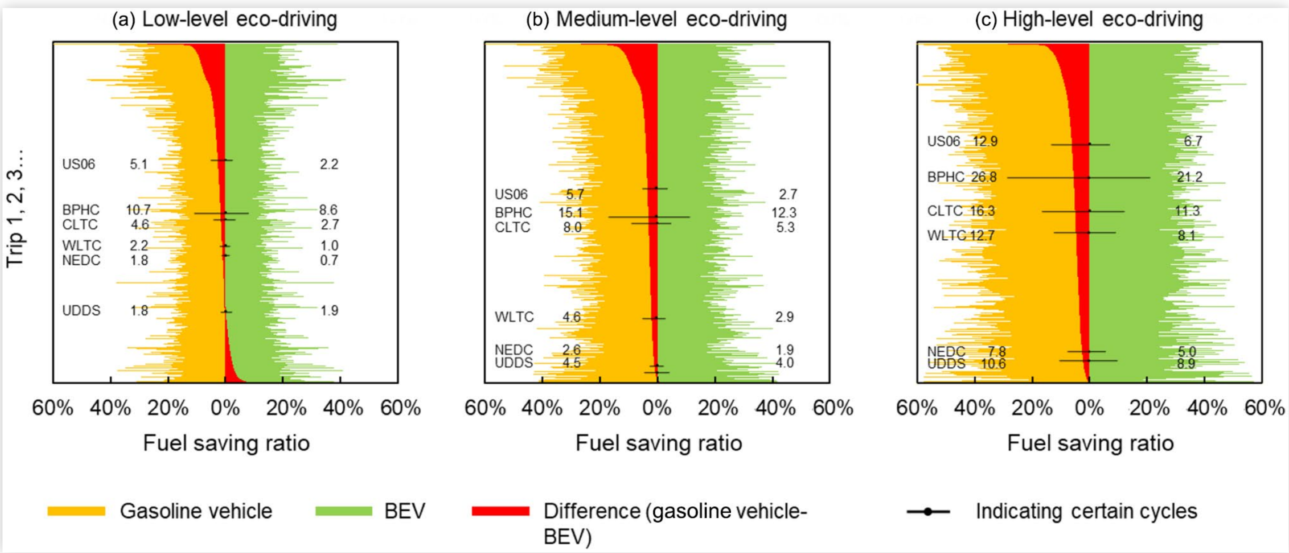
significant for test cycles with shorter mean speed (e.g., CLTC) and more aggressive driving (e.g., WLTC, UDDS). Estimating more realistic CAV energy savings will be possible when more CAV test data become available.

3.3. CAV Energy Consumption

Impacts of eco-driving levels. To isolate the impact of automation power consumption, the impacts of eco-driving levels were evaluated assuming zero automation power consumption. As shown in Figure 5, higher levels of eco-driving give greater fuel saving ratios for both gasoline vehicles and BEVs. For low, medium, and high levels of eco-driving, gasoline vehicles have fuel savings of 12% (6-23%), 17% (10-31%), and 27% (15-42%) while BEVs have fuel savings of 10% (5-19%), 13% (7-25%), and 21% (12-35%) fuel savings (median values of all trips and the 5th to 95th percentile ranges are given in brackets). The fuel savings for gasoline vehicles are higher than for BEVs by 2 to 6 percentage points. Conventional gasoline vehicles do not utilize regenerative braking, and eco-driving provides a much larger reduction in braking energy loss. Meanwhile eco-driving also leads to frequent engine operation at low loads for smoothing aggressive driving, corresponding to lower efficiency. Considering these two mechanisms, the eco-driving energy consumption savings for gasoline vehicles is lower than would be expected from the significant reductions in braking energy loss but still higher than BEVs. The difference between gasoline vehicles and BEVs is more significant for driving profiles that are more aggressive and/or have frequent stop-and-go (e.g., US06 and Beijing Peak Hour Cycle [BPHC], AF = 406 and 411 J/m, respectively) and less evident for less aggressive driving cycles (e.g., NEDC, UDDS, HWY, AF = 338, 314, 79 J/m, respectively).

