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Vehicle Electrification Impacts on Energy Consumption for Different Connected-Autonomous Vehicle Scenario Runs †

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Abstract: Transportation system simulation is a widely accepted approach to evaluate the impact of transport policy deployment. In developing a transportation system deployment model, the energy impact of the model is extremely valuable for sustainability and validation. It is expected that different penetration levels of Connected-Autonomous Vehicles (CAVs) will impact travel behavior due to changes in potential factors such as congestion, miles traveled, etc. Along with such impact analyses, it is also important to further quantify the regional energy impact of CAV deployment under different factors of interest. The objective of this paper is to study the energy consumption of electrified vehicles in the future for different penetration levels of CAVs deployment in the City of Chicago. The paper will further provide a statistical analysis of the results to evaluate the impact of the different penetration levels on the different electrified powertrains used in the study.

Keywords: transportation system modeling; connected-autonomous vehicle (CAV); electric vehicle (EV); energy consumption; vehicle simulation

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1. Introduction

Understanding the energy consumption of current and future vehicle technologies under real-world conditions is critical to estimating the overall impact of system models. Estimating the energy consumption during measured real-world drive cycles provides a good approximation, but does not ensure a consistent impact on the transportation system model as a whole [1]. This is why it is important to evaluate the energy impact on the drive cycles generated by the transportation system model itself.

The transportation system modeling tool, POLARIS [2,3] is used to develop and validate the transportation system model for different metropolitan cities of the United States. It uses population and vehicle synthesis, along with activity demand generation and traffic flow to model the system. An individual-level CAV technology choice framework is also implemented along with updated traffic flow modeling to account for CAVs. A study was implemented in POLARIS to analyze the impact of CAV technologies on travel demand and energy consumption in the City of Chicago.

The resulting stochastic speed profiles from POLARIS, combined with the data on driving cycles and fleet distribution are used as an input to Autonomie [4], a vehicle system modeling tool. Using the speed profiles, Autonomie was able to simulate the energy consumption of the transportation network for different vehicle technologies. Figure 1 illustrates the steps involved with the process.

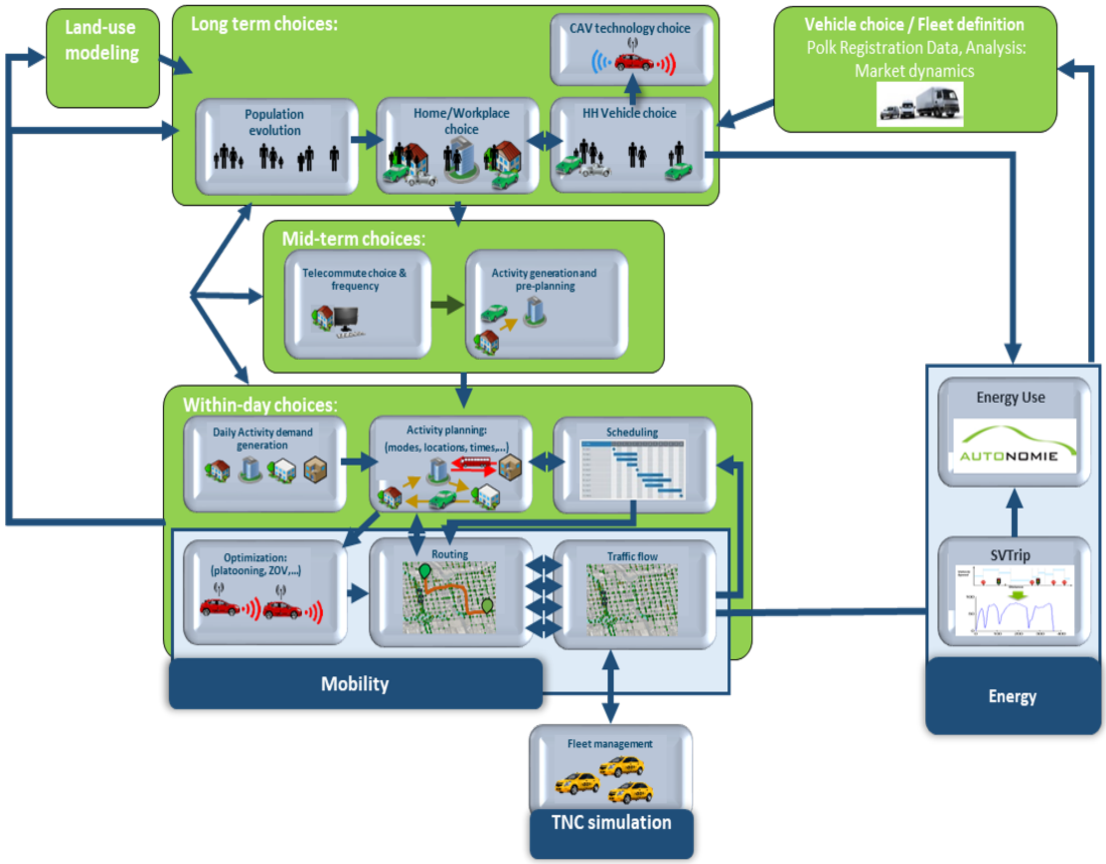


Figure 1. CAVs modeling using POLARIS & Autonomie.

