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Electrification of vehicle miles travelled within the household context: a case study from California, USA

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Summary

This study uses empirical data from 287 households with at least one plug-in electric vehicle (PEV) in California between 2016 and 2020. We estimate electric vehicle miles travelled (eVMT) and utility factor (UF) at the household level, i.e., taking into consideration all the vehicles. We also study the effect of household specific factors such as number of drivers, commute distance, share of PEV-usage among household drivers, frequency of charging on eVMT and UF.

Keywords: PEV, PHEV, BEV, user behavior, utility

1 Introduction

Electrified vehicle miles travelled (eVMT) and the utility factor (UF) —described as the share of eVMT within total vehicle miles travelled— are two of the most common metrics in analyzing the performance of plug-in hybrid electric vehicles (PHEVs) and understanding to what degree they provide 'emission-free' travel. The number of studies in the literature that uses empirical data to assess eVMT and UF are limited [1,2,3,4,5,6]. Some of those studies looked into how some factors such as all electric range (AER) impact eVMT and UF; however, factors within the household context are usually neglected.

In this study, we used an empirical data set to estimate eVMT and UF on the household level and apart from the range of plug-in electric vehicle (PEV), we looked into how factors within the household context (number of drivers, commute distance, share of PEV-usage among household drivers, frequency of charging, frequency of long-distance trips, frequency of overlaps between PEV trips and internal combustion engine vehicle (ICEV) trips, size of ICEVs in the household and MPG of ICEVs in the household) impact eVMT and UF.

2 Data and method

The data we use is from The Advanced Plug-in Electric Vehicle Travel and Charging Behavior Project which aims to provide an insight on how PEVs are used on a day to day and month to month basis within the household travel context by placing data loggers in participant households for a period of one year [4]. The project was initiated by the Plug-in Hybrid Electric Vehicle Center at University of California, Davis. Data was collected from summer 2015 to summer 2020, in California, USA, within 287 households by placing a monitor in all household vehicles for the duration of a year, except the ones driven less than 1000 miles per year. Each household owns one PEV. Among the 287 households, 20 have a Toyota Plug-in Prius, 45 have a Ford C-Max/Fusion Energi, 25 have a Toyota Prius Prime, 23 have a Chrysler Pacifica, 71 have a Chevrolet Volt, 43 have a Nissan Leaf, 23 have a Chevrolet Bolt, 37 have a Tesla Model S. Including the conventional vehicles in the households, the dataset has over 650 vehicles in total. Nissan Leaf, Chevrolet Bolt and Tesla Model S are the battery electric vehicles (BEV) in the data set, and the rest are plug-in hybrid electric vehicles (PHEVs). The model years for the PEVs in the dataset range from 2012 to 2019. Dataset also includes an extensive survey made with the PEV owners prior to the placement of the monitors.

An overview of the collected parameters is given below in Table 1.

Table 1: Collected Parameters

Trip information	Trip Start Time, Duration, Trip Distance (km), Trip Distance (mi), Fuel Consumption (l), Fuel Consumption (gal), gVMT, eVMT, zVMT
Vehicle identification	Vehicle ID No, Vehicle Type (PEV or ICE), Year, Make, Model, Miles per Gallon
Logger information	Logger Installation Date, First Fleet Trip Date, First File Date, Logger Uninstall Date, Initial Odometer Reading, Final Odometer Reading, Odometer Reading at Logger Uninstall
Household identification	Household ID No, List of PEVs in the Household, List of ICEs in the Household, Number of Drivers, Number of Non-Drivers, Size of the Household, Number of Vehicles in the Household, Number of Logged Vehicles in the Household, Vehicle-Driver Ratio
Charging information	Start Time, End Time, File ID, Start SOC (%), End SOC (%), Useable SOH, Charge Level, Charger Energy Non-Annualized, Charger Loss, Offset
Charging location information	Latitude, Longitude, Time Zone, Location (Home, Public or Work)

The range of the PEVs we use in our analysis are based on the info provided by the U.S. Environmental Protection Agency; which is 11 miles for Toyota Prius, 19 miles for Ford Energi, 25 miles for Toyota Prius Prime, 33 miles for Chrysler Pacifica, 35-38 miles for Chevrolet Volt, 73-84 miles for Nissan Leaf, 238 miles for Chevrolet Bolt and 249 miles for Tesla Model S. All driving and charging data were annualized prior to analysis.

We analyzed the impact of afore mentioned factors within the household context on eVMT and UF by using descriptive and inductive statistical methods, and regression analysis.