It is noted that the fuel-saving ratio of eco-driving across powertrains has rarely been quantified in existing CAV studies and is often overlooked by assuming the same level of fuel-saving ratio across different powertrain and segment options [14]. A few recent simulations over certain travel conditions reported inconsistent results across studies. Michel et al. (2016) reported comparable eco-driving fuel savings for gasoline vehicles and BEVs compared with the traditional driving of unconnected vehicles [3]. Iliev et al. (2019) found lower benefits from eco-driving at intersections for gasoline vehicles compared to BEVs and acknowledged the results did not agree with their initial expectations [5]. Kim et al. (2018) simulated speed patterns and powertrain operations over two routes with multiple intersections and found that gasoline vehicles have comparable (Route 1) or lower (Route 2) fuel-saving ratios than electrified vehicles [4]. The eco-driving strategies used in Iliev et al. (2019) [5] and Kim et al. (2018) [4] are similar to the low-level eco-driving scenario in the present study, i.e., smoother driving but no changes in average speeds. From Figure 5(a), we can see that while gasoline vehicles have lower fuel-saving ratios than BEVs from eco-driving for ~20% of the trips, the opposite is true for the other ~80% of trips. What Iliev et al. (2019) [5] and Kim et al. (2018) [4] observed resemble some specific cases covered in our analysis, which contains a notably larger size of trip samples. Our results show that the trips where gasoline vehicles have lower fuel-saving ratios than BEVs [i.e., ~20% of the trips gathered at the bottom side of Figure 5(a)] tend to have lower average speed (mean value = 12.4 km/h vs. 25 km/h) and are less aggressive (AF mean value = 341 J/m vs. 361 J/m) compared with the other ~80% of the trips. This is consistent with the observation in Kim et al. (2018) [4] that the gasoline vehicle has a lower fuel-saving ratio than the BEV on Route 2 with a lower average speed than Route 1. A similar argument also applies to results reported in Michel et al. (2016) [3] that gasoline vehicles and BEVs have comparable fuel-saving ratios

FIGURE 5 Gasoline and battery electric SUV fuel-saving ratios from eco-driving over ~8000 trips. Panel (a) is low-level eco-driving, i.e., smooth driving; Panel (b) is medium-level eco-driving, i.e., smooth driving and increased speeds at low-speed ranges; and Panel (c) is high-level eco-driving, i.e., a higher degree of smooth driving and increased speeds at low-speed ranges. The automation power consumption is set as zero to show the impact of eco-driving solely. Results for certain cycles are indicated using black lines, including the NEDC and its successor the WLTC developed by UN ECE; CLTC developed by the CATARC; the UDDS, the supplementary federal test procedure (US06), and the Highway Fuel Economy Test (HWFET) developed by US Environmental Protection Agency; and the BPHC [24]. The trips are shown in order from the greatest fuel-saving ratio (red) between the gasoline vehicle and the BEV at the bottom to the least at the top.



to eco-driving based on 18 selected trips. It is shown that comparable benefits (less than 2 percentage points difference) for gasoline and battery electric CAVs are observed for 48%, 18%, and 5% of the trips under low, medium, and high eco-driving scenarios, respectively, while notably different benefits (more than 10 percentage points difference) are observed for 3%, 5%, and 8% of the trips. Our results highlight the importance of simulations over a large number of driving profiles because the results of a few trips may differ from the results of more comprehensive trip profiles.

Combined impacts of eco-driving and automation power consumption at different speed ranges. The combined impacts of four levels of automation power consumption (0, 200, 1000, and 2000 W) and three levels of eco-driving (low, medium, high) are shown in Figure 6. The fuel savings presented below are median values for the trips that fall into the corresponding speed ranges. Four conclusions are evident from the inspection of Figure 6.