Previous studies demonstrated the importance and ability of evaluating the energy consumption of transportation system models in real world scenarios to analyze the intersection between transport policy and vehicle technology [5].

There are many traffic flow simulation tools that model CAV technologies as part of the U.S. Department of Energy Vehicle Technologies Office (DOE-VTO) Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Consortium. These models study the impact in mobility due to the introduction of CAVs through microsimulation traffic flow models, such as AimSun [6] and VisSim [7]; and mesoscopic traffic flow models such as POLARIS and BEAM [8]. There are differences in the assumptions and modeling techniques between these different transportation system tools. However addressing the assumptions of the different traffic flow models and their applications themselves is beyond the scope of this paper, which is to evaluate the energy consumption differences for one of the studies previously conducted in POLARIS.

The different literature studies and existing research in modeling the traffic flows for CAVs are discussed in greater detail in Auld et al., 2017 [9]. This paper only focuses on the energy consumption impacts of different vehicle powertrains for different CAV scenarios by isolating the impacts of vehicle electrification. Auld et al. also discusses the details in demand generation, traffic assignment and simulation of CAVs.

There were also several studies conducted to study the energy consumption of transportation system models using different methods. Colin et al. [8] models the charging behavior and infrastructure in BEAM. The study uses constant energy consumption unit values (kWh/km) for different average speeds in the traffic flow. However to model plug-in hybrids, there are a lot of instantaneous control behaviors (such as state-of-charge of batteries, etc.) that need to be accounted for when evaluating the energy consumption. Hence U.S. DOE-VTO supports using Autonomie, a full vehicle simulation tool to evaluate the energy consumption for transportation system simulation tools. Many projects funded through U.S. DOE-VTO are currently implemented using Autonomie for different transportation system simulations as it accurately represents the energy consumption impacts of the traffic flow. Autonomie further implements U.S. DOE-VTO technology targets for vehicle components (such as engine efficiency, battery specific energy, etc.) [10] and therefore, would be applicable in evaluating the impact of overall VTO portfoliio.

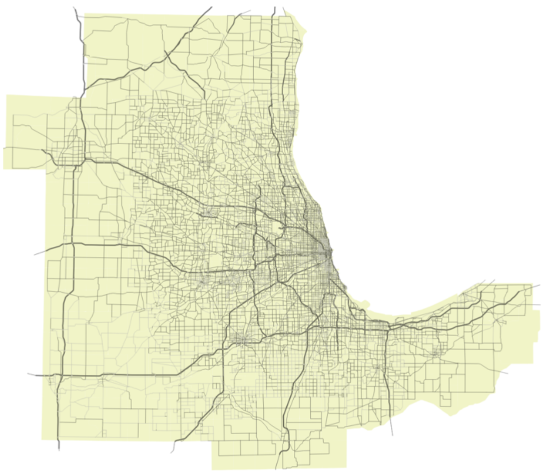
There are also several studies analyzing the potential impact of cooperative and adaptive cruise control (CACC), a key CAV technology, on traffic flow and energy consumption. According to Christopher et al. [11], CACC could lead to a following headway of 0.6 seconds. This would reduce the drag forces and decrease energy consumption. Analysis of field data shows 14% savings in fuel consumption of trucks [12]. Under different test environments, other studies estimate the reduction in trucks' fuel consumption between 10% and 21% [13], 8% and 11% [14], and 5% and 8% [15]. Similar studies performed on light duty vehicles demonstrate varying fuel efficiency improvements [16–18]. However these studies had been conducted in specific test tracks within laboratory settings and do not replicate the impact in real world driving. Using the combination of POLARIS and Autonomie enhances the ability to evaluate the real-world impact in metropolitan cities.

2. POLARIS

POLARIS is an agent-based, activity-based model of integrated traveler behavior and traffic flow. In a POLARIS simulation, the population is synthesized and activities for each individual are generated and then planned using different heuristic methods combined with discrete choice models. The activity start time and schedules are subject to change as the simulation is running and traffic congestion is updated. The individual vehicles are moved through the links and nodes using a mesoscopic simulation approach, based on the Newell kinematic waves model [19] subject to speeds and capacities at the links, as well as turning and capacity constraints at the intersections. The simulation serves as a feedback mechanism by providing the network performance for the route choice model, the demand model, and the intelligent transportation systems (ITS) model. A set of measures of effectiveness (MOE) are produced such as average speed, density, flow rate, and vehicle trajectories.

As part of the developments within SMART Mobility Consortium, different cities within the U.S. are being developed in POLARIS. Currently, there are models for Southwest Michigan [5], Bloomington, IN and Chicago, IL. POLARIS is being developed through collaboration of researchers around the world [20,21]; however, the transportation system models currently implemented in POLARIS are limited to United States.

The Chicago Metropolitan Area was developed in POLARIS in collaboration with Chicago Metropolitan Agency for Planning (CMAP). Figure 2 illustrates a snapshot from the Chicago road network that was developed.



The model consists of:

- 10.2 million travelers
- 27.9 million automobile trips
- 31,278 links in 1944 zones for the 20 county region

Figure 2. Chicago Metropolitan Area Road Network.

