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Impact of CAV Technologies On Energy Consumption of Advanced Electrified Vehicles

Ehsan Sabri Islam[1], Ayman Moawad[1], Namdoo Kim[1], Aymeric Rousseau[1]
[1]*Argonne National Laboratory, Lemont, IL 60438-4815, USA (eislam@anl.gov)*

Executive Summary

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-Automated Vehicles (CAVs) will impact the 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 different penetration levels of CAVs deployment in the City of Chicago and how it impacts the energy consumption of electrified vehicles in the future. 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.

1 Introduction

The transportation system modeling tool, Polaris [1] is used to develop and validate the transportation system model for Chicago Metropolitan Area. It utilizes population and vehicle synthesis, along with activity demand generation and traffic flow to model the system. Individual-level CAV vehicle technology choice framework is also implemented along with updated traffic flow modeling to account for CAVs.

The resulting stochastic speed profiles from Polaris, combined with the data on driving cycles and fleet distribution are used as an input to Autonomie, a vehicle system modeling tool. Autonomie[2] then simulates the energy consumption of the transportation network for different vehicle technologies. Figure 1 illustrates the steps involved with the process.

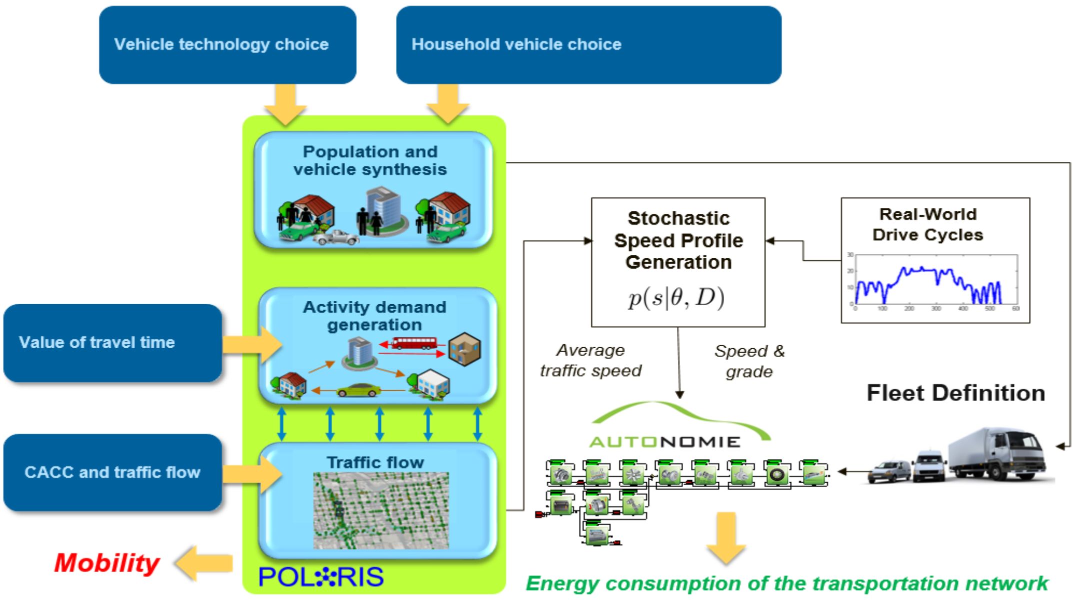


Figure 1: CAVs modeling using Polaris & Autonomie

Previous studies have 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 [3] [4].

2 Polaris Chicago CAV Model

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

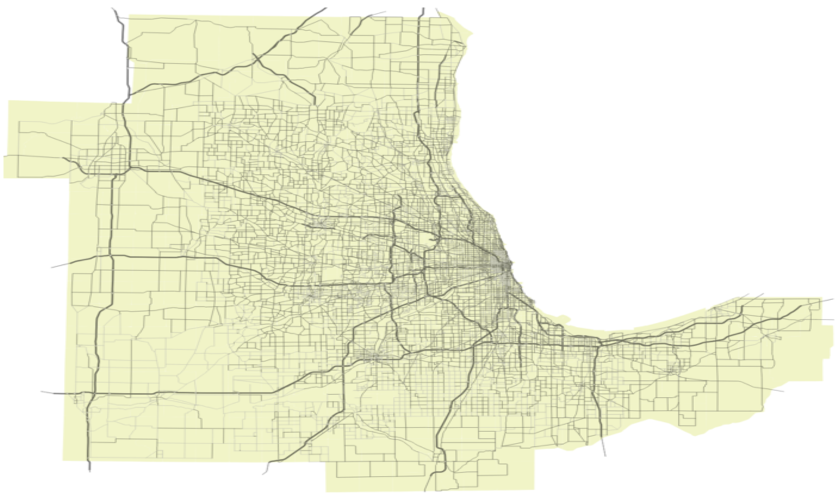


Figure 2: Chicago Metropolitan Area Road Network

The model consists of:

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

3 levels of CAV cost models have been setup to evaluate the impact of CAV penetration in the traffic flow. Table 1 details the different cases considered for the study.