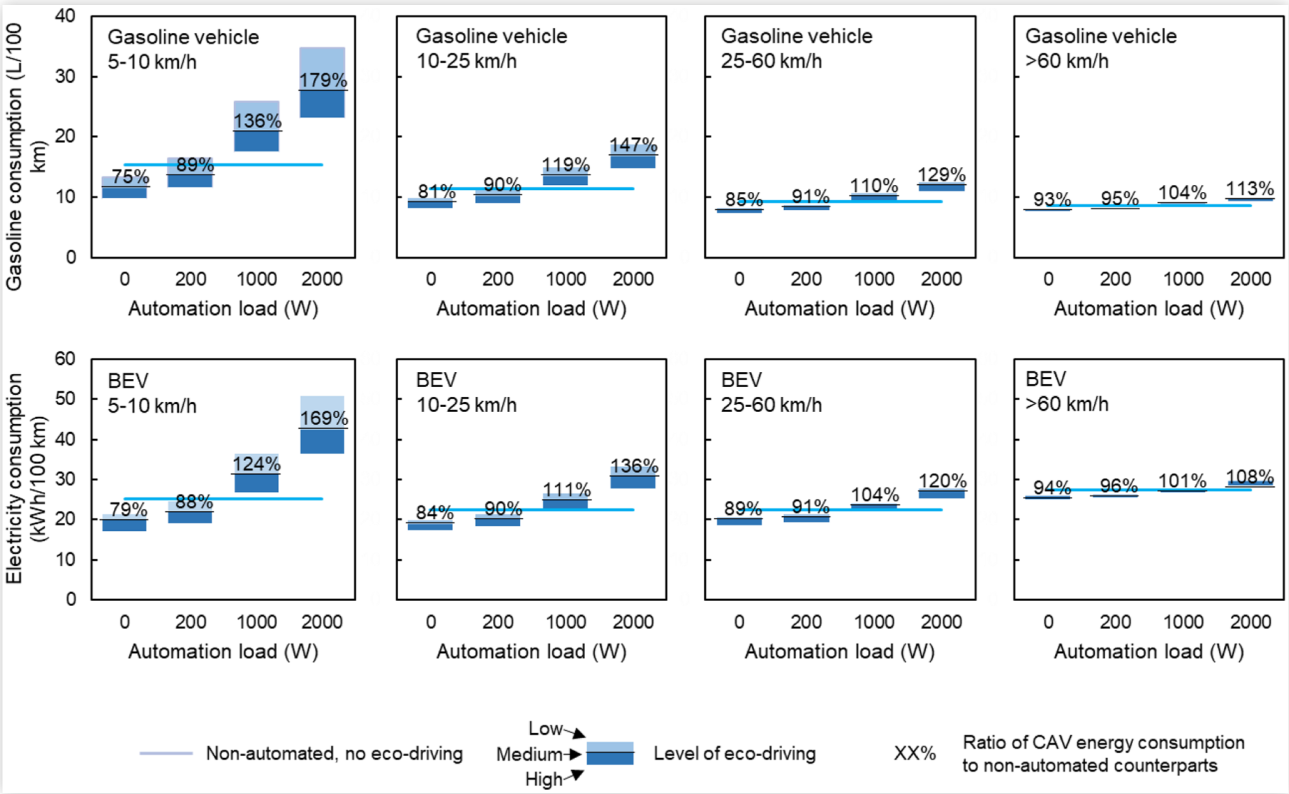
First, fuel savings from eco-driving are more significant at lower speeds than at higher speeds. This is shown by comparing the fuel consumption for the zero automation power consumption cases with the non-automated base vehicle. At extremely low-speeds (5-10 km/h trip average speed), eco-driving results in approximately 15-35% gasoline or electricity savings on a per-kilometer basis. The fuel savings are approximately 10-30% at medium speeds (10-25 km/h and 25-60 km/h) and 5-13% at high speeds (>60 km/h). These findings are the first assessment of eco-driving benefits for large-scale real-world trips as a function of average speed and are consistent with previous estimates of 11-20% fuel consumption reductions for average trips [14]. Comparing the results in Figures 4 and 6 shows that eco-driving benefits for real-world driving (5-35%) are larger than for certification test cycles (1-9%).

Second, the impact of automation power consumption on CAV energy consumption decreases with increasing trip average speed. An automation power consumption of 2000 W increases the gasoline SUV energy consumption per kilometer by 79%, 47%, 29%, and 11% for trips with average speeds of 5-10 km/h, 10-25 km/h, 25-60 km/h, and >60 km/h, respectively. The present analysis assumes no significant changes in automation power consumption at different speeds because there is no evidence to suggest otherwise. Trips with higher average speed and shorter duration have lower energy consumption on a per-kilometer basis.

Third, fuel penalties from automation power consumption may or may not offset the fuel-saving benefits of eco-driving depending on several factors. In all cases, an automation power consumption of 200 W results in comparable or lower fuel consumption, and a 2000 W power consumption results in higher fuel consumption than baseline vehicles. CAVs with 1000 W automation power consumption have comparable or lower fuel consumption at high-level eco-driving or trip average speeds >10 km/h for BEVs and >25 km/h for gasoline vehicles, but higher fuel consumption in other cases.