Three levels of CAV cost scenarios were setup to evaluate the impact of CAV penetration in the traffic flow. Here, the CAV cost refers to Willingness to Pay (WTP) for vehicle automation. There are multiple studies that model the WTP for vehicle automation through various surveys, modeling techniques and different variables used. Bansal et al. [22] addressees the survey conducted in Austin, Texas to study the WTP for vehicle automation. Shabanpour et al. [23] discusses the findings of these studies in further detail.

Table 1 details the different assumptions considered for the study. These assumptions were developed from various literature studies and were addressed in detail in Auld, 2017 [9].

Table 1. CAV case study setup.

Case	CAV Cost ($) (Willingness to Pay)	CAV Fleet Penetration (%)
1	15,000	13.4
2	5000	47.8
3	0	100

It can be seen that the penetration of CAVs increases significantly with decreasing cost of automation.

3. Autonomie

The Vehicle System Simulation tool Autonomie is used to perform simulations on drive cycles with the vehicle models that incorporate baseline and advanced vehicle technology targets as generated for U.S. DOE [10] and U.S. DOT [24]. The vehicle models used to evaluate the energy consumption on the drive cycles consist of gasoline conventional powertrains, power-split hybrid-electric vehicles (HEVs), plug-in HEVs and battery electric vehicles (BEVs) of different all-electric ranges (AERs). Multiple EPA class definitions of vehicles (Compact, Midsize, Midsize SUV and Midsize Trucks) have also been used to evaluate the energy consumption on the driving profiles. Market penetration models are used to select the advanced vehicle powertrain models for future years.

Table 2 details a subset of the different vehicle powertrains used to represent the fleets:

Table 2. Autonomie Vehicle Models Considered.

Powertrain	Vehicle Technology	
	Engine	**Transmission**
CONV (Mild Hybrid 48V)	SkyActiv	10-speed Automatic
Power-Split HEV	Power Split	
Voltec PHEV 50AER	Power Split	
BEV 200AER		

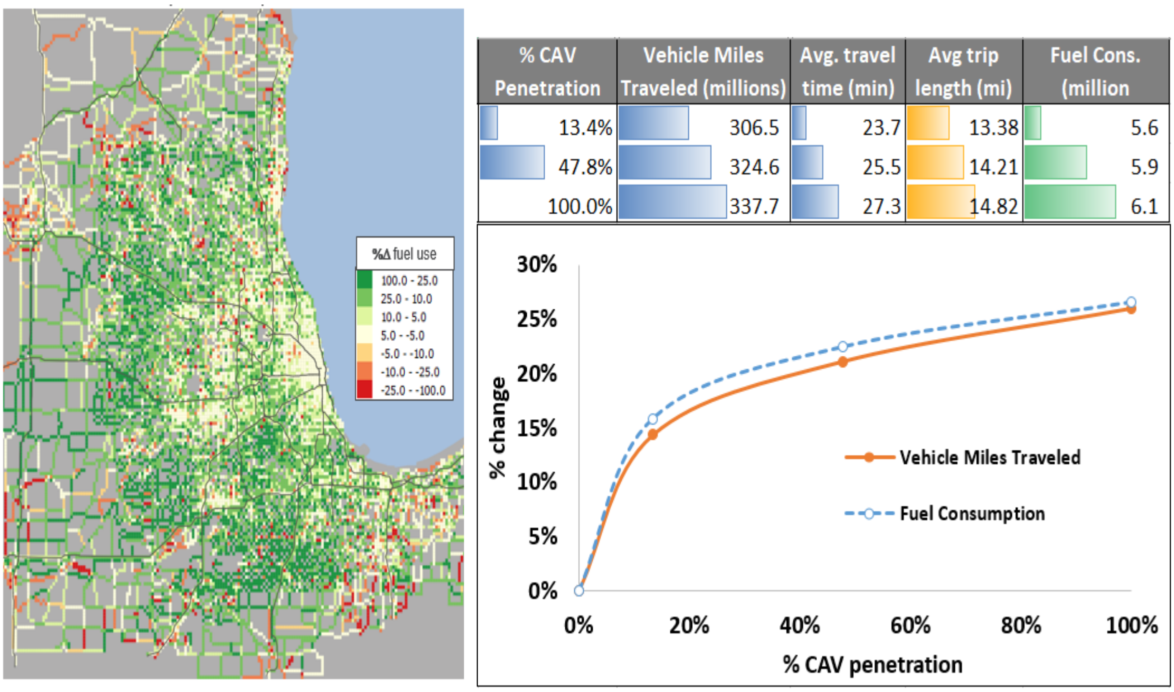
The component and vehicle assumptions are derived from the U.S. Department of Energy Targets. Table 3 lists the detailed component-level assumptions.

Table 3. Vehicle Component Assumptions.