Table 1: CAV case study setup

Case	CAV Cost ($)	CAV Fleet Penetration (%)
1	15000	13.4
2	5000	47.8
3	0	100

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 [5] and U.S. DOT [6]. 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
Mild Hybrid CISG	SkyActiv	10-speed Automatic
Power-Split HEV	Prius	
Voltec PHEV 50AER	Prius	
BEV 200AER		

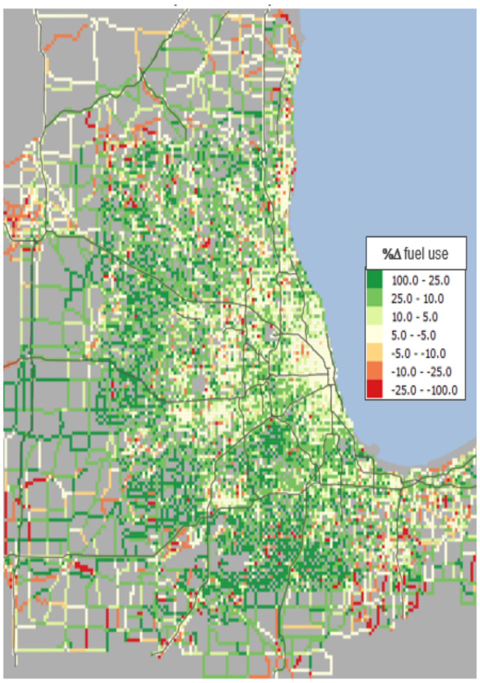
The component and vehicle assumptions are derived from the U.S. Department of Energy Targets. Table 3 lists the detailed component-level assumptions.

Table 3: Vehicle Component Assumptions

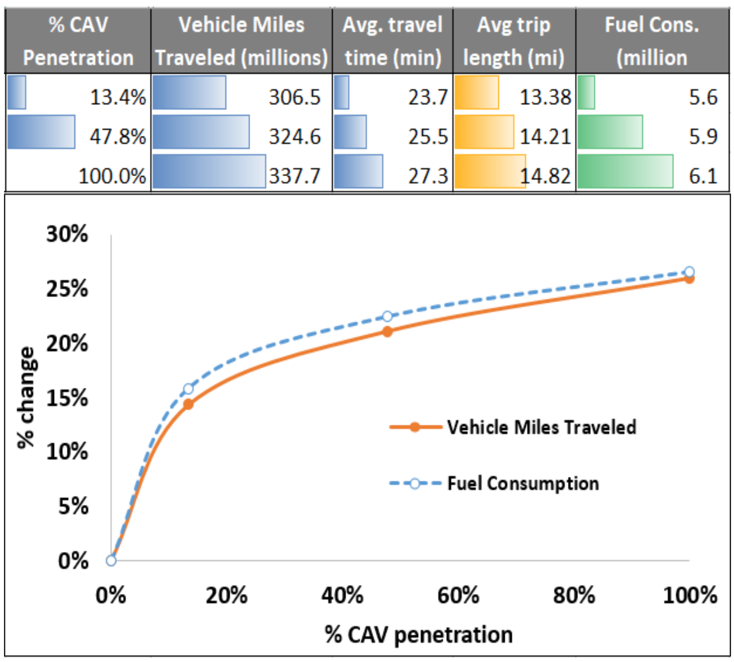
Component Assumption	Powertrain	Value
Battery Specific Power (W/kg)	HEVs	6000
	PHEVs	1500
	BEVs	870
Battery Energy Density (Wh/kg)	PHEVs	188.89
	BEVs	340
Engine Efficiency (%)	CONVs	38.78
	HEVs	52
Motor Efficiency (%)	BEV	97

4 Simulation Results Analysis

Figure 3a illustrates the range of fuel usage change between the baseline case and maximum CAV cost scenario of 15000$ and table 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 have been presented in J. Auld et. al. [7].