3 Analysis and results

We observe that there is a general increase in eVMT and UF with all-electric range, see Figure 1 and 2. When we look into the share of eVMT in the total household VMT (Figure 2), we observe that Chevrolet Volt, a PHEV with a range of 35-38 miles electrify 43% of the total household miles, whereas Nissan Leaf, a BEV with a range of 73-84 miles, is at 51%, Chevrolet Bolt, a BEV with a range of 238 miles, is at 59% and Tesla Model S, a BEV with a range of 249 miles, is at 68%. This finding shows that, in the context of the whole household, a PHEV like the Chevrolet Volt, can electrify a similar share of household miles compared to a low range BEV (Leaf) and can electrify around 70% as much household miles as high range BEVs (Bolt and Model S).

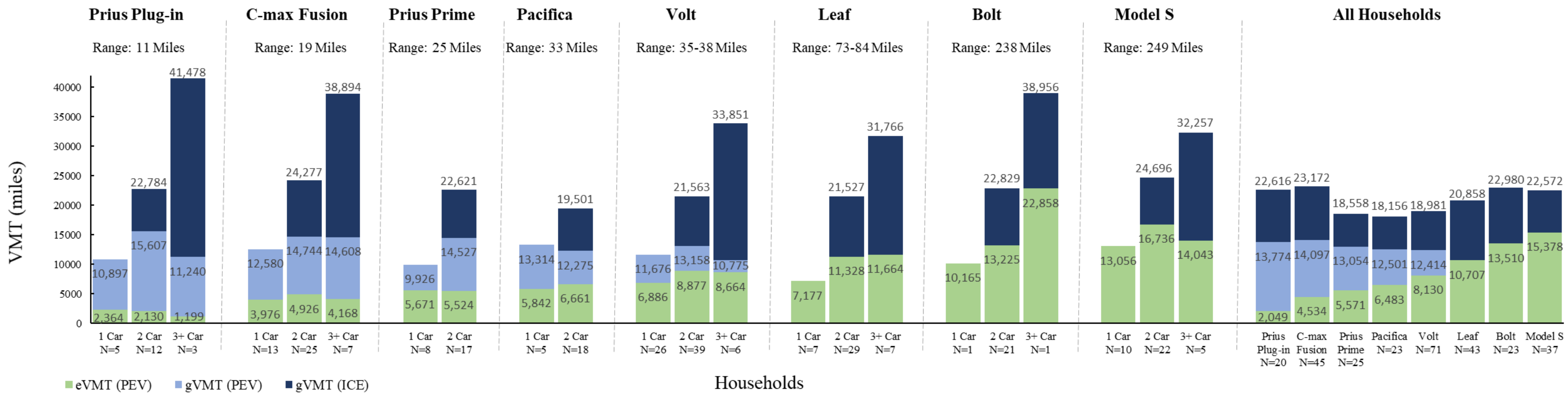

Figure 1: VMT of households, categorized by PEV-type and total number of cars in the household.

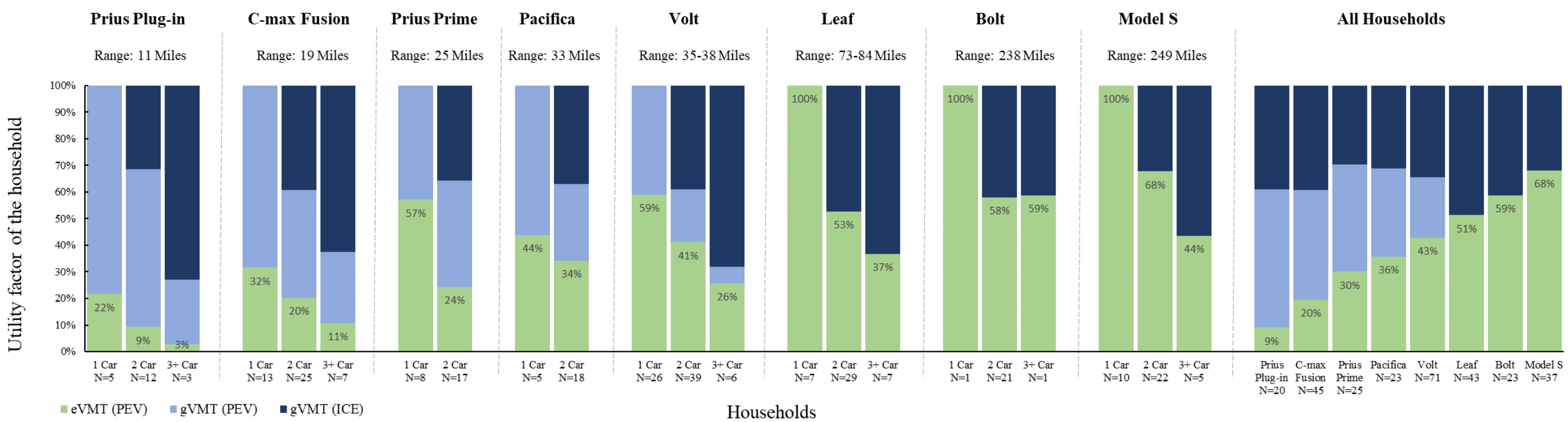

Figure 2: Utility factor of households, categorized by PEV-type and total number of cars in the household.