Component Assumption	Powertrain	Value
Battery Specific Power (W/kg)	HEVs PHEVs BEVs	6000 1500 870
Battery Energy Density (Wh/kg)	PHEVs BEVs	188.89 340
Engine Efficiency (%)	CONVs HEVs	38.78 52
Motor Efficiency (%)	BEV	97

4. Simulation Results Analysis

Figure 3a illustrates the percentage of fuel consumption (in kg) change between the baseline case (with maximum CAV cost scenario of $15,000) and case 3 (with no CAV cost) and Figure 3b summarizes the different parameters of interest (vehicle miles traveled, average trip length, fuel consumption, etc.) across the three different CAV penetration levels. The detailed results of mobility changes across the different CAV penetration cases were presented in Auld et al., 2017 [9].



% CAV Penetration	Vehicle Miles Traveled (millions)	Avg. travel time (min)	Avg trip length (mi)	Fuel Cons. (million
13.4%	306.5	23.7	13.38	5.6
47.8%	324.6	25.5	14.21	5.9
100.0%	337.7	27.3	14.82	6.1

(**a**) Geographic distribution of % fuel consumption changes between case 1 and 3 (**b**) Summary table of the different CAV penetration case runs

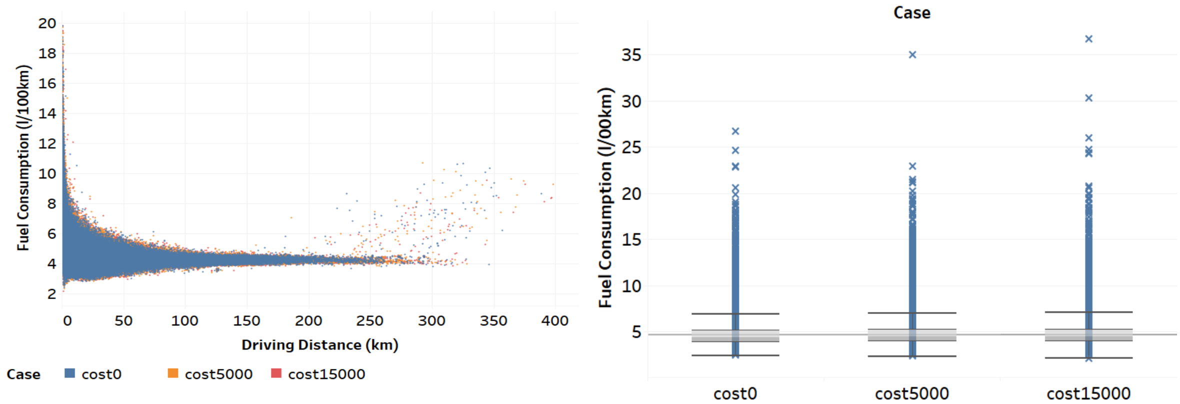
Figure 3. Summary of CAV study simulation run.

In Figure 3a, the dark green areas indicate higher total fuel consumption (in kg) for the CAV cost case of $0. This is because higher CAV fleet penetration results in increased traffic flow in urban areas, resulting in higher fuel consumption. However we observe a reduction in fuel consumption in the suburban areas. This is driven by how the traffic flow is generated due to the increased penetration of CAVs in the model. The Figure 3b shows the changes in total fuel consumption (in kg) and vehicle miles traveled (VMT) across the different CAV penetration levels. It shows that with increasing %CAV penetration, the total fuel consumption (in kg) increases much more aggressively compared to the VMT increments.

This section further details the breakdown of impact observed in energy consumption of the different CAV cost scenarios across the different vehicle powertrains.

4.1. Conventional Vehicle Powertrain

Figure 4a illustrates the distribution of fuel consumption with respect to driving distance for conventional vehicles for the three different penetration levels of CAVs. Figure 4b shows the box plot of fuel consumption of conventional vehicles for the three different penetration levels of CAVs.



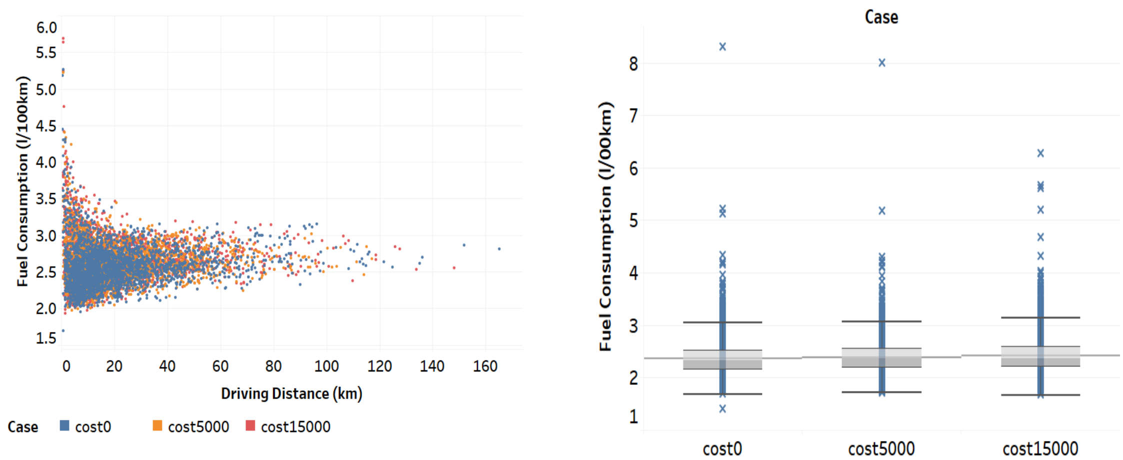
(**a**) Fuel consumption vs. driving distance of conventional vehicles (**b**) Fuel consumption box-plot for conventional vehicles

Figure 4. Fuel consumption distribution of conventional vehicles.