(a) Geographic distribution of Fuel Use Changes



% 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

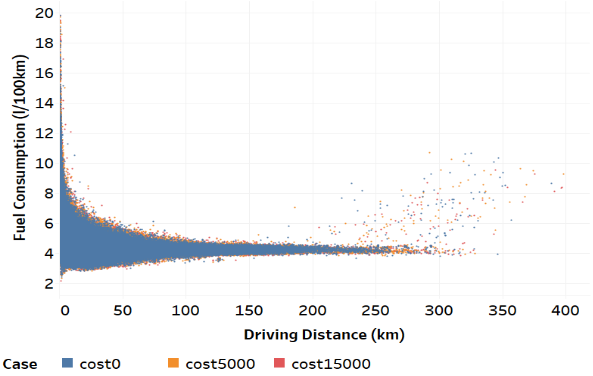
(b) Summary table of the different CAV penetration case runs

Figure 3: Summary of CAV study simulation run

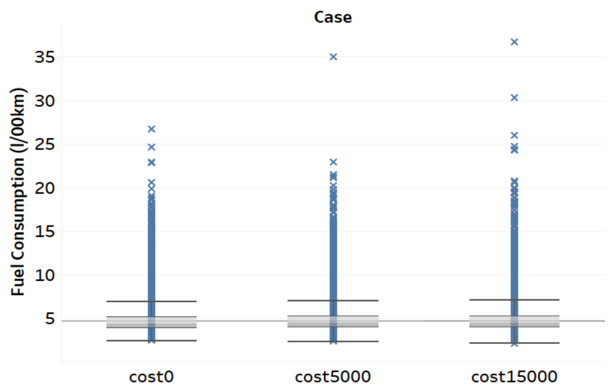
In figure 3a, the dark green areas indicate higher fuel consumption for the baseline CAV cost case of 0$. The figure in 3b shows the changes in fuel consumption across the different CAV penetration levels. This section further details the breakdown of impact observed across the different vehicle powertrains.

4.1 Conventional

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



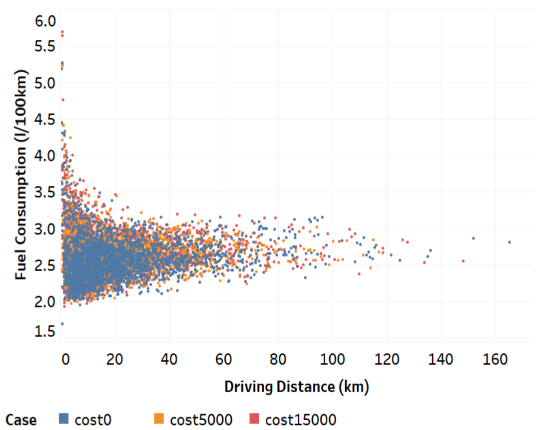
(b) Fuel Consumption box-plot for conventional vehicles

Figure 4: Fuel Consumption distribution of conventional vehicles

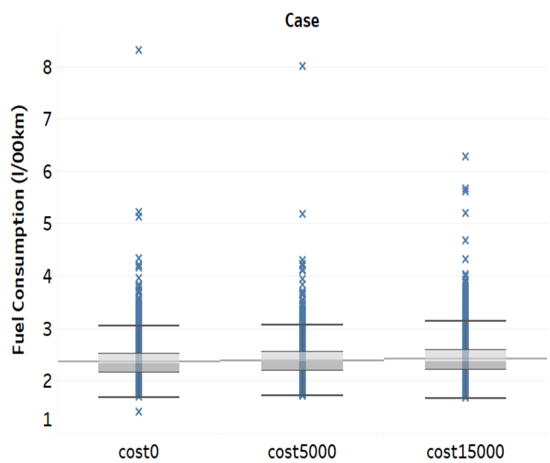
It can be observed that the variation in average fuel consumption rates for conventional vehicles across the three different CAV cost scenarios is negligible, although the full extent of the ranges could vary.