In order to assess the impact of factors within the household context, we performed multivariate regression analysis on eVMT and logistic regression on UF of the PEV and UF of the household since the utility factor is always between 0 and 1. In the regression analysis of UF of the PEV, BEV households were removed from the dataset for analysis, since BEVs result in a UF (PEV) of 1 at all times.

Below is our generic regression model:

$$Y_i = \beta_0 + \beta_1 \cdot \text{Range} + \beta_2 \cdot \text{Number of drivers} + \beta_3 \cdot \text{Commute distance} + \beta_4 \cdot \text{PEV Share} + \beta_5 \cdot \text{Frequency of charging} + \beta_6 \cdot \text{Frequency of long-distance trips} + \beta_7 \cdot \text{Frequency of overlaps} + \beta_8 \cdot \text{ICEV Size} + \beta_9 \cdot \text{ICEV MPG} + \varepsilon \quad (1)$$

$$i = \{1, \ldots, 3\} \text{ where } Y_1 = \text{eVMT}, Y_2 = \text{UF of the PEV}, Y_3 = \text{UF of the household},$$

Commute Distance is based on the main driver that uses the PEV; in instances where there were multiple commuters using the PEV, we used the most frequent commute distance by looking at the dataset; if there was no information provided in the survey, we assigned the most frequent trip in the dataset for that PEV as the commute distance. PEV Share is the percentage showing how much the main driver of the PEV uses the vehicle. Frequency of charging is the average number of charging events per day for the plug-in electric vehicle of the given household. Frequency of long-distance trips is defined as the percentage of single trips (not daily driving distance) made by the PEV that are above 50 miles. Frequency of overlaps is defined as the percentage of PEV trips that overlap, in terms of time of the day, with any of the internal combustion engine vehicle (ICEV) trips in the household. ICEV size in the household is defined as a dummy variable set to one if the smallest ICEV in the household was larger than the PEV and 0 otherwise. ICEV MPG in the household is defined as the weighted average of miles per gallon of ICEVs in the household where the weight coefficient was calculated as the percentage of the actual usage time (hours), obtained from the trip dataset, of the given ICEV among all the ICEVs in the household.

Results of the regression analysis for each of our main metrics are given in Table 2. Note that a multivariate regression was performed on eVMT and a logistic regression was performed on UF of the PEV and UF of the household. Logistic regression on UF of the PEV excludes BEV households, since their utility factor is always 1.

Table 2: Regression results for eVMT, UF of the PEV and UF of the household

Dependent:	eVMT		UF of the PEV		UF of the hh	
Intercept	-1309		-0.003		-0.061	
	(2030)		(0.104)		(0.101)	
Range	45.28	***	0.018	***	0.013	***
	(2.95)		(0.001)		(0.001)	
Number of drivers	319.45		0.024		0.001	
	(406.42)		(0.019)		(0.019)	
Commute distance	17.38		0.001		0.001	
	(16.22)		(0.001)		(0.001)	
Share of PEV usage of the main driver	1687		0.172		0.072	
	(1866)		(0.089)		(0.087)	
Frequency of charging	5353	***	0.189	***	0.129	***
	(568)		(0.0626)		(0.025)	

Frequency of long-distance trips	13596	-1.521	**	0.674
	(8898)	(0.451)		(0.434)
Frequency of overlaps	13596	-0.402		-0.671
	(2515)	(0.369)		(0.355)
Size of ICEVs in the household	-244.7	0.051		-0.017
	(519.8)	(0.025)		(0.024)
MPG of ICEVs in the household	-11.1	0.001		-0.001
	(25.33)	(0.0021)		(0.001)
Multiple R-squared	0.515	-		-
Adjusted R-squared	0.499	-		-
Confidence levels	*** %99.9, **%99, *%95, .%90			
Values represent estimates, standard error is given in parentheses.				