From Figure 4a, it can be seen that with respect to the driving distances of individual trips, the fuel consumption rate (L/100 km) is very similar across the different scenarios. Figure 4b further shows that the variation in average fuel consumption rates for conventional vehicles across the three different CAV cost scenarios is negligible, although the full extent of the ranges could vary. This is because the vehicle designs were indifferent for the different CAV scenario runs and hence do not show any drastic difference across the different cases.

4.2. Hybrid-Electric Vehicles (HEVs)

Figure 5a illustrates the distribution of fuel consumption rate (L/100 km) with respect to driving distance for HEVs for the three different penetration levels of CAVs. Figure 5b shows the box plot of fuel consumption of HEVs for the three different penetration levels of CAVs.



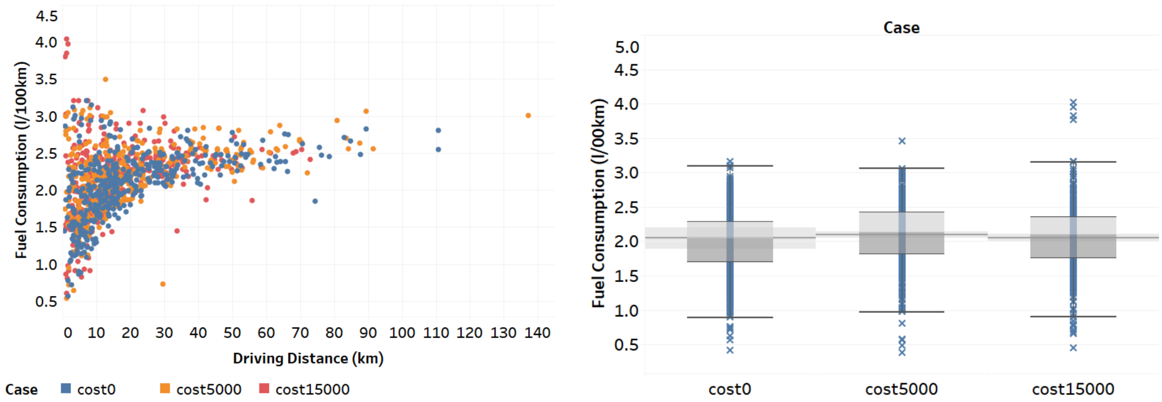
(**a**) Fuel consumption vs. driving distance of HEVs (**b**) Fuel consumption box-plot for HEVs

Figure 5. Fuel consumption distribution of HEVs.

Similar to Figure 4a, it can be seen that with respect to driving distance, the distribution of fuel consumption rate (L/100 km) for HEVs is very similar across the different cases in Figure 5a. Figure 5b further shows that the average fuel consumption rate (L/100 km) is similar across the different cases, although the full extent could vary due to different trips being affected through the traffic flow. For power-split HEVs, the fuel consumption is the driving factor and the impacts in electrical energy consumption is not as significant.

4.3. Plug-In Hybrid-Electric Vehicles (PHEVs)

Figure 6a illustrates the distribution of fuel consumption with respect to driving distance for PHEVs for the three different penetration levels of CAVs. Figure 6b shows the box plot of fuel consumption of PHEVs for the three different penetration levels of CAVs.



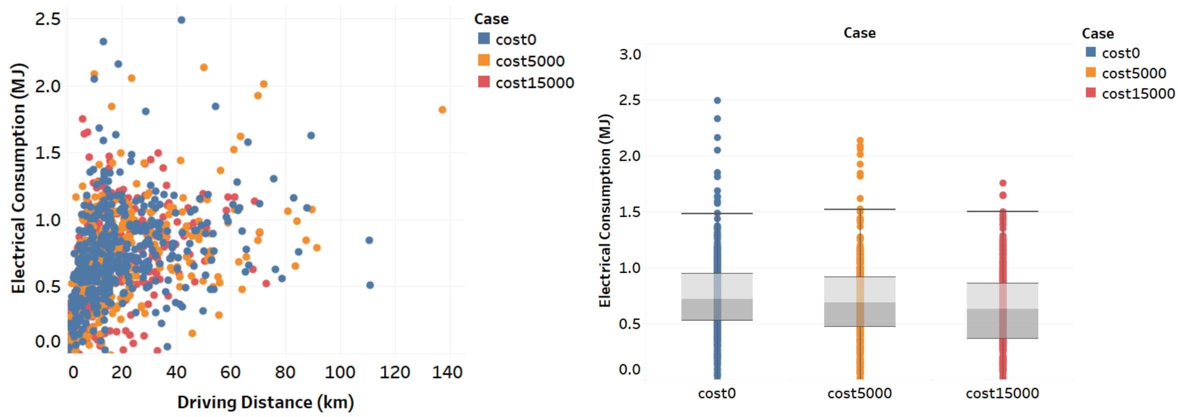
(**a**) Fuel consumption vs. driving distance for PHEVs

(**b**) Fuel consumption box-plot for PHEVs

Figure 6. Fuel consumption distribution for PHEVs.