4.2 Hybrid-Electric Vehicles (HEVs)

Figure 5a illustrates the distribution of fuel consumption 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



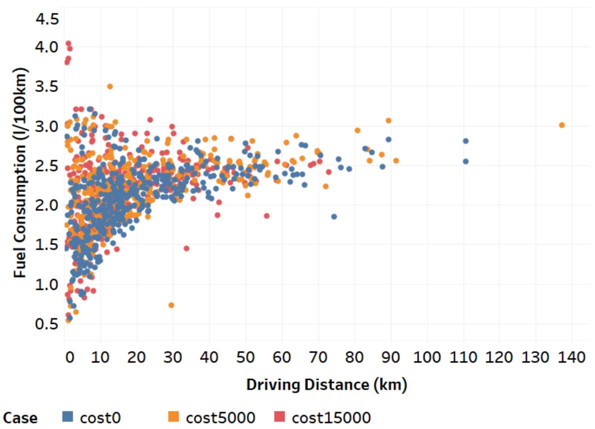
(b) Fuel Consumption box-plot for HEVs

Figure 5: Fuel Consumption distribution of HEVs

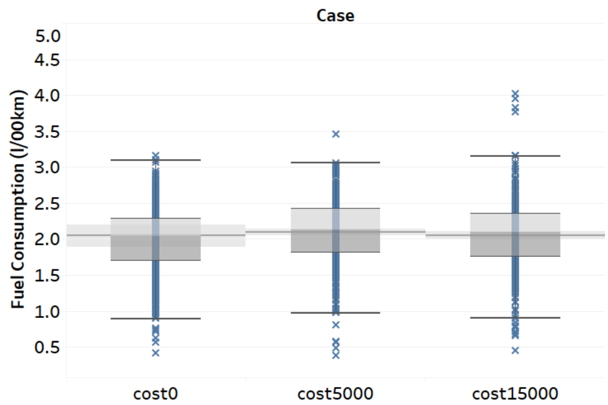
From the figures above, a slight variation in fuel consumption for HEVs can be observed across the three different CAV cost scenarios.

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.



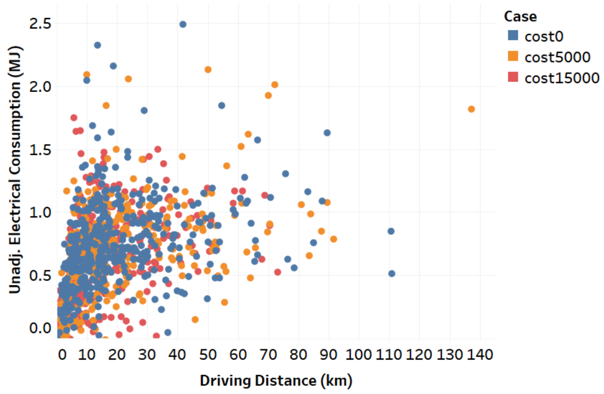
(a) Fuel Consumption vs. driving distance for PHEVs



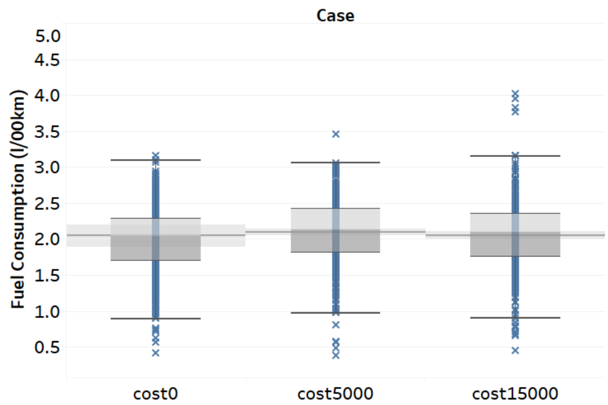
(b) Fuel Consumption box-plot for PHEVs

Figure 6: Fuel Consumption distribution for PHEVs

Figure 7a illustrates the distribution of electrical 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

4.4 Battery Electric Vehicles (BEVs)

Figure 8 illustrates the distribution of electrical consumption with respect to driving distance for BEVs for the three different penetration levels of CAVs.