Our results show that range is statistically very significant in the electrification of miles, and higher ranges result in higher eVMT, UF of the PEV and UF of the household. This result confirms the initial trend we had observed in Section 3.1 and is also in line with the findings of previous studies [7], [8], [9].

Frequency of charging is also statistically significant, showing up in all of our main metrics. However, it should be noted that the frequency of charging is based on the number of charging of events in this study and not the length of these charging events; in addition to that, the charging level is not taken into account. With regards to developments in charging infrastructure, more charging points might increase the frequency of charging.

Frequency of long-distance trips is statistically significant for the UF of the PEV. The results show that more frequent long-distance trips decrease the UF of the PEV, without having any impact on eVMT. This suggests that the decrease in UF of the PEV can only be explained by the increase in gVMT of the PEV, meaning a lower fuel economy as long-distance trips become more frequent. Plötz et al. [5] also reached the same conclusion in their paper on the impact of daily and annual driving on fuel economy, where they conclude that tendency for long-distance trips decreases the fuel economy and UF of a PHEV.

We don't observe statistical significance for number of drivers, commute distance, share of PEV usage of the main driver, frequency of overlaps, size of ICEVs in the household and MPG of ICEVs in the household.

Based on our findings regarding the frequency of long-distance trips and the intuitive assumption that higher commute distances would behave similar to frequent long-distance trips, our expectation was to find a statistically significant relationship between commute distance and UF of the PEV. However, to our surprise, our results show that commute distance has no influence on neither the eVMT nor the UF of a PEV. The reason for this result might be that the commute distances in our dataset do not have enough variation to result in a difference between short and long commute distances.

Number of drivers do not seem to be statistically significant for any of our metrics, suggesting that the ratio of PEV trips to ICEV trips stay relatively similar regardless of the number of drivers in the household, and a higher number of drivers does not lead to more use of ICEVs. The size of ICEVs in the household and the share of PEV-usage of the main driver were also found to be non-significant for all our metrics, the latter suggesting that shifting between drivers within the same household has no impact on neither eVMT nor any of the UFs.

In an earlier version of our dataset, with fewer vehicles and excluding long-range BEVs, we had observed a significant impact of frequency of overlaps and MPG of ICEVs in the household on UF of the household (both impacting negatively). However, with our current dataset, we don't observe such a statistically significant impact. An intuitive assumption would suggest that more overlaps between PEVs and ICEVs would result in higher gVMT and thus reduce UF of the household. One reason that we do not observe such a significant behavior might be that the number of overlaps either decreases with the inclusion of long-range BEVs or the impact of extra gVMT gets minimized due to already high electrification coming from long range BEVs. Similarly, one would assume that the existence of ICEVs with high MPGs could significantly impact the UF of the household; however we do not observe such an impact. The reason might be that with the use of long-range BEVs such as Bolt and Model S, the UF of the household could reach up to almost 70%, thus reducing the ratio of gVMT from ICEVs compared to the eVMT, thus making it less insignificant. The impact of ICEVs with high MPGs, can be more significant when the electrification is low (such as a household with low range PHEVs).

4 Discussion and conclusions

Our dataset is regionally bound to California and the households that were included could be considered as early adopters, with higher education and income levels. We recognize that this might have created a bias towards more conscious driving and charging behavior, and our results might have differed slightly if a larger and geographically more diverse population sample was used. However, California is one of the leading EV markets and at the time of the data collection for this study, California was at the initial stages of the early adopter group among the consumer categories of technology adopters [10]; therefore, we consider these limitations inevitable.

In this paper, we used a dataset of 287 households where each household had one PEV and analyzed through descriptive statistics and regression analysis how factors within the household context impact eVMT, UF of the PEV and UF of the household. Our results indicate that a PHEV with a higher all-electric-range results in more electrification and thus a higher UF for both the PHEV and the household. Furthermore, our results show that — considering the UF of the household— a PHEV like the Chevrolet Volt with half the range of a BEV like the Nissan Leaf can electrify a similar share of miles and it can electrify around 70% as much household miles as long-range BEVs (Bolt and Model S) within the household context. Our results also indicate that more frequent charging results in higher electrification of miles and a higher UF for both the PHEV and the household. However, it should be noted that we did not take charging duration into account. In addition, our results show that more frequent long-distance trips result in lower UF for the PHEV.

Concluding, our results provide an insight into the electrification of vehicle miles travelled within the household context which is rarely taken into consideration. The implication for policy makers is that PHEVs with a range of at least 35 miles have the potential to electrify a similar share of total household miles as some short range BEVs or can reach up to 70% as much electrification as some long range BEVs and thus can play an important role in decarbonizing the transport sector.

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