Figure 6a,b show that the fuel consumption rate (in L/100 km) is very similar across the different CAV cost scenarios. Figure 6a shows that the fuel consumption rates (in L/100 km) across driving distances of the various trips seem to not be influenced by the CAV cost scenarios.

Figure 7a illustrates the distribution of electrical energy consumption with respect to driving distance for PHEVs for the three different penetration levels of CAVs. Figure 7b shows the box plot of fuel consumption of PHEVs for the three different penetration levels of CAVs.



(**a**) Electrical consumption vs. driving distance for PHEVs

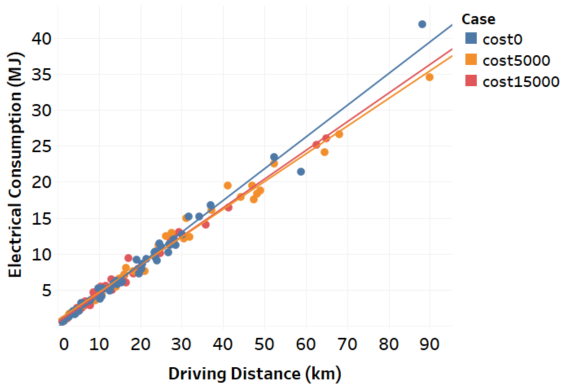
(**b**) Electrical consumption box-plot for PHEVs

Figure 7. Electrical consumption distribution for PHEVs.

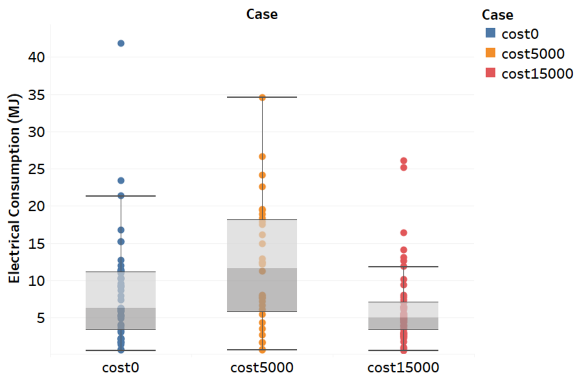
From Figure 7a, the variation in electrical energy consumption across driving distance is not apparent between the different CAV cost scenarios. However in Figure 7b, the variation in electrical energy consumption for the trips across the different CAV cost scenarios can be easily differentiated. Considering the full range of electrical energy consumption values, it seem to increase with lower CAV cost cases and hence higher CAV penetration in the traffic flow.

4.4. Battery Electric Vehicles (BEVs)

Figure 8a illustrates the distribution of electrical energy consumption with respect to driving distance for BEVs for the three different penetration levels of CAVs and Figure 8b shows the box plot of fuel consumption of BEVs for the three different penetration levels of CAVs.



(**a**) Electrical Consumption vs. driving distance for BEVs



(**b**) Electrical Consumption box-plot for BEVs

Figure 8. Electrical Consumption distribution for BEVs.

A larger variation in electrical consumption for BEVs can be observed across the three different CAV penetration levels, showing substantial influence of the resultant penetration rates compared to the other powertrains. From Figure 8a, it can be seen that there are three distinct trendlines that can be observed for unadjusted electrical consumption with respect to trip driving distance. In Figure 8b, the average electrical energy consumption across the different scenarios is further observed to vary and the variation is more apparent. This introduces a difference compared to what is observed for the other vehicle powertrains where no significant difference in fuel consumption is seen across the different CAV cost scenarios.

5. Effect of Penetration Level on Fuel Consumed

Figure 9 summarizes the distribution of driving distances and energy consumption for the different vehicle powertrains across different CAV scenarios.

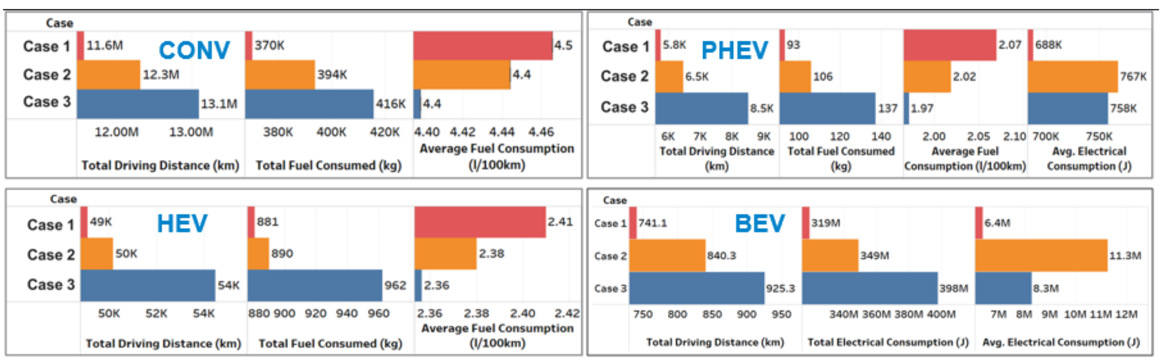


Figure 9. Simulation results summary across vehicle powertrains.