Fourth, BEVs tend to have greater proportional fuel savings or lower fuel penalties by up to 11 percentage points

FIGURE 6 Fuel consumption for CAV scenarios with different automation power consumption and levels of eco-driving. Median values for multiple trips that fall into corresponding ranges of average speed are shown.



than gasoline vehicles when considering the combined impact of eco-driving and automated power consumption for a CAV over a non-automated vehicle. The difference is more significant when automation power consumption is high. The main reason is that BEVs deliver electricity directly from the battery to CAV equipment with 97% efficiency [18], while gasoline vehicles generate electricity from the engine with an overall efficiency of ~21% (i.e., engine efficiency of ~32% and alternator efficiency of ~67% [16]). The impact of automation power consumption on energy consumption is substantially less for BEVs than for gasoline vehicles, but the difference in eco-driving benefits is relatively small.

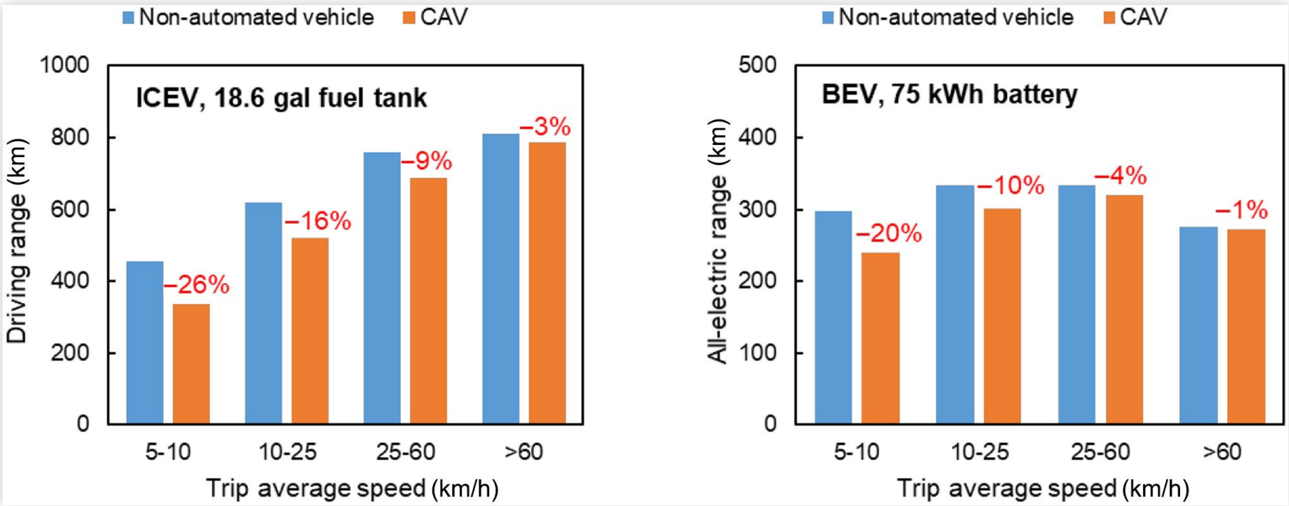
The impact of automation power consumption on driving range. The range issue for BEVs is critical. Here we consider medium-level eco-driving and 1000 W automation power consumption. As shown in Figure 7, the BEV loses 20% driving range at extremely low speeds (5-10 km/h) compared with non-automated vehicles at the same speed. A decreasing proportional loss of range is observed for CAV versus non-automated vehicles with increasing trip speed, e.g., for the BEV 10%, 4%, and 1% at 10-25 km/h, 25-60 km/h, and >60 km/h, respectively. The gasoline CAV has better fuel economy at higher speeds, and thus a longer range. Together with a decreasing percentage of range loss (26% at 5-10 km/h, 16% at 10-25 km/h, 3% at >60 km/h) due to automation, the gasoline CAV range increases as trip average speed increases.

Key insights. The results of the present study provide three key insights into CAV energy efficiency under various real-world driving conditions.