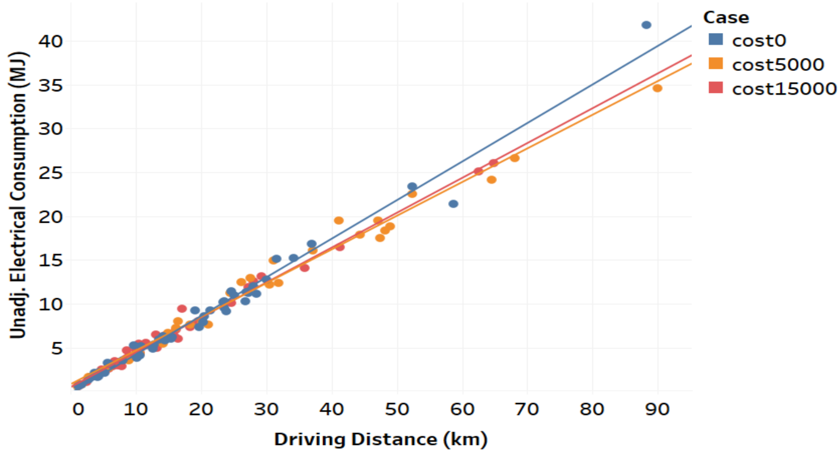


Figure 8: Electrical Consumption distribution of BEVs

Figure 9 shows the box plot of fuel consumption of BEVs for the three different penetration levels of CAVs.

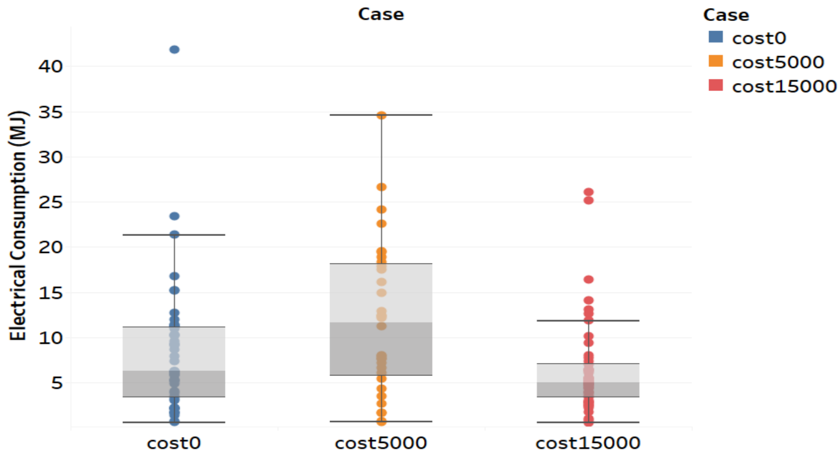


Figure 9: Electrical Consumption box-plot for BEVs

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.

Effect of penetration level on fuel consumed

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 the trips itself. An approach to isolate 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 W.h. 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 more pronounced for battery electric vehicles.

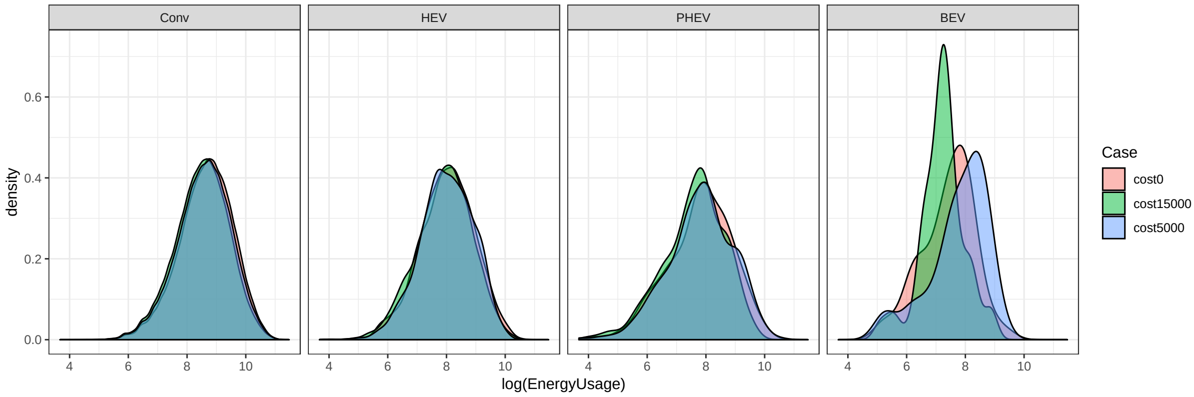


Figure 10: Density plot of log Energy usage per powertrain

The purpose of the log transform comes from the apparent gamma distributed response, which makes visual comparison difficult. We propose to model 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 [8]. As a matter of fact longer trips can vary in nature, with expected highway like type of driving. Further analysis also suggested, after conditioning on the trips distance, that the energy usage does have a close to gamma distribution.
We model each powertrain seperately. The model has the form:

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

with g an identity link function, X are the covariates of interest and β the true paramEters to estimate. The table below shows the resulting fit for Conventional, HEV and BEV vehicles along with the penetration levels estimates. Estimates are typically computed using maximum likelihood methods and full details can be found in [9].

```
## 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)
```

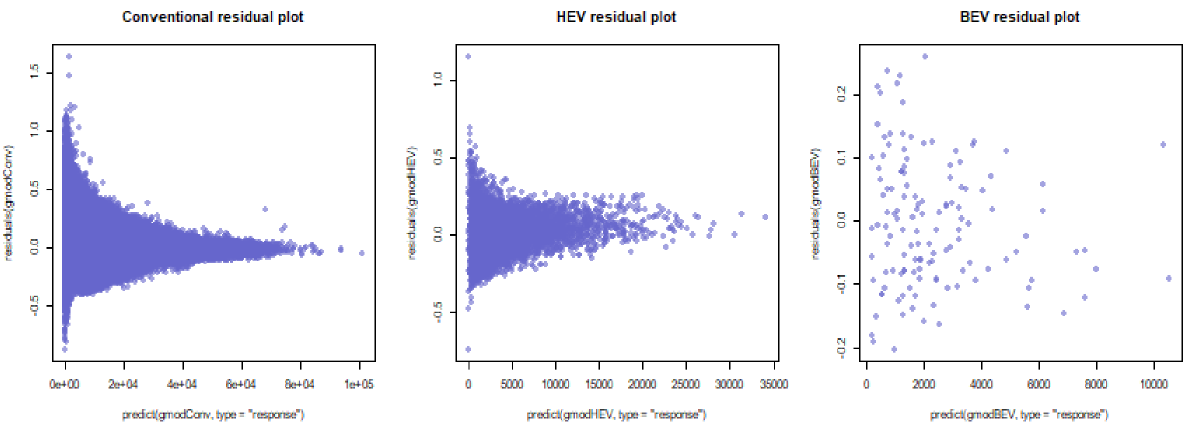


Figure 11: Residual plots

We first note from the residual plots shown in figure 11 that a variance function going as the squared of the mean response could be too strong. Especially for conventional vehicles. Even so, the fit is appropriate and the estimates along with the t values can be trusted.

An interpretation of the results shows that there is 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 and consequently 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, for HEVs in the case of an assumed automation cost of $5000 the energy usage is not affected enough to claim a change suggesting that energy levels of HEVs are similar for a $0 or $5000 of addional automation cost. However an additional $15000 does impact HEV energy usage with a significant estimate of addtional ~ 14 W.h. Finally BEVs seem to not be differ for all levels, this is reflected through the resulting high p-values of the estimates.

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

Conclusion

This study implemented a combined analysis of CAV energy impacts across different CAV cost scenarios. The study 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.

Through various 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 the driving distance into account. Further statistical analysis of the results, isolating the influence of the trip distances, show 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 have been 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.

Acknowledgments

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Authors

Ehsan Sabri Islam completed his M. Sc. from Purdue University and B.A.Sc in Mechatronics Engineering from University of Waterloo, Canada. His skills set and interests focus on applying Mechatronics principles to innovate systems and processes in advanced vehicle technologies and controls systems. At Argonne, he focuses his research on vehicle energy consumption analyses using large scale simulation.

Ayman Moawad is a research engineer at Argonne National Laboratory. He graduated from the Ecole des Mines, France, in 2009 with a Master of Science in Mechatronics, Robotics, and Computer Science. His research interests include energy consumption prediction and analysis of electrified vehicles, large-scale simulation, high-performance computing, machine learning, and data analysis.

Namdoo Kim graduated in 2007 from the University of Sungkyunkwan, Korea, with a Masters degree in Mechanical Engineering. He is currently working in Argonne National Laboratorys Vehicle Modeling and Simulation Group.

Aymeric Rousseau is the manager of the Systems Modeling and Control Section at Argonne National Laboratory. He received his engineering diploma at the Industrial System Engineering School in La Rochelle, France in 1997 and is currently pursuing his Executive MBA at Chicago Booth. For the past 20 years, he has been evaluating the impact of advanced vehicle and transportation technologies from a mobility and energy point of view including the development of Autonomie (vehicle system simulation) and POLARIS (large-scale transportation system simulation). In addition to leading numerous projects for OEMs and US Department of Energy, Aymeric Rousseau has been providing the vehicle energy consumption analysis for the US CAFE regulations and has authored or co-authored more than 80 papers related to vehicle electrification.