The previous analysis showed some visual differences in the amount of fuel consumed for the various CAV penetration levels. It is unclear whether the primary contributor to this difference is in the resulting travel behavior through the miles traveled or the nature of each trip itself. An approach to isolating the effect of automation on total fuel consumed is to control for the distance traveled via regression methods. Also, it is of interest to understand whether certain powertrains benefit more (energy consumed) than others from the presence of more connected and automated vehicles on the road.

In this section, we focus on the total amount of energy consumed EnergyUsage for all simulated powertrains in Wh. Figure 10 shows a density plot of the log energy usage for the different powertrains. We note slight energy differences for conventional, hybrid, and plug-in hybrid vehicles, but energy consumption differences are more pronounced for battery electric vehicles.

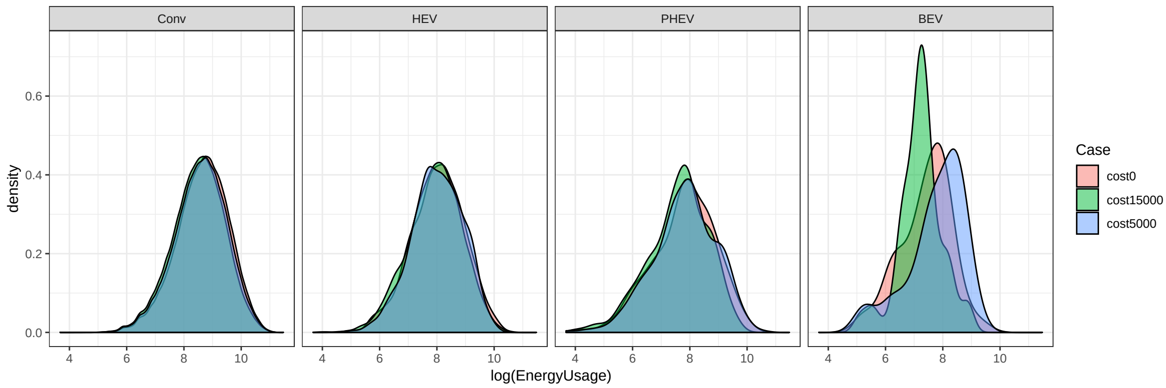


Figure 10. Density plot of log energy usage per powertrain.

The purpose of the log transform comes from the apparent gamma distributed response, which makes visual comparison difficult. We propose modeling the energy usage directly from the class of generalized linear models with a gamma density and an identity link. This approach naturally accounts for the skewness in the response and should avoid any potential heteroskedasticity of the residuals that would come from a Gaussian model. In Gaussian models for a response Y we have $\mathbb{V}[Y]$ constant as a function of mean response $\mathbb{E}[Y|X]$ which in this setting is inappropriate [25]. As a matter of fact longer trips can vary in nature, with expected highway-like type driving. Further analysis also suggests, after conditioning on the trips distance, that the energy usage does have a close to gamma distribution.

We model each powertrain separately. The model has the form:

$$g(\mathbb{E}[Y|X]) = X^T\beta$$

with g an identity link function, X the covariates of interest and β the true parameters to estimate.

Figure 11 shows the resulting fit for conventional, HEV and BEV vehicles along with the penetration levels estimates. Estimates are typically computed using maximum likelihood methods. Full details can be found in [26].

```
## Conventional fit
##                        Estimate Std. Error  t value  Pr(>|t|)
## (Intercept)          117.143594   0.421373  278.005 < 2.2e-16
## Casecost15000         11.888918   0.522802   22.741 < 2.2e-16
## Casecost5000          10.662201   0.535938   19.895 < 2.2e-16
## DrivingDistance_km_  376.896770   0.047217 7982.291 < 2.2e-16
##
## Dispersion parameter = 0.01456
## n = 1549244 p = 4
## Deviance = 21108.37346 Null Deviance = 1164654.14472 (Difference = 1143545.77126)
##
##  HEV fit
##                      Estimate Std. Error  t value  Pr(>|t|)
## (Intercept)           33.6651     3.0850  10.9124 < 2.2e-16
## Casecost15000         14.2065     3.9504   3.5962  0.000325
## Casecost5000           5.3013     4.2087   1.2596  0.207853
## DrivingDistance_km_  206.3293     0.3785 545.1267 < 2.2e-16
##
## Dispersion parameter = 0.01645
## n = 7581 p = 4
## Deviance = 120.20950 Null Deviance = 5886.37011 (Difference = 5766.16062)
##
##  BEV fit
##                      Estimate Std. Error t value  Pr(>|t|)
## (Intercept)           42.6753    11.8685  3.5957 0.0004629
## Casecost15000          9.8710    14.9598  0.6598 0.5105662
## Casecost5000          18.6043    16.6740  1.1158 0.2666454
## DrivingDistance_km_  116.5068     1.3976 83.3614 < 2.2e-16
##
## Dispersion parameter = 0.01055
## n = 130 p = 4
## Deviance = 1.29695 Null Deviance = 89.16471 (Difference = 87.86776)
```

Figure 11. Resulting fit for different powertrains with respect to different penetration level estimates.