First, the eco-driving fuel-saving benefits for gasoline vehicles (10-31%) are greater than for BEVs (7-21%) in the baseline scenario. However, there are cases where gasoline vehicles have *lower* benefits than BEVs (see Figure 5). This may explain the inconsistent results reported in previous studies as the results depend on driving profiles or routes used. Energy and environmental researchers should be aware of such variations and characterize driving dynamics in a representative manner to make accurate estimates. One challenging issue is the computationally intensive vehicle fuel simulations for large datasets. The regression model we developed provides results that are consistent with the more computationally demanding FASTSim simulations and facilitates a rapid estimation of eco-driving benefits based on the trip average speed and *AF*.

Second, the energy impacts of eco-driving and automation power consumption depend on the average trip speed. This suggests possible prioritized development strategies for CAVs in different fleets and driving scenarios. Automation power consumption in the range of 200-2000 W is considered plausible for future CAVs [13, 25]. While we observe increased fuel consumption for 2000 W in all cases, the impacts are lower at higher speeds. Fortunately, CAVs are likely to be deployed first in less complex and, hence, less congested

FIGURE 7 Change of driving range for CAVs considering combined effects of eco-driving (medium level) and automation power consumption (1000 W). Red numbers indicate the percentage driving range change compared to the non-automated base vehicle.



and higher average speed driving conditions where automation power consumption has lower impacts on energy efficiency. As automation technology develops, automation power consumption will decrease [26] and the capability of the system will enable CAV deployment in more complex congested urban settings where eco-driving has greater benefits. Benefits are most significant with a high level of eco-driving, which is possible via a highly connected urban mobility system with a considerable share of CAVs. A recent study shows that the greatest fleet-level energy efficiency benefits occur when CAVs have a market penetration of at least 20% [27]. The synergetic effects of CAV penetration and eco-driving are projected to deliver significant energy benefits in urban mobility.

Third, automation power consumption is confirmed to be highly influential on CAV fuel consumption, and we found the breakeven for CAVs to achieve comparable fuel economy to conventional vehicles is approximately 1000 W or below. Extremely congested conditions (trip average speed less than 25 km/h for gasoline vehicles or less than 10 km/h for BEVs) require lower automation power consumption or a high level of eco-driving for breakeven. The results are consistent with, and provide support for, those from the previous studies [15, 16], which found that automation power consumption below approximately 1000 W is needed for the eco-driving benefits to outweigh the automation burdens.

4. Conclusion and Future Work

The present study conducted simulations using ~8000 real-world driving cycles to evaluate eco-driving benefits and automation power consumption impacts on CAV energy consumption. The regression-based analytical relationships between vehicle energy consumption and trip characteristics established in this study could be used for rapid estimation of eco-driving benefits over a large dataset of driving profiles with accuracies similar to more computationally intensive tools. The fuel-saving benefits of eco-driving are generally greater for gasoline vehicles (e.g., 10-31% in the baseline scenario) than for BEVs (7-21%), with some exceptions. These large ranges of results may explain the apparently inconsistent results in previous studies and highlight the importance of representative characterization of real-world trip conditions. Eco-driving actions such as smooth driving and reduced low-speed driving deliver more significant benefits for trips with lower average speeds, e.g., <25 km/h typical of congested urban driving. Automation power consumption below approximately 1000 W is needed for eco-driving benefits to outweigh automation burdens. The per-kilometer energy consumption impact of automation power consumption decreases with increasing speed. For trips with average speeds > 60 km/h, even CAVs with automation loads of 2000 W have fuel economies similar to non-automated vehicles.

Finally, we highlight the need for further research in the following areas. First, while this study investigated the energy impacts of eco-driving based on real-world driving profiles, the eco-driving scenarios are derived using an empirical approach. Future work is needed to include real-world CAV driving data to provide more representative inputs into the regression model for more accurate estimations. Second, this study aims to assess the potential energy savings of CAVs across real-world driving conditions. More sophisticated modeling is required to develop CAV energy management strategies. For example, Tang et al. used extreme learning machine models to optimize CAV speed and acceleration and proposed a multi-objective strategy to improve fuel economy, comfort, and cost [28, 29]. Unlike the present study, the studies by Tang et al. [28, 29] have a smaller data size for real-world driving and do not consider the offsetting automation loads on fuel consumption. Third, the present study focused on the balance between eco-driving benefits and automation power consumption as they are the dominant direct operational effects of CAV energy consumption in urban mobility settings. There are factors beyond the scope of the present work but important to the potential sustainability benefits of CAVs include platooning, faster travel, rightsizing, and pooling, which need further study.

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