From the residual plots shown in Figure 12, we first note that a variance function going as the squared of the mean response could be too strong. This is especially true for conventional vehicles. Even so, the fit is appropriate and the estimates as well as the t values can be trusted.

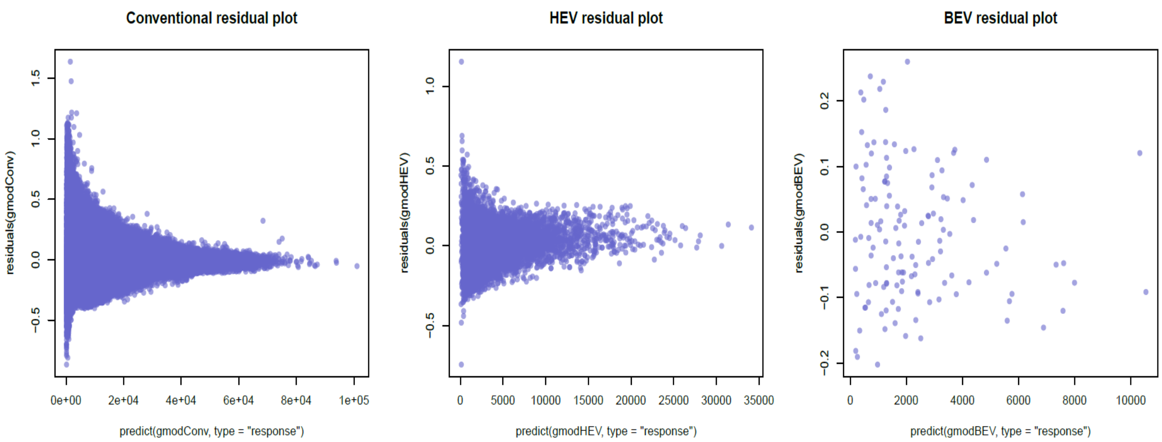


Figure 12. Residual plots.

An interpretation of the results shows evidence for differences in energy levels for conventional vehicles in the various penetration scenarios. We note that an increase in automation cost leads to lower penetration levels. Consequently, this tends to increase overall energy consumed. Although the order of magnitude is not large (around 10 to 11 W.h additional on average), it is statistically significant enough to be reported as a notable difference. On the flip side, HEVs and BEVs are not as much affected by the penetration levels. In fact, in the case of an assumed automation cost of $5000, the energy usage for HEVs is not affected enough to claim a change, suggesting that energy levels of HEVs are similar for $0 or $5000 of additional automation cost. However an additional automation cost of $15,000 does impact HEV energy usage with a significant estimate of an additional $\sim$ 14 W.h. Finally, BEVs seem not to differ for all levels, and this is reflected through the resulting high *p*-values of the estimates.

We emphasize that the power of this approach is that we managed to isolate energy differences on the penetration levels only by controlling for the trip distances. In fact, the outcome of this analysis is in contrast to the visual conclusion that one can draw by looking at Figure 10, especially for BEVs.

6. Conclusions

This study implemented a combined analysis of CAV energy impacts across different CAV cost scenarios. It demonstrates a powerful energy estimation tool for regional analysis that allows us to analyze the intersection between transport policy and vehicle technology. The purpose of the study is to evaluate the different impact of vehicle powertrains in energy consumption across the three cases studied.

With **100%** CAV penetration, the total driving distance for conventional powertrains increases by **13%** and the average fuel consumption decreases by **1.5%**. For HEV powertrains, the total driving distance increases by **10%** and the average fuel consumption decreases by **2.2%**. For PHEV powertrains, the total driving distance increases by **47%** and the average fuel consumption decreases by **4%**, and for BEV powertrains, the total driving distance increases by **25%** and the average electrical energy consumption increases by **33%**.

Through varied visual inspection, it can be seen that there is a minimum impact of the different vehicle powertrains across the three different CAV cost cases that can be explained without taking driving distance into account. Further statistical analysis of the results, isolating the influence of the trip distances, shows some influence of the conventional vehicles in determining the overall energy consumption across the three different cost cases. With higher CAV penetration, and hence increasing average trip lengths, conventional vehicles tend to operate with better fuel efficiency and hence contributes to the overall energy consumption across the different cases.

In this study, there were no changes in the assumptions of the vehicle design itself across the three CAV penetration levels. Further research studies would be implemented to better model connected and automated vehicles, accounting for additional electrical accessory loads and vehicle dynamics for different levels of connectivity and automation in vehicles.

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Abbreviations

The following abbreviations are used in this manuscript:

AER	All-Electric Range
ANL	Argonne National Laboratory
BEV	Battery-Electric Vehicle powertrain
CAV	Connected-Autonomous Vehicle
CONV	Conventional vehicle powertrain
HEV	Hybrid Electric Vehicle powertrain
PHEV	Plug-In Hybrid Electric Vehicle powertrain
U.S. DOE	United States Department of Energy
U.S. DOT	United States Department of Transportation

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